Environment and Planning B: Planning and Design 2008, volume 35, pages 1070 – 1097

doi:10.1068/b33022t

Transition challenges for alternative fuel vehicle and transportation systems

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Received 10 February 2006; in revised form 1 June 2007; published online 23 May 2008

Abstract. Automakers are now developing alternatives to internal combustion engines (ICE), including hydrogen fuel cells and ICE – electric hybrids. Adoption dynamics for alternative vehicles are complex, owing to the size and importance of the auto industry and vehicle installed base. Diffusion of alternative vehicles is both enabled and constrained by powerful positive feedbacks arising from scale and scope economies, research and development, learning by doing, driver experience, word of mouth, and complementary resources such as fueling infrastructure. We describe a dynamic model of the diffusion of and competition among alternative fuel vehicles, including coevolution of the fleet technology, behavior, and complementary resources. Here we focus on the generation of consumer awareness of alternatives through feedback from consumers' experience, word of mouth, and marketing, with a reduced-form treatment of network effects and other positive feedbacks (which we treat in other papers). We demonstrate the existence of a critical threshold for sustained adoption of alternative technologies, and show how the threshold depends on economic and behavioral parameters. We show that word of mouth from those not driving an alternative vehicle is important in stimulating diffusion. Expanding the model boundary to include learning, technological spillovers, and spatial coevolution of fueling infrastructure adds additional feedbacks that condition the diffusion of alternative vehicles. Results show scenarios for successful diffusion of alternative vehicles, but also suggest that marketing programs and subsidies for alternatives must remain in place for long periods for diffusion to become self-sustaining.

Introduction

At the end of the 19th century, New York, Boston, and Philadelphia were among the cities to welcome clean and silent electric automobiles to replace the polluting horse-drawn carriage. Users and inventors, including Thomas Edison, enthusiastically discussed the potential of electrics (Schiffer et al, 1994), and an electric car set the world speed record of 61 mph in 1899 (Flink, 1988). Yet sales of automobiles powered by internal combustion engines (ICE—all acronyms used in the paper are defined in table 1) quickly surpassed electrics and became the dominant design. Internal combustion, the auto, and cheap oil transformed the world, economically, culturally, and environmentally. Today, motivated by environmental pressures and rising energy prices, another transition, away from fossil-powered ICE vehicles, is needed.

Uncertainty abounds. Some envision an electric (plug-in) fleet (MacCready, 2004), while others call for hydrogen-fuel-cell vehicles (HFCVs) (Lovins and Cramer, 2004; Sperling and Ogden, 2004), ICE – electric hybrids (Demirdoven and Duetch, 2004),

Table 1. Acronyms used in the paper.

Acronym	Definition
AFV	alternative fuel vehicle
CNG	compressed natural gas
HFCV	hydrogen fuel cell vehicle
ICE	internal combustion engine
OEM	original equipment manufacturer (an auto company)
WtC	willingness to consider a platform

biofuels (Rostrup-Nielsen, 2005), compressed natural gas (CNG), or a mixed market [see Greene and Plotkin (2001), MacLean and Lave (2003), and Romm (2004) for discussion]. Dethroning ICE is difficult: multiple attempts to (re)introduce electric vehicles have failed (Hard and Knie, 2001), and initially promising programs to introduce natural gas vehicles stagnated in Italy and withered in Canada and New Zealand after initial subsidies ended (Flynn, 2002).

A common explanation for the failure of these programs is that the technologies are still immature and their costs too high (eg Flynn, 2002; Robertson and Beard, 2004; Romm, 2004). Certainly the high cost and low functionality of alternative fuel vehicles (AFVs), compared with ICE, limits their market potential today, because gasoline is priced below the level that would reflect its environmental and other negative externalities, particularly in the US. More subtly, the current low functionality and high cost of alternatives, and low gasoline taxes, are endogenous consequences of the dominance of the ICE and the petroleum industry, transport networks, settlement patterns, technologies, and institutions with which it has coevolved. The success of internal combustion suppresses the emergence of alternatives, maintaining the dominance of ICE.

These feedbacks mean, as we argue here, that achieving self-sustaining adoption would be difficult even if AFV performance equaled that of ICE today. The challenge facing policy makers seeking to promote a transition to sustainable alternative vehicles is how to overcome the barriers created by these feedbacks. Various challenges facing AFVs are recognized in the literature [regarding HFCVs, for example, Farrell et al (2003); National Academy of Engineering (2004); Ogden (2004)] but a thorough understanding of the dynamics of market formation for AFVs does not exist.

Our research aims to develop a behavioral, dynamic model to explore the possible transition from ICE to AFVs such as hybrids, CNG, biofuels, and HFCVs. Here we illustrate the importance of behavioral dynamics by focusing on the key processes conditioning innovation adoption: word of mouth, social exposure, and the willingness of consumers to consider an alternative platform. We also illustrate the importance of a broad model boundary by showing how the inclusion of additional feedbacks influences these dynamics. These feedbacks include research and development (R&D), learning by doing, technological spillovers across platforms, and the development of fueling infrastructure, all of which coevolve with the alternative vehicle installed base. We analyze diffusion dynamics through the development of a set of explicit behavioral dynamics models, using simulation to illustrate how diffusion proceeds under a variety of scenarios.

The paper is organized as follows. We first discuss the transition challenge for alternative vehicles, noting why AFV diffusion is potentially more complex than the diffusion of many new technologies. We provide a motive for the importance of a broad model boundary and the inclusion of behavioral factors conditioning consumer choice among vehicle platforms by discussing an earlier transition: the emergence of the horseless carriage. We then describe the broad boundary of the full dynamic model. Next we discuss the structure governing awareness and consumer choice in detail. Because parameters conditioning consumer choice and determining the attractiveness of conventional and alternative vehicles are highly uncertain, we focus on the global dynamics rather than on parameter estimation and forecasting. Results show that there is a tipping point in the diffusion of AFVs: successful adoption of alternative vehicles requires policies, such as subsidies for alternative vehicles and fueling infrastructure, that persist long enough to push the AFV installed base over a critical threshold.[1]

[1] Several terms are used for the total number of vehicles in use, including ‘fleet’, ‘car parc’, and ‘installed base’. The first generally refers to vehicles owned by firms or government agencies, while the second is commonly used to denote private vehicles. Throughout the rest of the paper we will be using the general term ‘installed base’.

Efforts falling short of the tipping point will not lead to sustained adoption. We show that the time required to achieve self-sustaining adoption is long—of the order of several decades—primarily due to the long life of vehicles. Through sensitivity analysis we also show how the threshold for self-sustaining adoption of alternative vehicles depends on key structures and parameters relating to consumer choice, awareness generation, and the average life of vehicles. We demonstrate the importance of a broad model boundary by showing that learning by doing, technological spillovers, and the development of complementary assets, such as fueling infrastructure, all significantly influence the tipping dynamics. We close with a discussion of the implications for policy makers seeking to promote a sustainable transition to alternative vehicles.

The transition challenge

Successful diffusion of AFVs is difficult and complex for several reasons. The enormous scale of the automobile industry and installed base creates a wide range of powerful positive feedback processes that confer substantial advantage to the incumbent ICE technology. Important feedbacks include vehicle improvements and cost reductions driven by scale economies, R&D, learning by doing, and field experience, all improving vehicle performance, sales, revenue, scale, and experience still further. Word of mouth and marketing stimulate awareness and adoption, boosting revenue and the installed base of new vehicles, generating still more word of mouth and marketing expenditure. Complementary resources play a key role. Alternatives, notably hydrogen-powered vehicles, require new infrastructure incompatible with ICE and petroleum. Drivers will not find AFVs attractive without ready access to fuel, parts, and repair services, but energy producers, automakers, and governments will not invest in AFV technology and infrastructure without the prospect of a large market—the so-called chicken and egg problem (Bentham, 2005; Farrell et al, 2003; National Academy of Engineering, 2004; Ogden, 2004). These positive feedbacks mean the evolution of new technologies is likely to be strongly path dependent [Arthur (1989); David (1985); Sterman (2000); also Moxnes (1992) explores path dependence in a model of competing energy technologies; and Fiddaman (2002) builds a behavioral dynamic model of climate–economy interactions and uses it to explore policies such as carbon taxes and cap-and-trade markets for carbon in the presence of induced technical change]. Additionally, AFV technologies enable radically new designs and materials (Burns et al, 2002). However, many of these innovations provide spillover opportunities to the dominant platform. For example, lightweight materials and drive-by-wire systems developed for AFVs can be used to improve the performance of conventional vehicles, undercutting AFV adoption. Finally, cars serve not only as transportation but as potent sources of personal identity and social status (Urry, 2004). Consumer choice is strongly shaped by cultural norms, personal experience, and social interactions (Hard and Knie, 2001; Kay, 1997; Miller, 2001).

Analysts suggest diverse approaches to stimulate a sustained transition to AFVs. Recognizing the many reinforcing feedbacks, some argue for incentives in the form of subsidies to consumers, automakers, or fuel providers to ‘prime the pump’ and overcome the chicken–egg problem (Farrell et al, 2003; National Academy of Engineering, 2004; National Ethanol Vehicle Coalition, 2005). But prior subsidy programs have often failed, or were not sustained long enough for AFV diffusion to become self-sustaining (Flynn, 2002). Without a deep understanding of the dynamic implications of an intervention, policies intended to stimulate may actually hinder large-scale adoption. For example, in the 1980s the Canadian government provided conversion rebates and fuel station grants to spur adoption of CNG vehicles. Stimulated by media attention, initial adoption was swift (15 000 vehicles with 80 refueling facilities during 1985). However the incentives did not reflect the challenges ahead. Initial players desperately tried to stay in business, but never became profitable. The failure led to a backlash of negative perceptions about alternative vehicles, for example, "Exaggerated claims have damaged the credibility of alternate transportation fuels, and have retarded acceptance, especially by large commercial purchasers" (Flynn, 2002, page 618). Once deemed a failure, technologies do not easily get a chance to rebound. For example, the US market for passenger diesel vehicles failed to take off in the 1970s and remains moribund, in contrast to the thriving market in Europe (Moore et al, 1998).

The transition to the current ICE-dominated system in the late 19th century provides insights into the challenges of creating an alternative transportation system (figure 1). The first automobiles generated a huge volume of discussion and press attention. Initial public opinion was often hostile, citing high costs, noise, danger, and high speeds. Experimentation was limited to a few 'outsiders' and affluent early adopters (Epstein, 1928; McShane, 1994; Smith, 1968). Although the automobile appeared on the streets of Philadelphia as early as 1804 (McShane, 1994), by 1900 the US had 18 million horses but only 8000 registered vehicles in a population of 76 million. What is more interesting, the installed base consisted mainly of steam and electric vehicles. Steam technology was mature, reliable, and familiar, and water and coal were widely available (Geels, 2005). Electric power was newer, but electric vehicles proved attractive in cities as taxis were quiet, started immediately, and did not smell. Battery performance was improving, and the future looked bright (Geels, 2005; Kirsch, 2000).

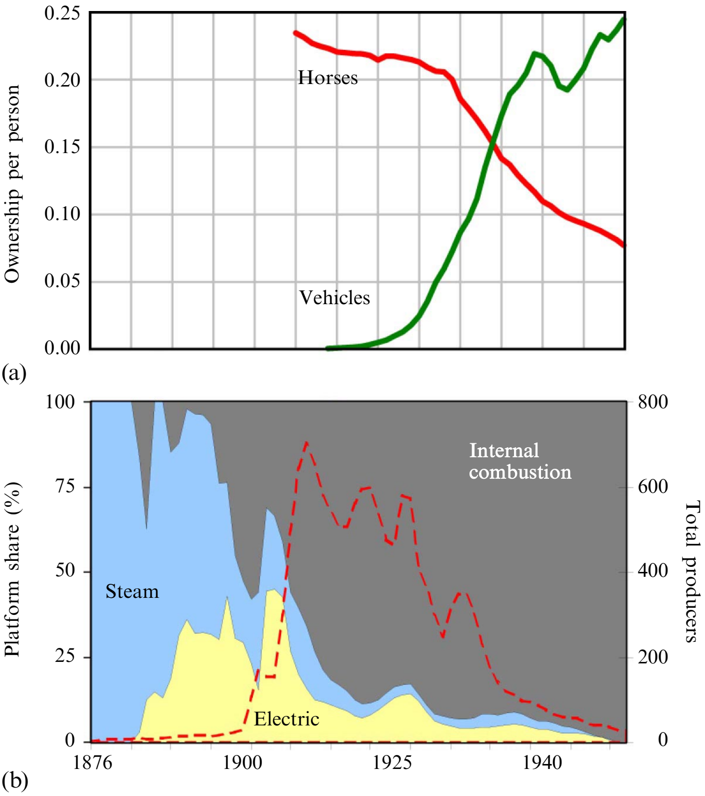

Figure 1. [In color online, see http://dx.doi.org/10.1068/b33022t] (a) Automobile and horse populations, US (1900 – 50) (source: US Bureau of the Census, 1997); (b) share of auto producers for each platform (internal combustion engines, steam, electric), with number of active producers (1876 – 1942) (source: compiled from Kimes and Clark, 1996).

The internal combustion engine was a late entrant—Benz demonstrated the first effective ICE vehicle in 1885 (Flink, 1970). Nevertheless, despite first-mover advantage, electric and steam vehicles were soon overtaken by ICE [figure 1(b)]. In 1912 registered electric cars peaked at 30 000, while the ICE installed base was already thirty times greater. Why did electrics fail, despite initial success and first-mover advantage? Changes in driver preferences played a role. The public developed an appetite for 'touring'—venturing into the countryside, where the advantages of electrics in cities were of little value. Power to recharge the batteries was not widely available, so few electrics were driven there. In turn, because few electrics ventured into the countryside, there was little incentive for entrepreneurs to develop recharging stations outside major cities, further limiting the appeal of electrics (Kirsch, 2000). ICE vehicles initially faced a similar situation, but fuel distribution through small retail establishments, itself facilitated by the automobile, enabled the gasoline distribution network to grow rapidly. Many towns had bicycle shops and mechanics skilled with the mechanical linkages and chain drives used in early ICE vehicles, while experience with batteries and electric motors was less widely distributed. The explosive growth of ICE vehicles also benefited from innovation spillovers—for example, replacement of the cumbersome hand-crank with electric starting in 1911 (Schiffer et al, 1994).

Word of mouth and related network effects played an important role in the rise of ICE. The larger the installed base of a platform, the greater the exposure to and knowledge of that platform among potential adopters, increasing the chances that they will consider and choose that platform. Such social exposure to new products, driven by contacts between adopters and potential adopters, is a cornerstone of innovation diffusion theory (Rogers, 1962).

More subtly, word of mouth among nondrivers played an important role. Early automobiles were feared due to their speed and perceived risks of explosion, but were also exciting novelties, attracting attention among those who had not yet purchased a car (McShane, 1994). These nondrivers, who were far more numerous than drivers, would then tell others about what they had seen, rapidly spreading awareness about each type of vehicle. Along with newspaper accounts and new journals dedicated to autos, word of mouth among nondrivers stimulated awareness of ICE faster than ICE vehicles could spread throughout the country (Flink, 1970; *The Horseless Age* 1896).

Thus social exposure to the auto, word of mouth among nondrivers, emerging preferences for and the improving convenience of long-distance travel, growing scale, experience, installed base and infrastructure, and innovation spillovers all interacted to spell the doom of the early market leaders. These intimate interdependencies between consumer choice and the evolution of technology still exist. The diffusion challenge for alternative vehicles today also differs from the 19th century, when low awareness, the huge potential for growth of the total installed base, undeveloped infrastructure, and lack of standards allowed ICE to overtake steam and electric despite their first-mover advantages and initially superior performance. Over a hundred years later, alternative vehicles face a mature industry, fully articulated infrastructure, powerful vested interests, and a society, economy, and culture tightly bound to ICE.

Research context

A robust policy analysis requires a model that integrates the various feedbacks described above. Our research aims to develop such a behavioral, dynamic model to explore the possible transition from ICE to AFVs such as hybrids, CNG, biofuels, and HFCVs. We built on models of the product lifecycle (eg Abernathy and Utterback, 1978; Klepper, 1996), but emphasize a broad boundary, endogenously integrating consumer choice—conditioned by product attributes, driver experience, word of mouth,

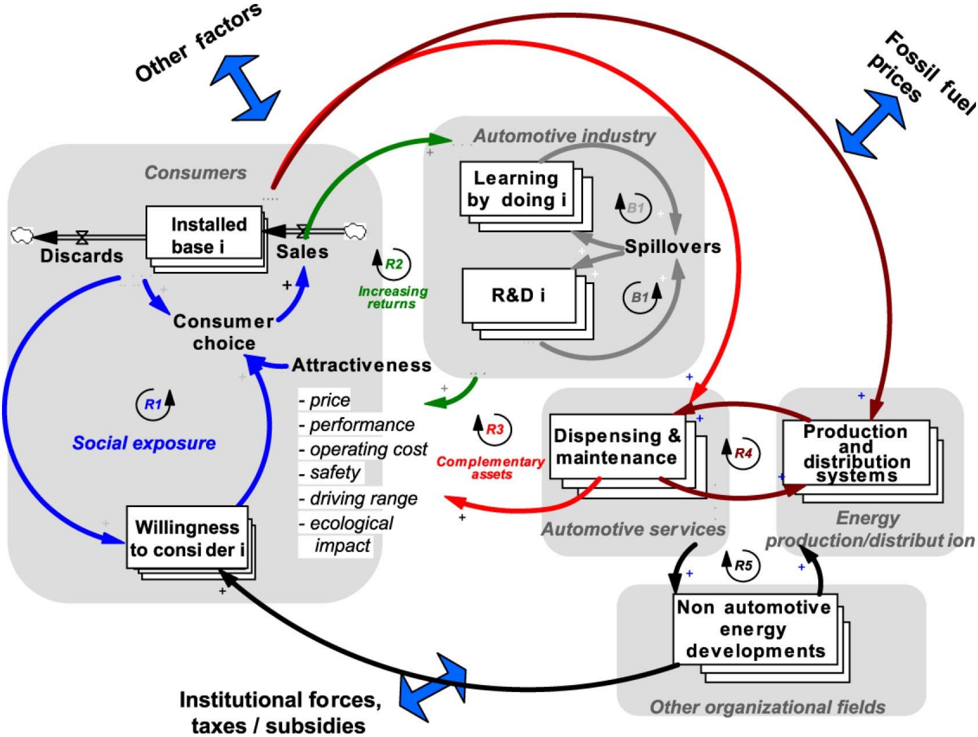

Figure 2. [In color online.] Full model boundary, stakeholders, and interdependencies (see Struben, 2006). This paper focuses on the social exposure dynamics guiding alternative fuel vehicle consideration and adoption.

marketing, and other channels—with scale economics, learning through R&D and experience, innovation spillovers, and infrastructure (figure 2).

The installed base of vehicles is disaggregated by platform (eg ICE, hybrid, CNG, HFCV); the model does not represent individual OEMs (original equipment manufacturers—the auto companies). Consumers' choice among platforms depends on their consideration set, and, within that set, the relative attractiveness of each consideration (Hauser et al, 1993). Consumers consider a particular option only when sufficiently familiar with it. A consumer's willingness to consider a vehicle type increases through direct exposure to the different platforms, marketing, media attention, and word of mouth. The attractiveness of each platform in the consideration set is a function of attributes including price, operating cost, performance, driving range, fuel and service availability, and ecological impact. We use standard multinomial logit choice frameworks (Ben-Akiva and Lerman, 1985; McFadden, 1978; 2001; Theil, 1969) to model consumer choice among platforms in the consideration set.

Attributes of attractiveness for each platform—performance, cost, range, etc—improve endogenously through learning by doing, R&D, and scale economies. R&D and learning by doing lead to improvement for an individual platform, but may also spill over to other platforms. Complementary assets—such as service, parts, maintenance, and fuel distribution infrastructure—critically influence a platform's attractiveness. In turn, the installed base conditions the profitability of such infrastructure. Infrastructure development also requires a fuel supply chain (Ogden, 2004), thereby creating additional positive feedbacks through interactions with other industries (eg as petroleum replaced coal for home heating, and as HFCVs may coevolve with stationary fuel cells).

In this paper we investigate in detail one set of feedbacks that condition alternative fuel vehicle diffusion: adoption generated by consumer's consideration of alternative vehicles through feedback from driving experience, word of mouth, and marketing. We draw on innovation-diffusion models (for example, Bass, 1969; Mahajan et al, 1990; 2000; Norton and Bass, 1987) and their applications in the auto industry (Urban et al, 1990; 1996). We integrate diffusion with discrete consumer choice models (Ben-Akiva and Lerman, 1985; McFadden, 1978), models often applied to transport mode choice (Domencich et al, 1975; Small et al, 2005), and automobile purchases (Berry et al, 1995; Train and Winston, 2005), including alternative vehicles (Brownstone et al, 2000; Dagsvik et al, 2002; Greene, 2001). Related research focuses on learning, R&D, and innovation spillovers, and models the coevolution of vehicle adoption and fueling infrastructure location decisions in an explicit spatial framework (Struben, 2006); Struben (2007) describes the full model. Here we use a reduced-form model to represent these and other effects, while highlighting the importance of consumer awareness and consideration of AFVs. This focus allows us to simplify the model exposition and build intuition regarding important processes conditioning consumer adoption and diffusion. In order to examine the robustness of the reduced-form model we then gradually relax simplifying assumptions to see how expanding the model boundary affects potential diffusion paths for AFVs. These additional interactions include processes such as learning by doing, technology spillovers across platforms, and the coevolution of the AFV market and fueling infrastructure, including explicit spatial inhomogeneities.

Our purpose is not to predict diffusion paths for specific AFVs. Such attempts are premature due to the great uncertainty in the attributes of AFVs (eg cost, performance, efficiency, range), in the policy environment (eg the cost of gasoline versus alternative fuels, subsidies for vehicles, and/or fueling infrastructure), and particularly in parameters conditioning consumer choice among AFVs. To address the great uncertainty in key parameters we focus on characterizing the global dynamics and mapping the parameter space. We conduct sensitivity analysis to identify high-leverage parameters, guiding subsequent effort to elaborate the model and gather needed data.

Structure and dynamics of adoption

We begin with the installed base and consumer choice among vehicle platforms. The total number of vehicles for each platform $j = \{1, ..., n\}$, V_j, accumulates new vehicle sales, s_j, less discards, d_j;

$$\frac{\mathrm{d}V_j}{\mathrm{d}t} = s_j - d_j \,. \tag{1}$$

Discards are age dependent. Sales consist of initial and replacement purchases. Initial purchases dominated sales near the beginning of the auto industry, and do so today in emerging economies such as China, but in developed economies replacements dominate. For simplicity we assume an exogenous fractional growth rate for the total installed base. Thus:

$$s_j = \sum_i \sigma_{ij}(d_i + gV_i)\,, \tag{2}$$

where σ_{ij} is the share of drivers of platform i replacing their vehicle with platform j, and g is the fractional growth of the installed base. The term $\sigma_{ij} gV_i$ ensures that the total installed base will grow at rate g and assumes, reasonably, that people buying their first car or adding another car to their household are familiar with platform i

in proportion to each platform's share of the total installed base. The share switching from platform i to j depends on perceived platform affinity, a_{ij}^{p}, a population-aggregated utility effect which, in standard multinomial logit choice models, is an exponential function of the utility of platform j as judged by the driver of vehicle i.(2) Because driver experience with and perceptions about the characteristics of each platform may differ, the expected utility of, for example, the same fuel cell vehicle may differ among those currently driving an ICE, hybrid, or fuel cell vehicle, even if these individuals have identical preferences. Hence,

$$\sigma_{ij} = \frac{a_{ij}^{\mathrm{p}}}{\sum_j a_{ij}^{\mathrm{p}}} . \tag{3}$$

Perceived affinity depends on two factors: while drivers may be generally aware that a platform exists, they must be sufficiently familiar with and knowledgeable about that platform for it to enter their consideration set. Next, for those platforms considered, expected utility depends on (perceptions of) various vehicle attributes. To capture the formation of a driver's consideration set we introduce the concept of a consumer's *willingness to consider* a platform. Willingness to consider (WtC) denotes more than simple familiarity. Many people are aware that hybrid vehicles exist, but do not take them seriously in their purchase decision. Willingness to consider a platform captures the cognitive, emotional, and social processes through which drivers gain enough information about, understanding of, and emotional attachment to a platform for it to enter their consideration set. The willingness to consider platform j by drivers of vehicle of i is denoted W_{ij}. Everyone considers ICE, so $W_{i,\,\mathrm{ICE}} = 1$, while $W_{ij} = 0$ for those completely unfamiliar with platform j; such individuals do not even consider such a vehicle: $W_{ij} = 0$ implies $\sigma_{ij} = 0$. Hence

$$a_{ij}^{\mathrm{p}} = W_{ij} a_{ij} , \tag{4}$$

where the affinity for platform j among those driving platform i, a_{ij}, depends on vehicle attributes for platform j, as perceived by driver i. Below we model affinity endogenously using a multinomial logit framework [eg equation (14)]. In order to explore the dynamics of the consideration set, however, we begin by assuming that the affinity of each vehicle platform is exogenous.

For the aggregate population average WtC varies over the interval [0, 1]. WtC increases in response to social exposure, and also decays over time:

$$\frac{\mathrm{d}W_{ij}}{\mathrm{d}t} = \eta_{ij}(1 - W_{ij}) - \phi_{ij} W_{ij} , \tag{5}$$

where η_{ij} is the impact of total social exposure on the increase in familiarity, and ϕ_{ij} is the average fractional decay of willingness to consider platform j among drivers of platform i.(3)

Total exposure to a platform arises from three components: (i) marketing, (ii) word-of-mouth contacts with drivers of that platform, and (iii) word of mouth about the platform among those not driving it, yielding:

$$\eta_{ij} = \alpha_j + c_{ijj} W_{jj} \frac{V_j}{N} + \sum_{k \neq j} c_{ijk} W_{kj} \frac{V_k}{N} . \tag{6}$$

(2) See equation (14). Formally, affinity is an exponential function of utility when the unobserved error terms are iid Gumbel distributed.

(3) The full formulation accounts for the transfer of WtC associated with those drivers who switch platforms (see appendix at http://dx.doi.org/10/1068/b33022t/). Struben (2006) shows that the simplification shown here does not affect the qualitative dynamics.

Here α_j is the effectiveness of marketing and promotion for platform j. The second term captures word of mouth about platform j vehicles—social exposure acquired by seeing them on the road, riding in them, talking to their owners. Such direct exposure depends on the fraction of the installed base consisting of platform j, V_j/N, and the frequency and effectiveness of contacts between drivers of platforms i and j, c_{ijj}. The third term captures word of mouth about platform j arising from those driving a different platform, $k \neq j$—for example, an ICE driver learning about hydrogen vehicles from the driver of a hybrid.[4]

It takes effort and attention to remain up to date with new vehicle models and features. Hence the willingness to consider a platform erodes unless refreshed through marketing or social exposure. The loss of consideration is highly nonlinear. When exposure is infrequent, WtC decays rapidly: without marketing or an installed base, the electric vehicle, much discussed in the 1990s, has virtually disappeared from consideration. But once exposure is sufficiently intense, a technology is woven into the fabric of our lives, emotional attachments, and culture: 'automobile' implicitly connotes 'internal combustion'—WtC for ICE = 1 and there is no decay of consideration. Thus the fractional decay of WtC is:

$$\phi_{ij} = \phi_0 \mathrm{f}(\eta_{ij}); \quad \mathrm{f}(0) = 1, \quad \mathrm{f}(\infty) = 0, \quad \mathrm{f}'(\cdot) \leqslant 0. \tag{7}$$

WtC decays faster (up to the maximum rate ϕ_0) when total exposure to a platform, η_{ij}, is small. Greater exposure reduces the decay rate, until exposure is so frequent that decay ceases. We capture these characteristics with the logistic function

$$\mathrm{f}(\eta_{ij}) = \frac{\exp[-4\varepsilon(\eta_{ij} - \eta^*)]}{1 + \exp[-4\varepsilon(\eta_{ij} - \eta^*)]}, \tag{8}$$

where η^* is the reference rate of social exposure at which WtC decays at half the normal rate, and ε is the slope of the decay rate at that point. To gain intuition for the dynamics of WtC, consider an extreme situation in which there are no AFVs on the road to generate social exposure, and in which AFV marketing suddenly ceases altogether. In this situation, ICE drivers can only learn about AFVs from other ICE drivers. With the base parameters (table 2), it takes more than five years for the fraction of consumers willing to consider an AFV to fall from 50% to 5%. In the presence of marketing or social exposure to AFVs, WtC decays even more slowly, and, with the base case parameters, WtC grows from 50% to 100% when AFVs constitute more than 5% of the total installed base. Varying η^* and ε enables sensitivity testing over a wide range of assumptions about the decay of WtC.[5]

Word of mouth and social exposure from AFV drivers create positive feedbacks that can boost consideration and adoption of AFVs (figure 3). First, a larger alternative installed base enhances WtC through social exposure, as people see the vehicles on the roads and learn about them from their drivers. A greater WtC for AFVs, in turn, increases the fraction of people who consider AFVs when replacing their current vehicle and, if AFV utility is high enough, increases the share of purchases going to AFVs (the reinforcing social exposure loop R1a). Further, as the AFV installed base grows, people increasingly see and hear about them, and they become more socially acceptable, suppressing the decay of WtC (reinforcing loop R1b).

[4] Equation (6) can be written more compactly as $\eta_{ij} = \alpha_j + \sum_k c_{ijk} W_{kj} (V_k/N)$; we use the form above to emphasize the two types of word of mouth (direct and indirect).

[5] Many other functional forms that obey equation (7) are possible. Struben (2004) shows that the results here are robust with respect to other plausible functional forms. We discuss sensitivity to the parameters in equation (7) below.

Table 2. Base-case parameters. AFV: alternative fuel vehicle; ICE: internal combustion engines; WtC: willingness to consider.

	Definition	Unit	Value	Note
g	growth rate of the total installed base	year^{-1}	0	See sensitivity analysis.
α_2	AFV marketing effectiveness	year^{-1}	0.01	See, for example, Easingwood et al (1981) and sensitivity analysis.
c_{122}	strength of word of mouth about AFVs for contacts between AFV and ICE drivers	year^{-1}	0.25	See, for example, Easingwood et al (1981) and sensitivity analysis.
c_{121}	strength of word of mouth about AFVs for contacts between ICE and other ICE drivers	year^{-1}	0.15	Weaker than that of drivers. See also sensitivity analysis.
ϕ_0	maximum WtC loss rate	year^{-1}	1	Heuristic, argued in paper (see sensitivity analysis).
η^*	reference rate of social exposure	year^{-1}	0.05	Heuristic—implies that inflection point for forgetting is at 10% of adoption.
ε	slope of WtC decay rate at reference rate	years	$1/2\eta^*$	Normalizes elasticity of WtC decay to exposure at 1—argued in paper (see sensitivity analysis).
λ	average vehicle life	years	8	Conservative: Greenspan and Cohen (1999) estimate over twelve years. See sensitivity analysis.
Parameters used for expanded model boundary				
β	sensitivity of utility to performance	–	0.3	Conservative heuristics—for example, Brownstone et al (2000).
ξ	elasticity of substitution between platform internal and external experience	–	1.5	Heuristic—argued in paper.
γ	learning curve strength	–	0.379[a]	Argote and Epple (1990).
E_0	reference years of effective experience	years	20	Heuristic—argued in paper.
τ_{ij}	experience spillover time	years	8	Heuristic—argued in paper.

[a] The learning curve exponent γ is calculated from the assumed fractional performance improvement per doubling of knowledge, $(1+\Delta)P_0 = P_0(2K_0/K_0)^{\gamma}$, or $\gamma = \ln(1+\Delta)/\ln(2)$. We assume a 30% learning curve, $\Delta = 0.3$, so $\gamma = 0.379$.

Second, the consideration of AFVs among those driving ICE vehicles increases through word-of-mouth contacts with other ICE drivers who have seen or heard about them, leading to still more word of mouth (reinforcing loops R2a and R2b). The impact of encounters among nondrivers is likely to be weaker than that of direct exposure to an AFV, so $c_{ijj} > c_{ijk}$, for $k \neq j$. However, the long life of vehicles means AFVs will constitute a small fraction of the installed base for years after their introduction. The majority of information conditioning the consideration of alternatives among potential adopters will arise from marketing, media reports, and word of mouth from those not driving AFVs. Word of mouth arising from interactions between

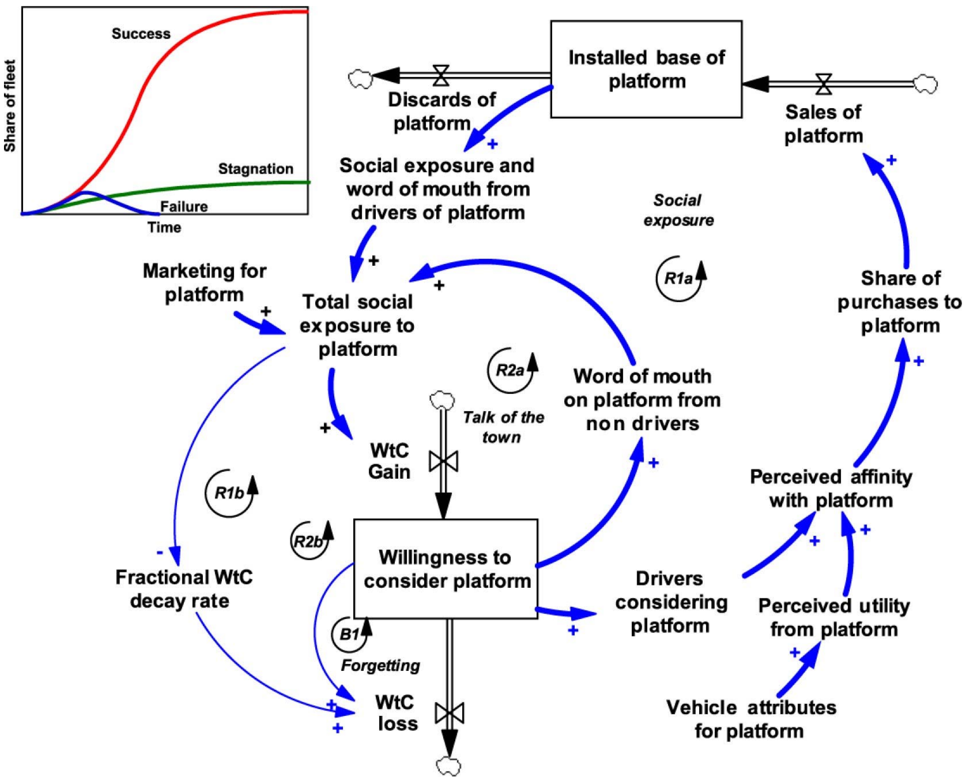

Figure 3. [In color online.] The principal positive feedbacks conditioning consumer willingness to consider (WtC) and choice for a platform, with expected modes of behavior.

AFV adopters and potential adopters will dominate only after large numbers have already switched from ICE to alternatives.

The dynamics of AFV consideration

The model generalizes to any number of vehicle platforms and constitutes a large system of coupled differential equations. To gain intuition into the diffusion of alternative vehicles, we analyze a simplified version with only two platforms, ICE ($j = 1$) and an AFV ($j = 2$). That is, we group all AFVs under one nest in the consumer choice process, implying that consumers first choose between ICE and an AFV, then among AFVs available on the market—for example, first deciding to consider a hybrid, then choosing among the hybrids offered by different carmakers.[6] The larger the number of different AFVs available, the greater the overall attractiveness of the AFV category will be—when the only hybrids available were the Honda Insight and Toyota Prius, their appeal to the average consumer was limited; but as hybrid sedans, SUVs, and luxury vehicles are released the appeal of the hybrid category grows. Today the number of AFVs available is small and their attributes (cost, size, power, range, etc) are unfavorable compared with ICE vehicles. Naturally, diffusion will be slow in the absence of large subsidies or sustained high gasoline prices. But would diffusion

[6] Research shows that purchase decisions are nested (Ben-Akiva, 1973): consumers first decide between distinct classes of vehicles (say ICE or AFVs) on the basis of the representative utility of each class, and next make selections within a class. Nests can be several levels deep. Struben (2006) discusses the technical issues in nested multinomial logit choice models in the context of AFV purchase decisions.

accelerate, and, more importantly, become self-sustaining, if the attractiveness of AFVs improved? To examine these questions we assume, optimistically, that the utility derived from the ensemble of AFVs equals that of the ICE ensemble, even though the number and variety of ICE vehicles is far greater than the number and variety of AFVs likely to be available in the near future. When the average utility of the AFV category equals that of ICE the equilibrium market share of each platform should be 50%, provided that consumers are willing to consider the AFV category. If, however, some consumers are insufficiently familiar with AFVs to consider them in their purchase decision, the equilibrium AFV share of the market will be less than half.

Table 2 shows base-case parameters. We choose parameters governing social exposure and consumer choice consistent with values reported in empirical studies in the marketing literature (eg Easingwood et al, 1981). Below we report sensitivity analysis and comment in more detail on the justification of the parameter choices.

Model behavior: willingness to consider AFVs

To illustrate the central dynamics, we first assume constant driver population and vehicles per driver, so the total installed base, $N = \sum V_i$, is constant. We relax this assumption below to examine the impact of rapid growth in the installed base, as in emerging economies. We can simplify the structure further by reasonably assuming that the willingness to consider ICE remains constant at 1 throughout the time horizon. Further, AFV drivers are assumed to be willing to consider AFVs. Thus

$$\mathbf{W} = \begin{bmatrix} 1 & W_{12} \\ 1 & 1 \end{bmatrix}, \tag{9}$$

significantly reducing the dimensionality of the model.

Long vehicle life means the composition of the installed base will remain roughly fixed in the first years after alternatives are introduced. Assuming the installed base of each platform is fixed reduces the model to a first-order system where the change in the willingness to consider AFVs among ICE drivers, $\mathrm{d}W_{12}/\mathrm{d}t$, is determined only by the level of consideration itself, along with constant effects of marketing and social exposure to the small alternative installed base.

Figure 4 shows the phase plot governing of the consideration of AFVs among ICE drivers for a situation with a strong marketing program for AFVs and a modest initial installed base (table 2 lists model parameters). The thick lines show the gain, loss, and net change in the WtC as they depend on WtC itself [equation (5)]. The dotted lines show how marketing, social exposure to drivers of the alternative vehicle, and word of mouth from nondrivers contribute to the gain in WtC [equation (6)]. When the fraction willing to consider AFVs is low, word of mouth from nondrivers is negligible, and the gain in WtC comes only from marketing and exposure to the few AFVs on the road. Since the total volume of exposure is small, the decay time constant for WtC is near its maximum [equation (7)]. As WtC increases, word of mouth about AFVs among ICE drivers becomes more important, and increasing total exposure reduces WtC loss.

The system has three fixed points. There are stable equilibria near $W = 1$, where WtC decay is small, and near $W = 0$, where word of mouth from nondrivers is small and WtC decay offsets the impact of marketing and exposure to the small AFV installed base. In between lies an unstable fixed point where the systems dynamics are dominated by the positive feedbacks R2a and R2b. The system is characterized by a threshold, or tipping point. For adoption to become self-sustaining, WtC must rise above the threshold, otherwise it (and thus consumer choice) will tend toward the low consideration equilibrium. The existence and location of the tipping point depends on parameters. Sensitivity analysis (Struben, 2006) shows that the low WtC equilibrium

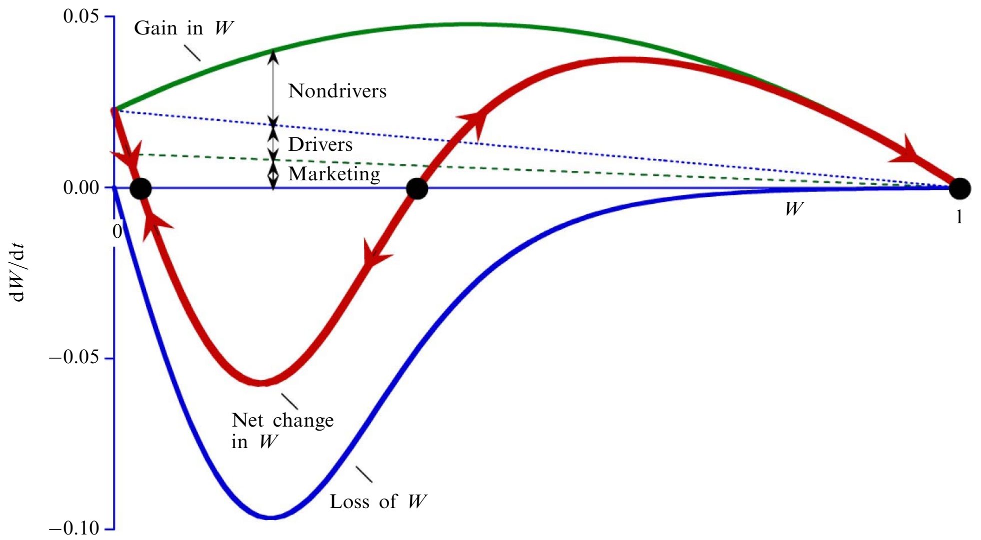

Figure 4. [In color online.] Phase plot for a one-dimensional system showing two stable, and one unstable, fixed points for the willingness of internal combustion engine drivers to consider the purchase of an alternative fuel vehicle (parameters in table 2).

increases, and the tipping point falls, as (i) the magnitude of marketing programs for AFVs, α_2, rises; (ii) the impact of word of mouth about AFVs between AFV and ICE drivers, c_{122}, increases; (iii) the size of the initial alternative installed base grows; (iv) the impact of word of mouth about AFVs within the population of ICE drivers, c_{121}, increases; and (v) as WtC is more durable (smaller ϕ_0 and η^* and larger ε). As these parameters become more favorable for AFV adoption, the unstable fixed point merges with the lower stable equilibrium; eventually the lower equilibrium disappears, yielding a system with a single stable equilibrium at high WtC.

A second-order model: consideration and adoption

We now relax the assumption that the share of alternative vehicles is fixed, adding the social exposure loops R1a and R1b. We simplify the dynamics of installed based turnover [equation (2)] by aggregating the installed base of each platform into a single cohort with constant average vehicle life $\lambda_j = \lambda$, yielding

$$d_j = \frac{V_j}{\lambda}. \tag{10}$$

The online appendix and Struben (2006) treat age-dependent discards and initial purchases. For now, let the installed base growth rate $g = 0$, implying a constant total installed base N. Then, since $V_2 = N - V_1$, the dynamics are completely characterized by the evolution of the alternative, which, from equations (1) and (2), is

$$\frac{\mathrm{d}V_2}{\mathrm{d}t} = \frac{\sigma_{22} V_2 + \sigma_{12}(N - V_2) - V_2}{\lambda}. \tag{11}$$

From equations (3) and (4) the fraction of drivers purchasing an AFV is

$$\sigma_{i2} = \frac{W_{i2} a_{i2}}{W_{i1} a_{i1} + W_{i2} a_{i2}}. \tag{12}$$

As before, we assume AFV drivers are fully familiar with AFV attributes and consider AFVs in their next purchase decision, and that everyone considers ICE. Assuming for now that the perceived affinities a_{jj} are also constant, σ_{22} is constant at $a_{22}/(a_{22}+a_{21})$ and

$$\sigma_{12} = \frac{W_{12}a_{12}}{a_{12}+W_{12}a_{12}}. \tag{13}$$

These assumptions reduce the system to a pair of coupled differential equations with state variables V_2 (the AFV installed base) and W_{12} (the willingness of ICE drivers to consider AFVs).

Figure 5 shows the phase space of the system for several parameter sets, plotting the consideration of AFVs among ICE drivers, W_{12}, and the AFV share of the total installed base, V_2/N. Because the system now involves only these two state variables, each point in the phase space $(W_{12}, V_2/N)$ determines the rate of change for both state variables [equations (5) and (11)], hence completely determining the dynamics. The nullclines (thick lines) are the loci of points for which the rate of change in a state variable is zero. Fixed points exist where nullclines intersect (large dots). In all cases we optimistically assume the ensemble of AFVs available on the market equals ICE in features, cost, and variety, implying that the utility of the two platforms is equal and

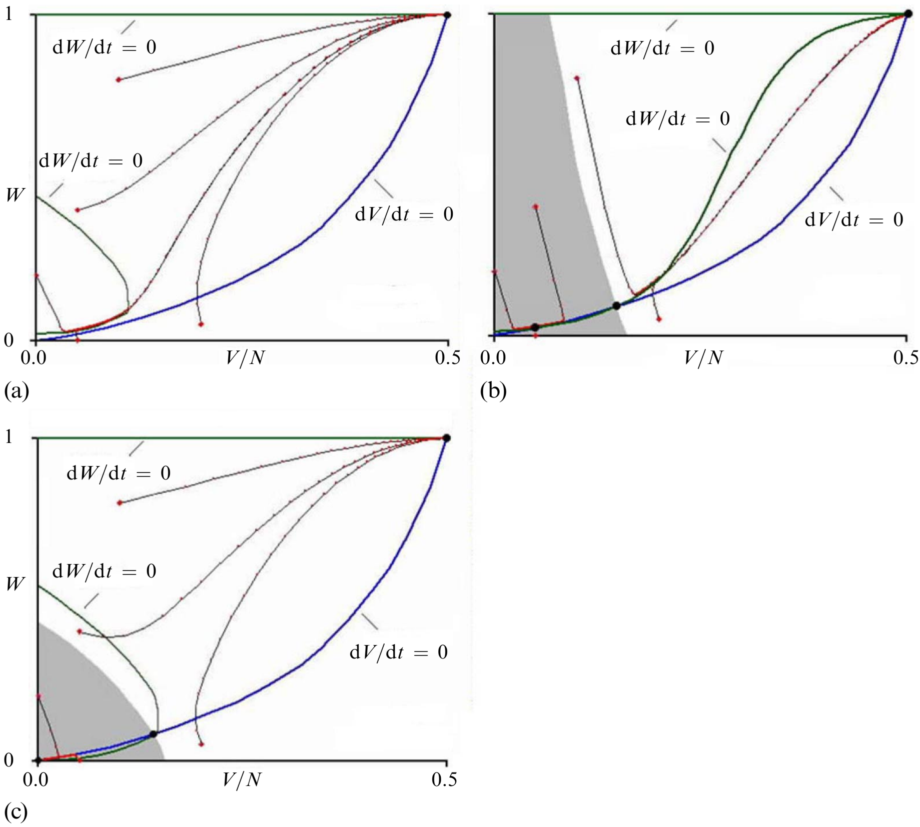

Figure 5. [In color online.] Phase space for a two-dimensional system with endogenous willingness to consider and vehicle installed base. Fixed points exist at intersections of nullclines; dots show sample trajectories. The grey area shows the basin of attraction for the low-diffusion equilibrium. The strength of marketing, α, and nondriver word of mouth, c_{ijk} are: (a) $\alpha = 0.01$, $c_{121} = 0.15$; (b) $\alpha = 0.01$, $c_{121} = 0.00$; (c) $\alpha = 0.00$, $c_{121} = 0.15$. Other parameters are as given in table 2.

the AFV purchase share is 0.5 when drivers are willing to consider both platforms. Therefore (1, 0.5) gives a stable equilibrium.

Figure 5(a) shows the phase space assuming a moderately effective AFV marketing program and no nondriver word of mouth. There are fixed points, as in the one-dimensional case, and the state space is divided into two basins of attraction (dark and light regions). Thin lines show the trajectories of the state variables for various initial conditions (small dots). With a small initial AFV installed base, AFV consideration and the installed base decay to low levels, even if the initial WtC is high. On the other side of the separatrix dividing the basins, WtC rises and more ICE drivers switch to AFVs, thereby further increasing WtC and triggering still more switching. Figure 5(b) shows a case with no AFV marketing but moderate nondriver word of mouth. As in the one-dimensional case, indirect word of mouth among ICE drivers shrinks the basin of attraction for the low-adoption equilibrium. In figure 5(c) marketing and nondriver word of mouth are large enough such that there is only one fixed point: any initial condition will lead, ultimately, to an equilibrium with high WtC and AFV adoption.

In figure 5 marketing impact is constant. In reality, marketing is endogenous. Successful diffusion boosts revenues, enabling marketing to expand, while low sales limit resources for promotion. Declining marketing effort lowers α_2, moving the low-diffusion equilibrium toward the origin and enlarging its basin of attraction. Figure 6 illustrates this with a set of simulations beginning with no WtC or instilled base for the alternative. An aggressive promotion campaign, $\alpha_2 = 0.025$, begins at $t = 0$. In each simulation the campaign ends after T years where $0 \leqslant T \leqslant 50$. In each simulation the AFV share of sales increases rapidly, even when WtC is low. However, the installed base grows slowly, because of the long life of vehicles. We conservatively assume vehicle life to be only eight years, shorter than the estimates for light duty vehicles in the US of 10–15 years (Greenspan and Cohen, 1999). When the campaign is short, WtC and market share drop back after the marketing campaign ceases, despite initial success: the campaign did not move the system across the basin boundary. Such collapse has been observed. For example, attempts to introduce CNG vehicles in Canada and New Zealand faltered after a decade of subsidies, and promotion campaigns expired, despite initial diffusion. We define the critical marketing duration, T^*, as the length of time marketing programs must persist to raise the AFV installed base and WtC out of the low-adoption basin of attraction such that adoption proceeds to the high-market-share equilibrium. As shown, with the optimistic parameters used here the critical promotion duration is $T^* \approx 19.9$ years. In this simulation, when the promotion campaign is terminated, the willingness to consider AFVs among ICE drivers is 0.23 and AFVs have captured 22% of the market, while their installed base share is 11%.[7] In equilibrium, the AFV market share and the share of the installed base rise to about 16%, while consideration of AFVs among the remaining 84% of ICE drivers falls to about 0.11. The trajectory of WtC and AFV market share at the critical marketing duration follows the unstable basin boundary between high and low AFV adoption. Longer marketing programs drive the system into the regime in which AFV adoption is self-sustaining, while shorter programs fail to move the AFV market over the tipping point,

(7) The 22% AFV market share arises as follows: from equations (3) and (4), the share of sales among drivers of each platform $\sigma_{ij} = W_{ij} a_{ij} / \sum_j (W_{ij} a_{ij})$. Since AFV and ICE vehicles are assumed to be equally attractive, $a_{ij} = a$, $\sigma_{ij} = W_{ijj} / \sum_j W_{ij}$. About 11% of total vehicle demand arises from AFV drivers replacing their current AFV. Since all AFV drivers are willing to consider both ICE and another AFV, $\sigma_{\text{AFV, AFV}} = 1/(1+1) = 0.5$. Among the 89% of drivers replacing an ICE vehicle, willingness to consider AFVs is 0.23, so $\sigma_{\text{AFV, ICE}} = 0.23/(0.23+1) = 0.187$. Thus total AFV market share is $(0.11)(0.50) + (0.89)(0.187) \approx 0.22$.

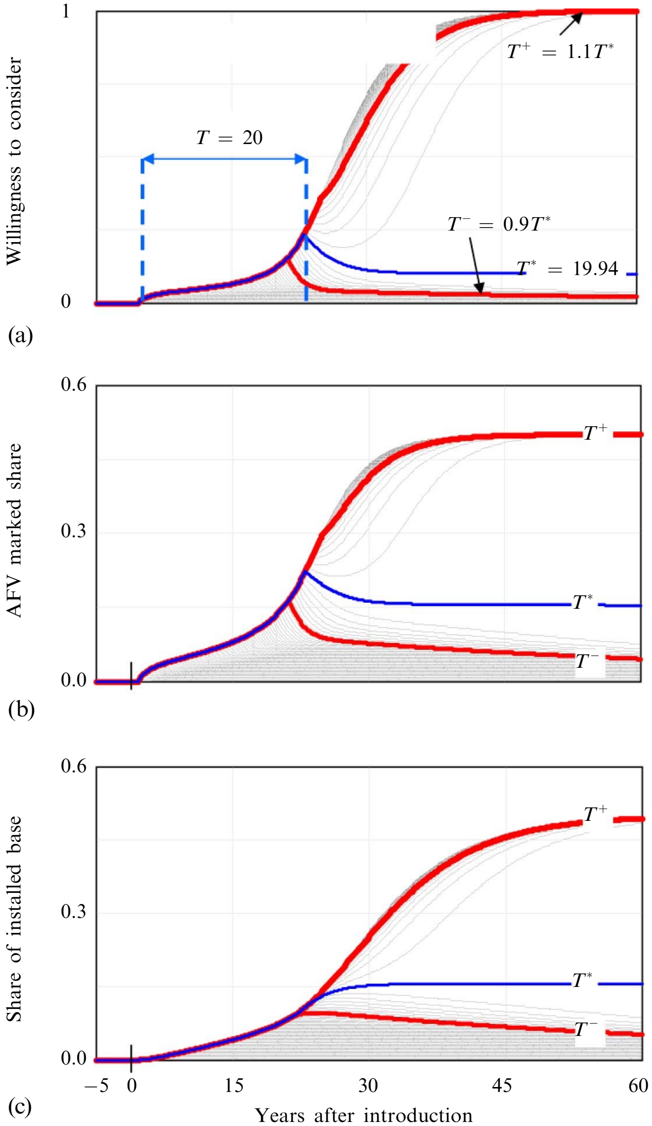

Figure 6. [In color online.] Willingness to consider alternative fuel vehicles (AFVs) (a), AFV market share (b), and the share of the installed base (c) among internal combustion engine drivers with an aggressive AFV marketing and promotion campaign. The duration of the marketing program ($\alpha_2 = 0.025$) varies between 0 and 50 years. Thick lines show market evolution at the critical marketing duration separating the high-diffusion and low-diffusion equilibria $T^* = 19.94$ years), and the trajectories for program durations are varied by ±10%.

leading to the failure of the AFV market. These dynamics are illustrated by the two other thick lines in figure 6, where the duration of the AFV marketing program is varied by ±10% around the critical value. Their paths deviate dramatically. When the marketing campaign lasts only two years longer than the tipping point, the AFV market takes off rapidly, with more than half of ICE drivers willing to consider AFVs just two years after the campaign ends. When the campaign ends after about eighteen years, just short of the tipping point, the willingness to consider AFVs among ICE drivers falls, dragging AFV market share down and leading to decline in the AFV share of the installed base. The dynamics are similar for situations in which the effectiveness of marketing is varied instead of the duration of the marketing program.

Expanding the model boundary to recognize that marketing effort is endogenous closes another positive feedback that may hinder diffusion of alternative vehicles. The long life of the vehicle installed base and slow initial development of WtC imply that AFV marketing and subsidy programs must be sustained for long periods before diffusion crosses the tipping point and the AFV market becomes self-sustaining.

Sensitivity to parameters and market growth

The technical characteristics of AFVs, including performance, range, fuel efficiency, and cost, are subject to large uncertainties. The policy environment, including possible taxes on gasoline and subsidies for AFVs, is also highly uncertain. Finally, because AFVs, particularly those powered by novel fuels, including biodiesel and hydrogen, are not yet widely available, the parameters conditioning consumer awareness and purchase decisions are poorly constrained by available market research. Sensitivity analysis is therefore essential to respond to the large uncertainties, to build intuition regarding the dynamics of AFV diffusion, and to examine the robustness of policies.

Base-case values for the main behavioral parameters conditioning WtC and consumer choice are based on estimates from the marketing literature—including durable consumer goods such as microwaves, color televisions, and refrigerators (eg Bass, 1980; Bass et al, 1994; Easingwood et al, 1989; Mahajan et al, 1990; Sultan et al, 1990). The key parameters are marketing effectiveness (the external influence coefficient in the Bass model) and contact effectiveness of drivers (the internal influence coefficient). Typical estimates for these parameters for consumer durables range from 0.00 to 0.02 for marketing effectiveness and 0.0 to 0.3 for contact effectiveness, while the role of nonadopters (in our context, nondrivers generating word of mouth about AFVs) is not considered. We selected a marketing effectiveness of 0.025 and a contact effectiveness of 0.25 for the base run. These values are likely to be optimistic for AFVs for various reasons. First, they are on the high side compared with typical estimates from the marketing literature. Second, most diffusion models do not distinguish the multiple positive feedbacks that condition adoption, including learning by doing, R&D, and network externalities. Consequently the impact of all such positive feedbacks is loaded into the word-of-mouth effect, overestimating contact effectiveness. Third, empirical marketing research tends to report estimates for successful products as failed products do not generate sufficient data to estimate diffusion model parameters, thereby introducing selection bias favoring high estimates. Finally, automobiles are more expensive and durable, and the purchase decision more complex and emotionally laden, than that for products such as microwaves, televisions, and refrigerators.

We now consider how the results vary with these and other parameters (figure 7). The base case is the simulation in figure 6, in which marketing programs to promote AFVs are maintained for twenty years, long enough for AFV diffusion to become self-sustaining. Figure 7 shows the sensitivity of the AFV installed base share to broad variation in key parameters. Each panel shows the time required for AFVs to reach 15% and 25% share of the installed base. The reference points indicate the values for the base run (about thirty and forty-five years, respectively). First we consider the sensitivity of AFV diffusion to the parameters governing awareness and WtC: the impact of social exposure arising from drivers, from word of mouth generated by nondrivers, and from marketing and promotion. As expected, the stronger these effects, the faster diffusion proceeds. Note, however, that values more optimistic than the base case have relatively modest impact and exhibit strongly diminishing returns, while values less than the base case dramatically slow AFV diffusion. For example, doubling the

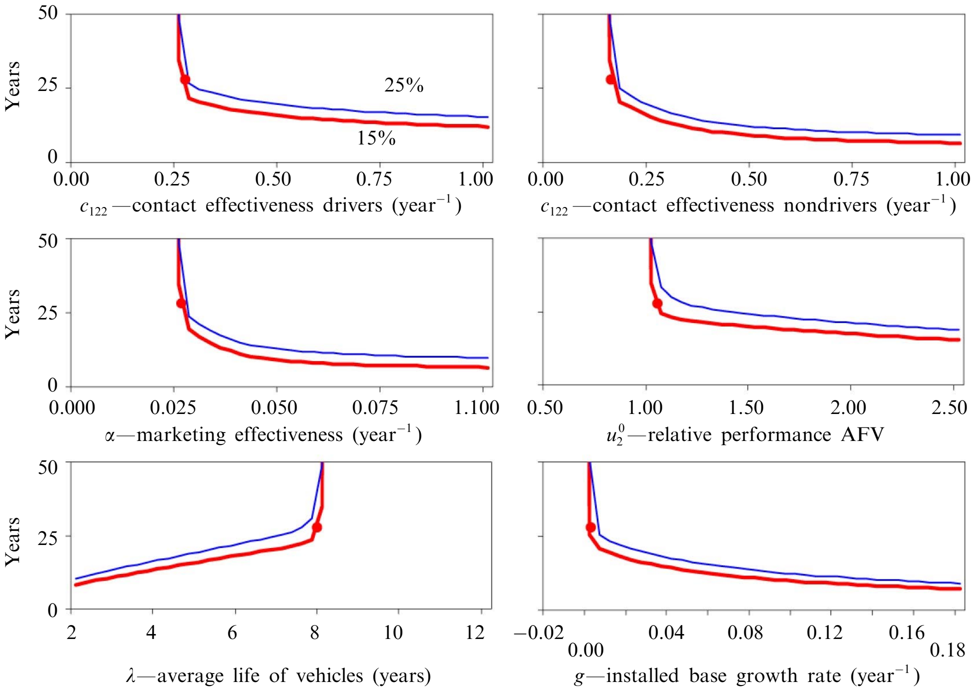

Figure 7. [In color online.] Sensitivity of the alternative fuel vehicle (AFV) installed base share to key parameters. Each panel shows the time required for the AFV to achieve 15% and 25% share of the total installed base. The reference points (dots for 15% market share) indicate the values in the base run (figure 6) with an aggressive promotion and subsidy program lasting twenty years.

impact of social exposure to AFVs cuts the time required to reach 15% of the installed base from thirty to about twenty years. The patterns for the impact of nondriver word of mouth and marketing effectiveness are similar. One exception is marketing: greater marketing impact has a large effect; note also that achieving such impact is expensive as it requires significantly greater advertising, marketing, and promotion (subsidies), and assumes that makers of conventional ICE vehicles will not undercut AFV promotions by increasing their own marketing and promotions.

Figure 7 also shows the impact of varying the utility of AFVs relative to that of ICE vehicles. We vary the relative utility of the AFV, u_2^0, with $a_{i2}^* = a_{i2} \exp(\mu u_2^0)$, over the range $0.5 \leqslant u_2^0 \leqslant 2.5$—that is, from half the ICE value to 250% of ICE [see equation (14) below]. Naturally, inferior technologies (AFVs with utility less than that of the ICE ensemble, ie $u_2^0 < 1$) do poorly. Somewhat surprisingly, however, even highly attractive vehicles require long periods to achieve a significant share of the installed base. There are two main reasons for this outcome. First, even if AFVs are highly attractive, potential purchasers must first become aware of, and sufficiently familiar with, these vehicles for them to enter their consideration set. The knowledge and comfort required to consider AFVs grow only slowly, due to the small initial AFV installed base. Second, the long life of vehicles means the installed base turns over only slowly even if the share of purchases going to AFVs is high.

Figure 7 also shows that AFV diffusion is highly sensitive to the average lifetime of vehicles. Longer lifetimes compared with the base case dramatically slow AFV diffusion, while shorter vehicle lives speed diffusion. For short-lived and relatively inexpensive consumer goods, intensive marketing programs can quickly generate a large enough installed base for the resulting social exposure to quickly move the system into the high-adoption basin of attraction. Such rapid change in the installed base is not possible for automobiles. The long life of vehicles means that the installed base is very large relative to new vehicle sales, particularly in developed economies where the installed base is growing slowly. For example, the US auto parc is roughly 220 million light-duty vehicles (cars and light trucks), with sales averaging about 16 million/year (Heavenrich, 2006; US Department of Energy, 2004). Even if AFVs suddenly gained 50% of sales of all new cars and light trucks, the AFV share of the installed base would be only 3.5% after one year and roughly 18% after five years. The sensitivity to average vehicle life suggests that speeding the deregistration and scrapping of older, less efficient ICE vehicles may be a high leverage policy to speed AFV diffusion.

So far we have considered a constant total installed base ($g = 0$). In reality population and vehicle ownership per household tend to grow over time. Growth in the installed base is low in developed economies—for example, about 1.5% per year in the US between 1990 and 1997 and 1.8%/year in Europe—while growth in developing economies is much faster—averaging, for example, about 18%/year in China (United Nations, 1997). Some of this growth arises from expanding population, but by far the greatest source of growth is increasing incomes, allowing the number of vehicles per household to grow. For example, population growth, averaging roughly 1% per year in China and the US and approaching zero in Europe and Japan (United Nations, 1997), is far lower than growth in the vehicle installed base (Dargay and Gately, 1997). Figure 7 shows the sensitivity of AFV diffusion to various rates of growth in the number of vehicles per household, from -0.02 per year $\leqslant g \leqslant 0.18$ per year, holding population constant. Negative growth dramatically slows AFV diffusion—with total sales below discards, the installed base turns over far more slowly (the effect is analogous to a longer average vehicle life). Further, the number of AFVs sold each year falls, even if their share remains constant. Consequently, social exposure is weaker and it is far more difficult to escape the low diffusion basin of attraction. Conversely, faster growth rates speed diffusion as the ICE installed base is more quickly diluted with AFVs, boosting social exposure. Nevertheless, diffusion times exhibit strongly diminishing returns as the growth rate increases.

Expanding the model boundary

Sensitivity analysis should include structural as well as parametric tests (Sterman, 2000). We now consider how the results may vary when the boundary of the model is expanded to include other important feedback processes conditioning the evolution of the AFV industry and which may interact with the dynamics of awareness and adoption. We first discuss the role of endogenous vehicle performance improvement and then the role of fueling infrastructure.

Endogenous vehicle performance improvement

Currently alternative technologies are not competitive with ICE. However, scale economies, learning effects, and related interactions with the technology, manufacturing, and fueling supply chains promise to significantly lower costs and improve performance (figure 2). Positive feedbacks arising from learning, network externalities, and complementary infrastructure lead to path dependency, and significantly condition diffusion policies to promote adoption [Arthur (1989); David (1985); Katz and Shapiro (1985); also, Sterman (2000) describes several dozen positive feedbacks affecting diffusion and firm growth]. Struben (2006) examines the impact of such feedbacks in detail; here we aggregate all vehicle characteristics—including purchase cost, fuel efficiency, power, features, and range—into a single attribute denoted vehicle performance, P. Affinity takes the reference value a^* when performance equals a reference value P^*:

$$a_{ij} = a^* \exp\left[\beta\left(\frac{P_j}{P^*} - 1\right)\right], \tag{14}$$

where the expression in the exponent represents vehicle utility and β is the sensitivity of utility to performance.[8] The exponential utility function means the share of purchases going to each platform [equation (3)] follows the standard logit choice model.

Performance follows a standard learning curve, rising as relevant knowledge of and experience with the platform, K, improves,

$$P_j = P_j^0\left(\frac{K_j}{K^0}\right)^{\gamma}, \tag{15}$$

where performance equals an initial value P_j^0 at the reference knowledge level K^0, and γ is the learning curve strength.

Much of the knowledge gained for one platform can spill over to others. For example, improvements in electric motors developed for, say, hydrogen fuel-cell vehicles can benefit ICE – electric hybrids; lightweight materials developed for AFVs can benefit all platforms, including ICE vehicles. Spillovers can be modeled in several ways (Cohen and Levinthal, 1989; Jovanovic and MacDonald, 1994). Since knowledge is multidimensional (eg powertrain, suspension, controls), one firm and platform may lead on certain aspects of technology and lag on others, simultaneously being both the source and beneficiary of spillovers. To allow for varying substitution possibilities, we model the knowledge base for each platform as a CES (constant elasticity of substitution) function of the platform's own experience, E_j, and the (perceived) experience of other platforms, E_{ij}^P:

$$K_j = K^0\left[\kappa_j\left(\frac{E_j}{E^0}\right)^{-\rho} + (1-\kappa_j)\sum_{i,\, i\neq j}\Psi_{ij}\left(\frac{E_{ij}^P}{E^0}\right)^{-\rho}\right]^{-\frac{1}{\rho}}, \tag{16}$$

where E^0 is the reference experience level, $\rho = (1-\xi)/\xi$ and ξ is the elasticity of substitution between the firm's own experience and the experience of others, κ is the fraction of knowledge arising from the platform's own experience, and Ψ_{ij} is the strength of spillovers from platform i to j.

Constraining $\sum_{i,\, i\neq j}\Psi_{ij} = 1$ defines the reference knowledge level K^0 as the knowledge base when the experience of each platform equals the reference experience level E^0.

Imitation, reverse engineering, hiring from competitors, and other processes enhancing spillovers take time. Hence spillovers depend on *perceived* experience, which lags actual experience. For simplicity we assume first-order exponential smoothing with spillover adjustment lag τ_{ij}:

$$\frac{\mathrm{d}E_{ij}^P}{\mathrm{d}t} = \frac{E_i - E_{ij}^P}{\tau_{ij}}. \tag{17}$$

Spillover time constants may differ across platforms. Small firms may lack the resources to imitate innovations as quickly as their large rivals.

Finally, we proxy a platform's experience and learning from all sources with cumulative sales:

$$\frac{\mathrm{d}E_j}{\mathrm{d}t} = s_j\,. \tag{18}$$

[8] The sensitivity $\beta = \mu\beta'$ is determined by the scale parameter μ, which captures the impact of random factors and population size effects on heterogeneity, and individual sensitivity to performance, β'. In practice, μ and β' are not separately identifiable and are combined into β (Ben-Akiva and Lerman, 1985).

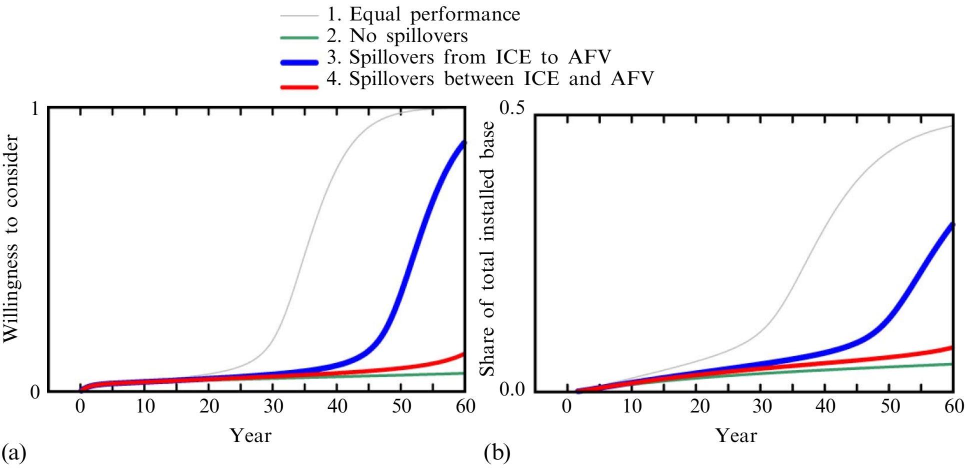

Figure 8. [In color online.] (a) Willingness to consider alternative fuel vehicles (AFV) and (b) AFV installed base share, with endogenous learning and innovation spillovers. ICE denotes internal combustion engines.

Parameters will depend on differences in the technologies. For example, ICE experience is relevant to biodiesel vehicles, but less relevant to General Motors' HyWire HFCV (Burns et al, 2002), which radically alters most design elements. We assume a 30% learning curve and moderately high elasticity of substitution, $\xi = 1.5$, for both platforms. Initial conditions are as in figure 6; table 2 lists other parameters.

Figure 8 illustrates the impact of performance improvement. For comparison, the trajectory labeled 'equal performance' shows diffusion when the AFV enters the market with experience, and therefore utility, equal to ICE—learning has already leveled the playing field. The other simulations assume, more realistically, that AFVs possess the same *potential* performance as ICE, but begin with low experience and immature technology, yielding low initial performance relative to ICE. In the 'no spillover' case each platform improves only through its own experience. AFV adoption stagnates at a low level. Poor initial performance limits sales, suppressing the accumulation of experience that could boost performance. The system is trapped in the low-diffusion basin of attraction. The 'spillover ICE to AFV' case activates spillovers from ICE to AFVs (but not vice-versa). AFVs quickly benefit from the large experience base of ICE (through transfers to engineers, patents, access to suppliers, and other resources). Performance rises quickly, and diffusion, though still requiring many decades, becomes self-sustaining. The 'spillovers between ICE and AFV' case allows AFV innovations to spill over to the incumbent (eg lighter materials, drive-by-wire systems). ICE vehicles now improve even as the alternative does, reducing AFV attractiveness and slowing diffusion. If such spillovers are strong enough, the performance gap between ICE and AFVs may never close enough for the system to escape the low-diffusion basin of attraction. Due to the many positive feedbacks governing the system dynamics, diffusion patterns are quite sensitive to the strength of the learning curve and spillovers, suggesting benefits from disaggregating the many sources of performance improvement (R&D, learning by doing, spillovers, scale economies, etc) and empirically estimating their impacts.

Spatial coevolution with fueling infrastructure

The analysis above did not include the development of fueling and maintenance infrastructure, and therefore applies best to AFVs, such as hybrids, that use the existing gasoline distribution system. For technologies such as HFCVs, fuel and other infrastructure must be built up together with the installed base. Often stereotyped as 'chicken – egg' dynamics, these coevolutionary dynamics are more complex. The local scale of interactions is paramount. Fuel availability differs for individual drivers, based on their location and driving patterns relative to the location of fuel stations.

The full model we are developing integrates the dynamics discussed so far with vehicle – fuel infrastructure interactions in an explicit spatial framework [Struben (2006; 2007) and Supple (2007) provide details]. A region such as a state is divided into small patches. The location of fueling infrastructure is endogenous. Station entry and exit are determined by the expected profitability of each location, which, in turn, depends on the demand for fuel at that location and the density of competition from nearby stations. Households within each patch choose AFVs according to the structure described above, with WtC conditioned by both global and local effects. For example, national advertising promoting AFVs is a global impact, while social exposure to AFVs is local: people see AFVs owned by their neighbors and driven in the same patches through which they drive, but are only weakly exposed to AFVs further away. In addition, the perceived utility of each platform depends on the effort required to find fuel. Refueling effort is a function of (i) the risk of running out, which depends on vehicle range and the location of fuel stations relative to the driver's desired trip distribution, and (ii) expected refueling time, which includes the time spent driving out of the way to reach a fuel station and crowding at fuel stations. Driver behavior is also endogenous. For example, the number and length of trips increase as fuel availability rises. Effective vehicle range is also endogenous: drivers facing low and uncertain fuel availability, say because fuel stations are sparse or crowded, will seek to refuel before their tanks near empty. Such topping-off reduces effective vehicle range, requiring more frequent refueling stops and increasing congestion at fuel stations. Higher refueling effort lowers the attractiveness of AFVs, reducing both AFV purchases and their use for longer trips, creating additional positive feedbacks that can hinder AFV diffusion.

Figure 9 shows a simulation calibrated for California. To highlight the impact of spatial vehicle – fuel infrastructure interactions, the simulation assumes that all drivers are willing to consider the AFV ($W_{ij} = 1, \forall i, j$). Further, we set the performance of the hypothetical AFV equal to that of ICE. These assumptions are highly optimistic— actual AFVs offer low performance relative to ICE and are not universally included in drivers' consideration sets—but isolate the dynamics caused by the interactions among the installed base and fueling infrastructure in an important region with considerable heterogeneity in human and vehicle population density. The initial ICE installed base and infrastructure distribution are set to current California values (roughly 16 million vehicles and 8000 gas stations, concentrated in urban areas). The simulation begins with an AFV installed base of 25 000 vehicles and about 200 fueling stations (approximate values for CNG in California in 2002, including private fleets and stations). We assume, optimistically, that all AFV fuel stations are accessible to the public. To encourage the development of AFV fueling infrastructure, fuel stations are heavily subsidized for the first ten years.

Figure 9 shows the AFV installed base and alternative fuel stations. Despite performance equal to ICE, universal consideration of AFVs and large subsidies to fuel station owners, overall diffusion is slow, and after forty years has largely saturated. Fuel stations grow roughly with the installed base, though many are forced to exist when subsidies expire in the tenth year (entry slows and exits rise before the end of the subsidies as forward-looking entrepreneurs anticipate the expiration of the subsidies). Though not shown, miles driven per year for the typical AFV are also far less than for ICE vehicles. The spatial distribution after fifty years shows that essentially all AFVs

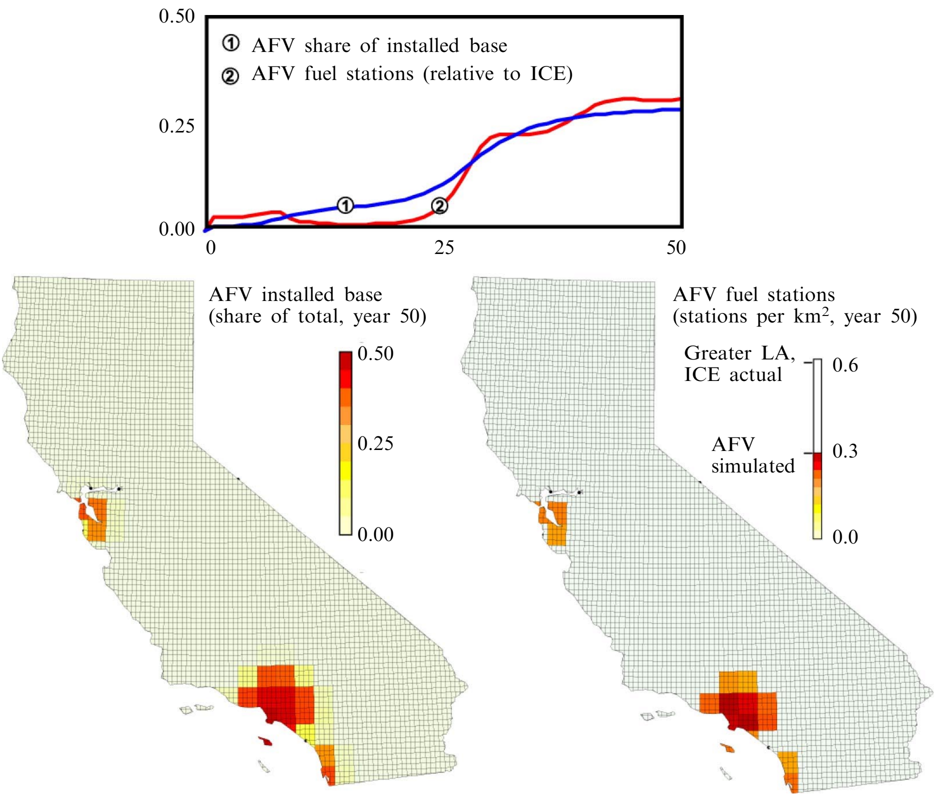

Figure 9. [In color online.] Behavior of the spatially disaggregated model, calibrated for California. AFV and ICE denote alternative fuel vehicle and internal combustion engines, respectively.

and fueling stations are concentrated in the major urban centers. Limited AFV adoption is a stable equilibrium in the cities, because high population density means fuel stations can profitably serve the alternative installed base, and the resulting availability of fuel indices enough people to drive the alternative vehicle, thereby sustaining the fuel providers. The area with the highest fuel station concentration, roughly covering the greater Los Angeles area, has a station density of about half that of gasoline stations. However, though a few alternative fuel stations locate in rural areas when subsidies are available, they are sparse in rural areas, so rural residents and city dwellers needing to travel through these regions find AFVs unattractive. Further, urban AFV adopters, facing low fuel availability outside the cities, use their AFVs in town, but curtail long trips, using their ICE vehicles instead. Consequently, demand for alternative fuel in rural areas never develops, preventing a profitable market for fuel infrastructure from emerging, which, in turn, suppresses AFV adoption and use outside the cities.

While islands of limited diffusion might be sustained in the cities, broad adoption of AFVs can easily founder even if their performance equals that of ICE. Such dynamics have implications for AFV diffusion beyond the infrastructure and adoption interactions. For example, while not considered in the simulation shown, low diffusion limits knowledge accumulation, which can improve AFV performance. Further, auto OEMs would likely respond to the demand for AFVs in cities by offering small, efficient, inexpensive models adapted for commuting but ill suited for touring. Such vehicles would be even less attractive for long trips and use in rural areas, and would likely restrict adoption to affluent households who can afford an AFV for commuting and an ICE vehicle for weekend excursions.

The spatial dynamics of the AFV and fuel markets significantly alter the conditions for sustained adoption. Policies designed to achieve self-sustaining AFV adoption must not only solve the 'start up' problem of initial awareness generation but must also overcome the urban–rural asymmetry in adoption. Many programs to introduce AFVs have failed, arguably due to limited understanding of these dynamics. Work underway will integrate awareness and willingness to consider AFVs with the spatial dynamics. In such cases diffusion may be even slower as the dynamics of consideration and fuel infrastructure interact.

Discussion

Modern economies and settlement patterns have coevolved around the automobile, internal combustion, and petroleum. The successful introduction and diffusion of alternative fuel vehicles is more difficult and complex than that for many products. The dynamics are conditioned by a broad array of positive and negative feedbacks, including word of mouth, social exposure, marketing, scale and scope economies, learning from experience, R&D, innovation spillovers, complementary assets including fuel and service infrastructure, and interactions with fuel supply chains and other industries. A wide range of alternative vehicle technologies, from hybrids to biodiesel to fuel cells, compete for dominance; the lack of standards increases uncertainty and inhibits investment. And the large role of the automobile in personal identify and social status means purchase decisions involve significant emotional factors.

We have developed a behavioral, dynamic model to explore the diffusion of and competition among alternative vehicle technologies. The full model has a broad boundary and captures a wide array of the feedbacks described above, including the spatial distribution of vehicles and fueling infrastructure. To gain insight into the dynamics, we explored a simplified version, focusing on the generation of consumer awareness of alternatives and consumers' choice between conventional and alternative vehicles. We introduced the concept of the willingness to consider a vehicle platform (WtC) in order to capture the cognitive and emotional processes through which drivers gain enough information about, understanding of, and emotional attachment to a platform for it to enter their consideration sets when purchasing a vehicle. WtC can be generated by marketing and media, by direct social exposure and word of mouth created by contacts between ICE and AFV drivers, and by indirect word of mouth arising from conversations about AFVs among ICE drivers.

The positive feedbacks conditioning driver familiarity with and consideration of alternative vehicles generate system dynamics characterized by multiple equilibria. The system is attracted to high WtC and significant adoption of alternative vehicles, or stagnation with low WtC and adoption. These fixed points are separated by a threshold, or tripping point. Awareness and adoption must exceed the threshold to become self-sustaining. The existence and location of the tripping point and the size of the basin of attraction of the low diffusion equilibrium depend on parameters. Stronger marketing and direct word of mouth favor diffusion. However, the impact of direct word of mouth will be small when AFVs are introduced because the long lifetime of vehicles causes the share of alternatives in the installed base to lag significantly behind their share of new vehicle sales. In such settings, indirect word of mouth about alternative vehicles among ICE drivers can significantly lower the threshold for sustained adoption—provided that word of mouth is favorable.

Growth in the total vehicle speeds adoption of AFVs by increasing their share of the installed base faster, thus stimulating social exposure, learning, and other positive feedbacks. Consequently, the potential for self-sustaining adoption of AFVs may be greater in developing nations such as China and India where the installed base of ICE vehicles is smaller and growth faster. In mature markets such as in the US, Europe, and Japan, the challenges remain great. The long life of vehicles means that the share of AFVs in the installed base will increase only slowly even if AFVs capture a large share of new vehicle sales. Indeed, subsidies and marketing programs aimed at selling AFVs may lengthen effective vehicle life: as consumers trade in their ICE vehicles for AFVs, used car prices will drop. Lower used car prices will both undercut AFV sales and make it economic to keep old, inefficient ICE vehicles on the road longer (for related cases see Sterman, 2000, §2.2 and §6.3.6). The strong dependence of diffusion potential on the lifetime of vehicles demonstrated in the sensitivity analysis (figure 7) suggests that policies aimed at removing old ICE vehicles from the installed base may have high leverage. Such policies might be implemented through feebate programs (Ford, 1995; Greene et al, 2005; Lovins and Aranow, 2004) or subsidies offered to vehicle owners who not only buy an AFV but have their ICE vehicle shredded rather than sold into the used car market.

Endogenous improvement in vehicle attributes from learning, R&D, scale economies, etc, adds important additional positive feedbacks that can further hinder the diffusion of alternative vehicles. Current AFVs are expensive and offer lower performance relative to ICE; many AFV technologies are not yet commercially available (eg HFCVs). Though AFVs undoubtedly would improve with scale, R&D, and experience, these innovation drivers remain weak as long as there is substantial uncertainty and limited adoption. Further, technology spillovers from alternative vehicle programs to the incumbent can further suppress adoption. Heywood et al (2003) estimate that the performance of hydrogen vehicles will not equal that of ICE, hybrids, or clean diesel for twenty years. During this time the dominant ICE technology can benefit from many innovative ideas—lighter materials, performance-enhancing software—likely to emerge from alternative vehicle programs. Finally, the local, spatial coevolution of adoption and fuel infrastructure can significantly impede broad-scale diffusion, even if AFVs equal ICE in cost and features.

The results suggest fruitful areas for empirical work and model elaboration—for example, estimating the impact of marketing, direct social exposure, and indirect word of mouth on the consideration set and consumer choice. Vehicle features and performance could be disaggregated. Interactions with other industries and the fuel supply chain should be captured. For example, the petroleum and energy markets are prone to large price fluctuations caused by lags in the adjustment of demand and supply to price (Ford, 1999; Sterman, 2000). The high real oil prices of 1973–84 led to large improvements in vehicle efficiency. Similarly, the rise in real oil prices beginning in 2005 might stimulate AFV adoption enough to push the industry past the tipping point so that diffusion becomes self-sustaining even after real oil prices fall back. The long time required for the AFV market to develop in the simulations, however, suggests that a successful transition to AFVs will likely require policies that raise the real price of gasoline to levels that reflect its fully internalized cost, thus providing the persistent incentive favoring AFVs which is needed to reach the tipping point.

The model results identify feedback structures that play a strong role in AFV diffusion and sensitive parameters that are currently poorly constrained by available market research. Most importantly, the results demonstrate that a broad model boundary is required to capture the wide array of interactions and feedbacks that determine the dynamics of alternative vehicle diffusion.

Acknowledgements. Financial support was provided by the National Renewable Energy Laboratory (grant XCO-5-55516-01) and the Project on Innovation in Markets and Organizations at the MIT Sloan School of Management. We thank the editor and referees, Nelson Repenning, Derek Supple, Cory Welch, and seminar participants at NREL, the 2005 International System Dynamics Conference, and MIT for helpful comments, and Cory Welch for data access.

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Transition challenges for alternative fuel vehicle and transportation systems

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Full model overview

The model described in the article is designed to capture the diffusion of and competition among multiple types of alternative vehicles, along with the evolution of the ICE fleet. For example, the model can be configured to represent ICE and alternatives such as ICE-electric hybrid, CNG, HFCV, biodiesel, E85 flexfuel, and electric vehicles. However, in the paper we focus on intuition about the basic dynamics around the diffusion of alternatives to ICE by considering two platforms, ICE and an alternative vehicle, and make a number of other simplifying assumptions that allow us to explore the global dynamics of the system. In this appendix we discuss the full model, highlighting those structures required to capture the competition among multiple alternative platforms and multiple attributes of vehicle performance.

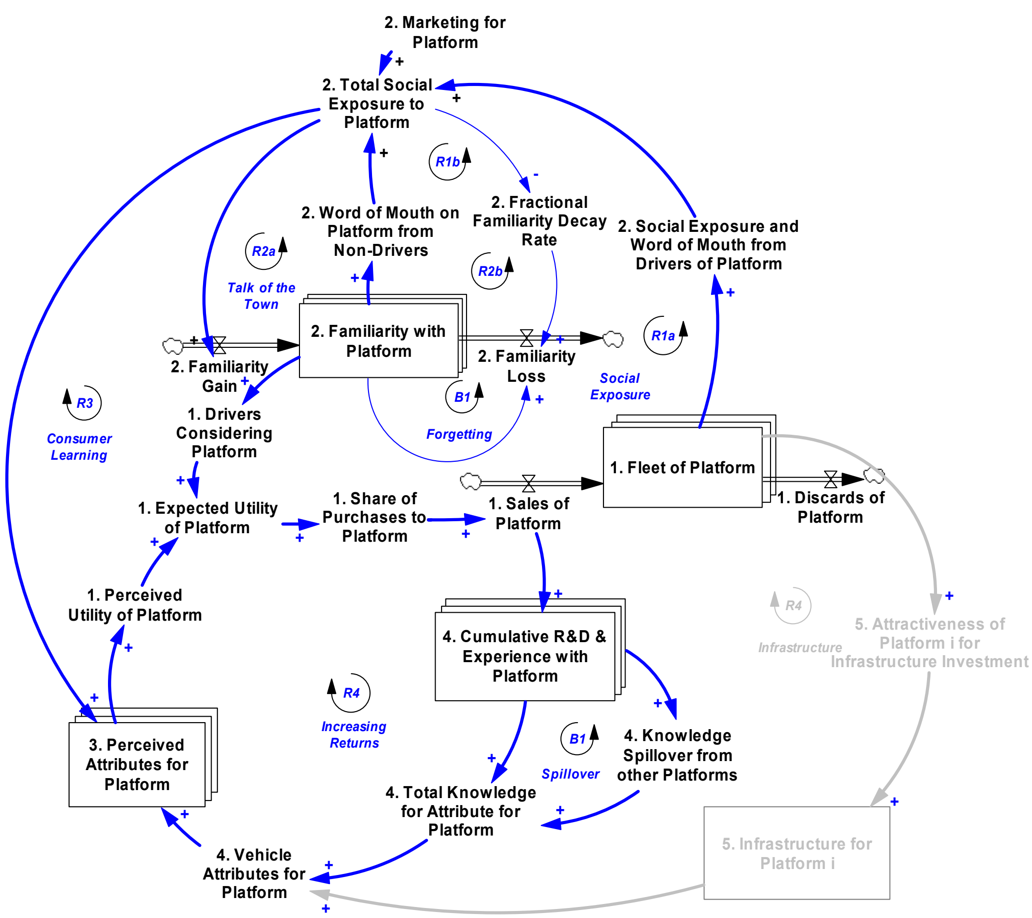

Figure 1. Main model Structure

Figure 1 shows the main model structure as discussed in the paper. Variables are numbered according to the section where they are treated (1. Vehicle adoption; 2. Familiarity; 3. Learning about attribute performance; 4. Endogenous attribute improvement; 5. Infrastructure).

1. Notes on vehicle adoption

a. Vehicle Fleet Aging Chain

For simplicity, the age structure of the fleet is not treated in the paper. Below we lay out how this is incorporated in the full model.

The total number of vehicles for each platform *j, j={1,…, J }*, of each age cohort *m,* V_{j_m}, accumulates net vehicle replacements and aging (see Figure 2):

$$\frac{dV_{j_m}}{dt} = v^r_{j_m} + v^a_{j_m} \tag{A-1}$$

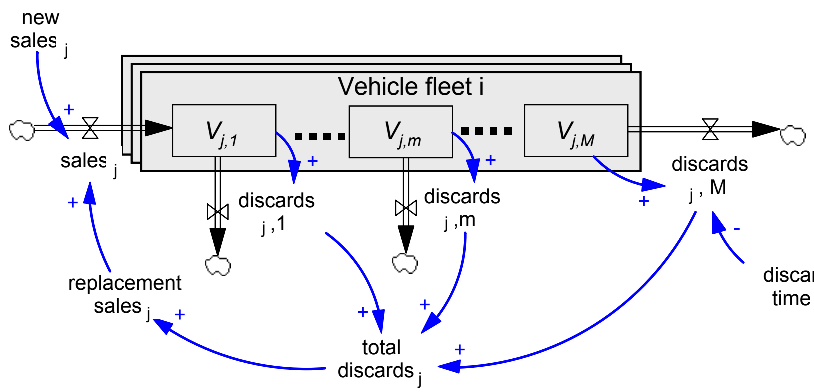

Figure 2 Vehicle replacement with aging chain

Aging captures vehicles coming from a younger cohort less those aging into the next cohort:

$$v^{a}_{j_m} = v^{a+}_{j_m} - v^{a-}_{j_m} \tag{A-2}$$

with

$$v^{a+}_{j_m} = \begin{cases} 0 & m=1 \\ v_{i_{m-1,m}} & m>1 \end{cases} \qquad v^{a-}_{j_m} = \begin{cases} v_{i_{m,m+1}} & m \le M \\ 0 & m=M \end{cases} \tag{A-3}$$

while

$$v_{i_{m,m+1}} = f^{s}_{i_m} V_{i_m} \Big/ \tau^{c} \tag{A-4}$$

Where $f^{s}_{i_m}$ is the survival fraction for each cohort.[1,2]

Net vehicle replacements are new vehicle sales, s_{j_m}, less age dependent discards, d_{j_m} :

$$v^{r}_{j_m} = s_{j_m} - d_{j_m} \tag{A-5}$$

We do not consider the used car market here. New vehicle sales enter the first age cohort, thus:

$$s_{j_m} = \begin{cases} s_j & m=1 \\ 0 & m>1 \end{cases} \tag{A-6}$$

Total sales for platform j, s_j, consist of initial and replacement purchases:

$$s_j = s^{n}_{j} + s^{r}_{j} \tag{A-7}$$

The full model allows for growth in the fleet as population and the number of vehicles per person grow. In the paper population and the number of vehicles per person are assumed constant,

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[1] Annual survival (and/or scrappage) rates by model year can be derived from registration data (e.g. by L. Polk &Co, AAMA).

[2] In equilibrium average vehicle life λ^{v} is found by: $\lambda_j = \sum_{m=1}^{M-1}\left(\prod_{m'=1}^{m-1} f^{r}_{j_{m'}}\right)\lambda^{c} + \prod_{m'=1}^{M-1} f^{r}_{j_{m'}}\lambda^{c_M}$

implying the total fleet is in equilibrium and initial purchases are zero. Vehicles sales for platform *j* arise from the replacement of discards from any platform *i* and cohort *m*, $d^r_{i_{m'}}$:

$$\sum s^r_j = \sum_{i,m'} \sigma_{i_{m'}j} d^r_{i_{m'}} \tag{A-8}$$

where $\sigma_{i_n j}$ is the share of drivers of platform *i* cohort *n* replacing their vehicle with a new vehicle of platform *j*. The share switching from *i* to *j* depends on the expected utility of platform *j* as judged by the driver of vehicle *i,* cohort *n,* $u^e_{i_n j}$, relative to that of all options $u^e_{i_n j'}$.

Thus:

$$\sigma_{i_m j} = \frac{u^e_{i_m j}}{\sum_{j'} u^e_{i_m j'}} . \tag{A-9}$$

To capture a driver's consideration set we introduce the concept of familiarity among drivers of vehicle *i* with platform *j*. The model can be elaborated to include cohort-specific levels of familiarity, recognizing that drivers of, say, a 10 year old ICE vehicle have a different (presumably lower) familiarity with new ICE vehicles than the driver of a 1 year old vehicle. Such distinctions may matter when vehicle attributes change rapidly, as is likely for early AFVs as experience and technology rapidly improve. (Further disaggregation would eventually lead to an agent-based representation where each driver has an individual-specific level of familiarity with different platforms). These issues will be treated in future work. For simplicity we assume here that familiarity is equal across all cohorts of a given platform and remains F_{ij} , thus expected utility is:

$$u^e_{i_m j} = F_{ij} * u_{i_m j} . \tag{A-10}$$

b. Initial purchases and fleet growth

New car sales for fleet *j* are:

$$s_j^n = \sigma_j^n s^n \tag{A-11}$$

where the share σ_j is equal to the share of replacement sales: $\sigma_j^n = s_j^r \big/ \sum_i s_i^r$.

Total new car sales allow the total fleet $V = \sum_{j,m} V_{j_m}$ to adjust to its indicated level V^*:

$$s^n = \frac{\max\left[0, \left(V^* - V\right)\right]}{\tau^v} \tag{A-12}$$

where total desired vehicles $V^* = \rho^v * H$ is product of the target or desired number of vehicles per household ρ and total households *H*, and τ^v is the fleet adjustment time. The max function ensures sales remain nonnegative in the case where V^* falls below *V* (a possibility if there is a large unfavorable shift in the utility of AFVs when the installed base is small).

Discards, d_{j_m} are found by:

$$d_{j_m} = \begin{cases} (1 - f_{j_m}^s) V_{j_m} \big/ \lambda^c & m < M \\ V_{j_m} \big/ \lambda^{cM} & m = M \end{cases} \tag{A-13}$$

where λ^c is the cohort residence time; λ^{cM} is the residence time of the last cohort.

The number of discards people choose to replace is give by:

$$d_{j_m}^r = f^r d_{j_m} \tag{A-14}$$

where f^r is the nonnegative part of the difference between total discards and the indicated contraction rate as a fraction of the total discard rate:

$$f^r = \frac{\max\left[0, d - v^{c*}\right]}{d} \tag{A-15}$$

Here $d = \sum_{i,m} d_{i_m}$ is total discards, and $v^{c*} = \frac{\max\left[0, V - V^*\right]}{\tau^v}$ is the indicated fleet contraction rate. The fleet of a particular platform can contract when, for example, the perceived utility of that platform suddenly falls (say, due to unfavorable shifts in fuel costs or perceived safety, reliability, or costs) and if the existing installed base is small enough and young enough so that discards from normal aging are small.

2. Notes on Familiarity

a. Familiarity co-flows

The familiarity of drivers of platform *i* with platform *j* is updated through social exposure, as discussed in the paper. When a driver switches from platform *i* to *k*, their familiarity with platform *j* is transferred from F_{ij} to F_{kj}. For example, consider a model in which three platforms are portrayed, say, ICE, hybrids, and HFCVs (denoted platforms 1, 2, and 3, respectively). When an ICE driver switches to a hybrid, the familiarity of that driver with HFCVs, previously denoted F_{13}, now becomes F_{23}. In the two platform simulations considered in the paper these dynamics do not matter since all drivers are assumed to be fully familiar with ICE, and AFV drivers are assumed fully familiar with AFVs, so the only dynamic relates to the growth of familiarity of ICE drivers with AFVs (F_{12}).

To model the transfer of familiarity as drivers switch platforms, it is convenient to consider the evolution of familiarity at the population level:

$$\frac{d\left(F_{ij}V_j\right)}{dt} = V_i\frac{dF_{ij}}{dt} + F_{ij}\frac{dV_i}{dt} = f_{ij}^u + f_{ij}^t \qquad \text{(A-16)}$$

where the first term, which we call f_{ij}^{u}, captures updating of familiarity with platform *j* by drivers of platform *i*, as discussed in the paper. The second term, denoted f_{ij}^{t}, captures the transfer of familiarity arising from drivers who switch platforms. When familiarity is updated much faster than fleet turnover (and therefore switching), the second term has limited impact on the dynamics of familiarity. On the other hand, when fleet turnover is very fast, the transfer of familiarity as drivers switch platforms can be important.

Familiarity updating is formulated as described in the paper: updating of total familiarity is the average update from social exposure, including familiarity decay (equation 5 of the paper), over the total number of drivers V_i:

$$f_{ij}^{u} = \left[\eta_{ij}\left(1-F_{ij}\right)-\phi_{ij}F_{ij}\right]V_i \qquad \text{(A-17)}$$

where η_{ij} is the total impact of total social exposure to platform *j* on the increase in familiarity for drivers of platform *i*, and ϕ_{ij} is the fractional loss of familiarity about platform *j*.

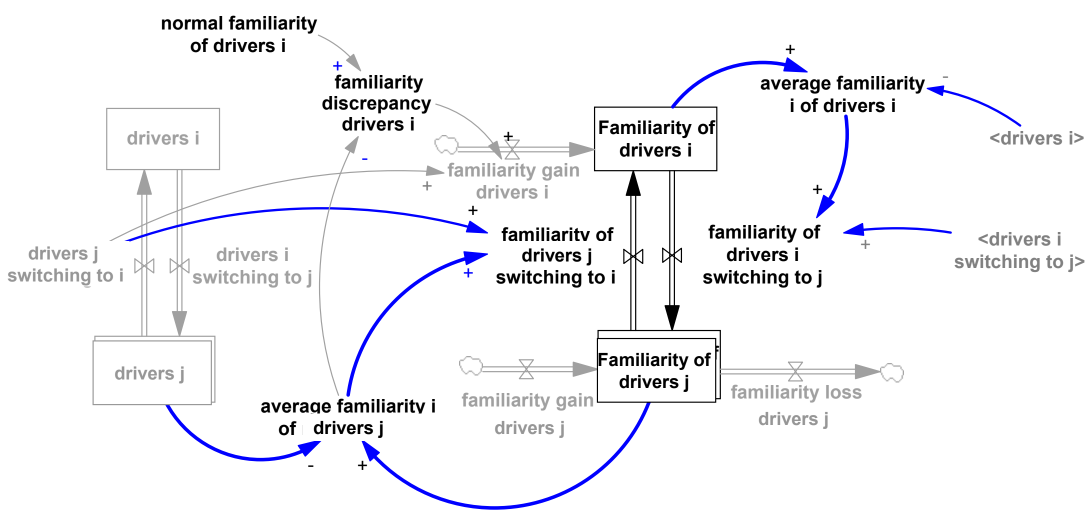

Figure 3. Familiarity change for drivers that switch between platforms

The transfer term captures two "co-flows" (Sterman 2000) that track the movement of the familiarity of a driver of platform *i* with platform *j*, one arising from vehicle sales and one arising from discards:

$$f_{ij}^{t} = f_{ij}^{s} - f_{ij}^{d} \, . \tag{A-18}$$

The first term, f_{ij}^{s} , captures the transfer of familiarity through sales:

$$f_{ij}^{s} = s_i^{n} F_{ij} + \begin{cases} \sum_k s_{ki}^{r} F_{kj} & i \neq j \\ \sum_{k \neq j} s_{ki}^{r} & i = j \end{cases} \tag{A-19}$$

This term contains the flow of new drivers purchasing platform *i*, and their average familiarity with platform *j*, assumed to equal the familiarity of current drivers of *i* with platform *j*. The second term is the transfer of familiarity associated with the flow of drivers of platform *k* replacing their vehicles with one of platform *i*. The average familiarity of these drivers with platform *j* is transferred as they switch. We assume drivers become fully familiar with the platform they are driving, so those who purchase a vehicle of platform *j* (the case *i*=*j*) achieve full familiarity with platform *j* (in a time much shorter than the other time constants).

The second term in equation (A-18) captures the transfer of familiarity with platform *j* associated with drivers of platform *i* through discards:

$$f_{ij}^{d} = d_i F_{ij} \tag{A-20}$$

where $d_i \equiv \sum_m d_{i_m}$ is total discards .

The transfer term f_{ij}^{t} was used in the simulations of the paper, for the relevant cases (Figure 5 and further). The transfer of familiarity as drivers switch platforms has a small but significant contribution to the dynamics: early alternative fuel adopters who switch back from the alternative to ICE have full familiarity with the AFV, and contribute strongly to word of mouth. Technically, a balancing loop is generated, in similar fashion as marketing effectiveness, with strength $\left[1-u_{jj}/\sum_i u_{ji}\right]/\lambda^v$.

However, a more complicated result emerges when learning about performance through social exposure is introduced (see section 3), as early adopters might learn about mediocre performance. Hence, their word of mouth results in lower perceived attractiveness of alternatives among others.

3. Notes on attribute learning

In the paper perceived vehicle performance is treated as a scalar that aggregates the effects of all vehicle performance attributes, P_l, including price, operating cost, power, driving range, fuel and service availability, and ecological impact, $l=\{1,\ldots L\}$. In the full model each performance attribute can be represented separately. Then perceived utility combines the perceived individual attributes, yielding a multinomial logit formulation:

$$u_{ij} = u^* \exp\left(\sum_l \beta_l P_{jl} / P_l^*\right) \tag{A-21}$$

Here u^* is the utility derived from any platform when all the attributes l have a performance level equal to their respective reference values P_l^*; β_l is the sensitivity of utility to performance for attribute l.

Each performance attribute follows a standard learning curve, improving as relevant knowledge of related to each performance attribute, K_{jl}, improves,

$$P_{jl} = P_{jl}^0 \left(K_{jl} / K_l^0 \right)^{\gamma_l} \quad \text{(A-22)}$$

P_{jl}^0 is the performance level for attribute *l* when the knowledge for its attribute equals a reference knowledge K_l^0. The strength of the learning curve, γ_l, can differ for different vehicle attributes, reflecting their different complexity and technical potential. For example, the cost of electric vehicles may fall faster (through better design and scale effects) than battery performance might improve.

Effective knowledge K_{jl} can differ per attribute. Effective knowledge at the attribute level is tightly related to the technological capabilities that produce the various modules of the vehicle (drive train, body, brake system, fuel system,…). However, relations between modules are complex. Organizations improve performance for each attribute by gaining knowledge at the level of modules, and improving those. However, module performance is linked (weight reductions improve power and range for a given drive system; greater energy density in fuel cells or batteries improves cost, weight, power, and/or range. Hence the strength and impact of knowledge spillovers might differ for each attribute. The dynamics of performance improvement and spillovers at this level of specificity are discussed elsewhere (Struben 2006).

Further, the process of learning about a perceived attribute state *l* of platform *j*, as perceived by a driver of platform *i*, for cohort *m*, $P_{i_m jl}$ is similar to that of familiarity: people learn about the state of the different attributes through various channels such as marketing, advertising and media reports, direct exposure (drivers of platform *i* learn about platform *j* from those driving it), and word of mouth exposure through drivers of platforms *k* (or through non-drivers, *k≠j*).

However, people also learn gradually about vehicle attributes by direct experience with the platform. Total learning sums the contributions of all these channels. Capturing these processes, rather than assuming direct perception of the real performance, is important due to the long life of vehicles. These dynamics are also discussed in (Struben 2006).

4. Running the model

The model used to generate the simulations in the paper is available at web.mit.edu/jjrs/www/AFV_Files/AFV_Transition_Model1.vmf. The model is built in the Vensim simulation environment <http://vensim.com>. To run the model, users can download a free model reader from http://www.vensim.com/reader.html.

Navigate through the model by selecting different views (by clicking on the view names below left, or through page up/down buttons). Vensim Reader provides a quick tutorial for how to perform a run and change parameters. To replicate the simulations of Figures 4-7 in the paper, use the settings as indicated below (use the defaults of the model unless another value is listed). All indicated variables can be selected and changed in the “control view”.

Figure 4

Paper	Model	unit	value
-	INITIAL TIME	dmnl	0
-	SW Endogeneous Drivers (Switch)	dmnl	0
-	Initial Installed Base Fraction 2	dmnl	0.05
-	Initial Familiarity12	dmnl	[0, 1]

The "Phase Plots and Diagrams" view provides phase plots (left top and bottom) that show the results in a similar format as Figure 4 in the paper. We have generated the results for the figure by emulating this first order structure in an Excel spreadsheet and were crosschecked with the model. One can replicate the results as follows: after other variables are set properly, go to the "Phase Plots and Diagrams" view and vary "Initial Familarity12" for subsequent runs (use values between 0 and 1 and small intervals; this variable can also be changed in the "Phase Plots and Diagrams" view), and interpret the results on screen. One can also use the "SyntheSim" feature (see help) and follow the same procedure.

Figure 5

Paper	Model Variable	unit	Value 5a	Value 5b	Value 5c
-	INITIAL TIME	dmnl		0	
α_2	AFV Marketing Effectiveness Shock	1/year	0.01	0	0.01
c_{121}	Effective Contact Rate Non Drivers	1/year	0	default	default
-	[Initial Familiarity12, Initial Installed Base Fraction 2]	dmnl		[0, 0.05], [0.20, 0], [0.05, 0.20], [0.40, 0.05], [0.80, 0.10]	

The “Phase Plots and Diagrams” view provides a phase plot (right) that can show the results trajectory by trajectory in the same format as the paper. The results can be replicated by performing the runs one by one. The results were derived though a command script (see help), which can be replicated in the full Vensim version, by using the AFV_Transition_M1_Fig5.cmd file (in zip format). After other parameters have been set properly, one can also use the Synthesim Feature (see help): go to the “Phase Plots and Diagrams” view and vary “Initial Familarity12” and “Initial Installed Base Fraction 2” (these variable can also be changed in the “Phase Plots and Diagrams” view), and interpret the results on screen.

The nullclines and basin of attraction were derived through sensitivity runs (not available in Vensim Reader), by varying Initial Familiarity12 and Initial Installed Base Fraction 2 respectively between 0 and 1, and 0 and 0.5, with an interval of 0.01 (yielding 5151 starting points). Results were exported for time is 0 and time = 1000 years. For the results at time zero, points were identified as being on a nullclines, when net familiarity change rate was zero, or when net change rate for the installed base was zero. The final time (t=250 years) results were used to identify the basin of attraction: initial condition points for which the final time values tended toward the low equilibrium were assigned to the low basin of attraction.

The model also has a piecewise linear approximation for the effect of social exposure (which can be used by setting “Sw Logistic Curve Effect on Forgetting” to 0). As can be seen, simulated value of the linearized version are very close to those using logistic curve. For these runs the nullclines and attractors can be derived exactly.

Figure 6

Paper	Model Variable	unit	Value
α_2	AFV Marketing Effectiveness Shock	1/year	0.025
-	Marketing Duration	years	[10,50]

In this figure we have used the sensitivity run feature, varying "Marketing Duration" between 10 to 50 years, with intervals of 0.5 years. This feature is not available with Vensim Reader. To replicate Figure 6, vary the marketing duration for subsequent runs (from 10 to 50 years, with intervals of 0.5 years), or use the "SyntheSim" feature (see help) to gradually increase the "Marketing Duration", with real time view.

Figure 7

Paper	Model Variable	unit	Value
c_{122}	Strength of word of mouth about AFVs for contacts between AFV and ICE drivers	1/year	0.25 [0-1]
c_{121}	Strength of word of mouth about AFVs for contacts between ICE and other ICE drivers	1/year	0.15 [0-1]
α_2	AFV Marketing Effectiveness Shock	1/year	0.025 [0-0.1]
u_2^0	Relative Utility from AFV	-	1 [0.5-2.5]
λ	Average vehicle life	years	8 [2-12]
g	Growth rate of the total car parc	1/year	0 [-0.02-0.18]

In this figure we have used the sensitivity run feature, setting the model parameters equal to those for Figure 6, with "Marketing Duration" equal to 20 years. In each of the 6 graphs we varied one parameter only, with the ranges as indicated in the tables. Intervals were 5% of the total range for each variable. The plots indicate the time when the installed base reached 15% and 25% of the total installed base respectively. The sensitivity feature is not available with Vensim Reader. To replicate the graphs of Figure 7, vary the relevant variable for subsequent runs, or use the “SyntheSim” feature (see help) to gradually increase the relevant variable, with real time view.

Figure 8

Paper	**Model Variable**	**unit**	**Value 7-1**	**Value 7-2**	**Value 7-3**	**Value 7-3**
c_{121}	Sw Experience Effect on	1/year	default	1	1	1
κ_2	Knowledge Share Internal Entrant	dmnl	default	default	0.5	0.5
κ_1	Knowledge Share Internal Incumbent	dmnl	default	default	default	0.5

5. References

Sterman, J. (2000). *Business dynamics : systems thinking and modeling for a complex world.* Boston, Irwin/McGraw-Hill.

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