Transition challenges for alternative fuel vehicle and transportation systems

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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 due to the size and importance of the auto industry and vehicle fleet. Diffusion of alternative vehicles is both enabled and constrained by powerful positive feedbacks arising from scale and scope economies, R&D, 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, consumer 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.

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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 61mph in 1899 (Flink 1988). Yet sales of automobiles powered by internal combustion engines (ICE) quickly surpassed electrics and became the dominant design (Table 1 defines all acronyms used in this paper). 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 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 Deutch 2004), biofuels (Rostrup-Nielsen 2005), compressed natural gas (CNG), or a mixed fleet (see Greene and Plotkin 2001, MacLean and Lave 2003, 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 (e.g. Flynn 2002; Robertson and Beard 2004; Romm 2004). Certainly the high cost and low functionality of alternative fuel vehicles (AFVs) compared to 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 internal combustion engine 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 policymakers 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, e.g. 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: consumer familiarity, word of mouth and social exposure. We also illustrate the importance of a broad model boundary by showing how the inclusion of additional feedbacks influences these dynamics. These feedbacks include 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 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 diffusion of many new technologies. We motivate 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 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 fleet over a critical threshold. 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—on 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, 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 discussion of the implications for policymakers 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 fleet 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 (Farrell et al. 2003; National Academy of Engineering 2004; Ogden 2004; Bentham 2005). These positive feedbacks mean the evolution of new technologies is likely to be strongly path dependent (David 1985; Arthur 1989; Sterman 2000; Moxnes 1992 explores path dependence in a model of competing energy technologies; 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 (Kay 1997; Hard and Knie 2001; 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 (National Academy of Engineering 2004; Farrell et al. 2003; 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). 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; Smith 1968; McShane 1994). 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. More interesting, the fleet 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 (Kirsch 2000; Geels 2005).

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 1b). In 1912 registered electric cars peaked at 30,000, while the ICE fleet was already 30 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, e.g., 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 familiarity with that platform among potential adopters, increasing the chances that they will 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 100 years later, alternative vehicles face a mature industry, fully articulated infrastructure, powerful vested interests, and a society, economy, and culture tightly bound to ICE.

Full Model boundary

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 build on models of the product lifecycle (e.g., Abernathy and Utterback 1978, Klepper 1996), but emphasize a broad boundary, endogenously integrating consumer choice—conditioned by product attributes, driver experience, word of mouth, marketing, and other channels—with scale economies, learning through R&D and experience, innovation spillovers, and infrastructure (Figure 2).

The installed base of vehicles is disaggregated by platform (e.g., 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 (Hauser et al. 1993). Consumers consider a particular option only when sufficiently familiar with it. Familiarity 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 (Theil 1969; McFadden 1978; McFadden 2001, Ben-Akiva and Lerman 1985) 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), creating additional positive feedbacks through interactions with other industries (e.g., as petroleum replaced coal for home heating, and as HFCVs may co-evolve with stationary fuel cells).

In this paper we focus on adoption generated by consumer awareness through feedback from driving experience, word-of-mouth and marketing, drawing on innovation diffusion models, e.g., Bass (1969), Norton and Bass (1987), Mahajan et al. (1990), Mahajan et al. (2000), and their applications in the auto industry (Urban et al. 1990; Urban et al. 1996). We integrate diffusion with discrete consumer choice models (McFadden 1978, Ben-Akiva and Lerman 1985), 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; Greene 2001; Dagsvik et al. 2002). 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). Here we use a reduced form model of these effects to highlight the importance of consumer awareness and familiarity with AFVs. In the discussion we illustrate the impact of disaggregating to include 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 (e.g., cost, performance, efficiency, range), in the policy environment (e.g., the cost of gasoline vs. 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 familiarity and adoption

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

$$\frac{dV_j}{dt} = s_j - d_j \tag{1}$$

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 fleet. Thus:

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

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 fleet. The term $\sigma_{ij} g V_i$ ensures that the total fleet 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 i to j depends on the perceived affinity, a_{ij}^p which is, in standard multinomial logit choice models, an exponential function of the utility of platform j as judged by the driver of vehicle i.[1] 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,

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

Perceived affinity depends on two factors: first, while drivers may be generally aware that a platform exists, they must be sufficiently familiar with 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 familiarity among drivers of vehicle i with platform j, F_{ij}. Familiarity captures the cognitive and emotional processes through which drivers gain enough information about,

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[1] See eq. 14. Formally, affinity takes the exponential form of utility when the unobserved error terms are iid Gumbel distributed.

understanding of, and emotional attachment to a platform for it to enter their consideration set. Everyone is familiar with ICE, so $F_{i,ICE} = 1$, while $F_{ij} = 0$ for those completely unfamiliar with platform j; such individuals do not even consider such a vehicle: $F_{ij} = 0$ implies $\sigma_{ij} = 0$. Hence

$$a_{ij}^{p} = F_{ij} * a_{ij} \tag{4}$$

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 (e.g Eq. 14). To explore the dynamics of familiarity, however, we begin by assuming that the affinity of each vehicle platform is exogenous.

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

$$\frac{dF_{ij}}{dt} = \eta_{ij}\left(1 - F_{ij}\right) - \phi_{ij}F_{ij} \tag{5}$$

where η_{ij} is the impact of total social exposure on the increase in familiarity, and ϕ_{ij} is the fractional loss of familiarity about platform j among drivers of platform i.[2]

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:

$$\eta_{ij} = \alpha_j + c_{ijj}F_{jj}\left(V_j/N\right) + \sum_{k \neq j} c_{ijk}F_{kj}\left(V_k/N\right) \tag{6}$$

Here α_j is the effectiveness of marketing and promotion for platform j. The second term captures word of mouth about platform j—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 fleet 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

[2] The full formulation accounts for the transfer of familiarity associated with those drivers who switch platforms (see appendix). Struben (2006) shows that the simplification shown here does not affect the qualitative dynamics.

different platform, $k \neq j$, for example, an ICE driver learning about hydrogen vehicles from the driver of a hybrid.[3]

It takes effort and attention to remain up to date with new vehicle models and features. Hence familiarity erodes unless refreshed through marketing or social exposure. The loss of familiarity is highly nonlinear. When exposure is infrequent, familiarity decays rapidly: without marketing or an installed base, the electric vehicle, much discussed in the 1990's, 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"—familiarity with ICE = 1 and there is no decay of familiarity. Thus the fractional decay of familiarity is:

$$\phi_{ij} = \phi_0 f\left(\eta_{ij}\right); \qquad f(0) = 1, f(\infty) = 0, f'(\cdot) \leq 0. \tag{7}$$

Familiarity decays fastest (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

$$f\left(\eta_{ij}\right) = \frac{\exp\left(-4\varepsilon\left(\eta_{ij} - \eta^*\right)\right)}{1 + \exp\left(-4\varepsilon\left(\eta_{ij} - \eta^*\right)\right)} \tag{8}$$

where η^* is the reference rate of social exposure at which familiarity decays at half the normal rate, and ε is the slope of the decay rate at that point. Varying η^* and ε enables sensitivity testing over a wide range of assumptions about familiarity decay.

These channels of awareness generation create positive feedbacks that can boost familiarity and adoption of AFVs (Figure 3). First, a larger alternative fleet enhances familiarity as people see the vehicles on the roads and learn about them from their drivers. Greater familiarity, in turn, increases

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

the fraction of people including AFVs in their consideration set and, if AFV utility is high enough, the share of purchases going to AFVs (the reinforcing Social Exposure loop R1a). Further, as the AFV fleet grows, people driving other platforms increasingly see and hear about them, and the more socially acceptable they become, suppressing familiarity decay (reinforcing loop R1b).

Second, familiarity with 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 fleet for years after their introduction. The majority of information conditioning familiarity with 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 adopters and potential adopters will become significant only after large numbers have already switched from ICE to alternatives.

Analysis of familiarity dynamics

In this section we analyze the dynamics that result from the familiarity structure. 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 consumers first choose between ICE and an AFV, then among AFVs available on the market, e.g., first deciding to consider a hybrid, then choosing among the hybrids offered by different carmakers. [4] The larger the number of different AFVs available, the greater the overall attractiveness of the AFV category will be—when

[4] Research shows that purchase decisions are nested (Ben-Akiva 1973): consumers first decide between distinct classes of vehicles (say ICE, AFVs), based on 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.

the only hybrids available were the Honda Insight and Toyota Prius, their appeal to the average consumer was limited; 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 to ICE vehicles. Naturally, diffusion will be slow absent large subsidies or sustained high gasoline prices. But would diffusion 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. Struben (2006) provides details on the implementation of the nested multinomial choice model; parameters are provided in Table 2. We choose parameters governing social exposure and consumer choice consistent with values typically found in empirical studies in the marketing literature (e.g., Easingwood et al. 1981). Below we report sensitivity analysis and comment in more detail on the justification of the parameter choices.

Model Behavior: Familiarity

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

$$\mathbf{F} = \begin{bmatrix} 1 & F_{12} \\ 1 & 1 \end{bmatrix}, \tag{9}$$

significantly reducing the dimensionality of the model.

Long vehicle life means the composition of the fleet will remain roughly fixed in the first years after alternatives are introduced. Assuming the fleet of each platform is fixed reduces the model to a first-order system where the change in familiarity with AFVs among ICE drivers, dF_{12}/dt, is determined only by the level of familiarity itself and constant effects of marketing and social exposure to the small alternative fleet.

Figure 4 shows the phase plot governing familiarity with AFVs among ICE drivers for a situation with a strong marketing program for AFVs and a modest initial fleet (table 2 lists model parameters). The thick lines show the gain, loss, and net change in familiarity as they depend on familiarity itself (Eq. 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 familiarity (Eq. 6). When familiarity with the alternative is low, word of mouth from nondrivers is negligible, and the gain in familiarity 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 familiarity is near its maximum (Eq. 7). As familiarity increases, word of mouth about AFVs among ICE drivers becomes more important, and increasing total exposure reduces familiarity loss.

The system has three fixed points. There are stable equilibria near F=1, where familiarity decay is small, and near $F = 0$, where word of mouth from nondrivers is small and familiarity decay offsets the impact of marketing and exposure to the small alternative fleet. In between lies an unstable fixed point where the system 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, familiarity 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 2004) shows the low familiarity equilibrium 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 fleet grows; (iv) the impact of word of mouth about AFVs within the population of ICE drivers, c_{121}, increases; and (v) as familiarity 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 familiarity.

A second order model: familiarity 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 fleet turnover (eq. 2) by aggregating each fleet into a single cohort with constant average vehicle life $\lambda_j = \lambda$, yielding

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

The online appendix (web.mit.edu/jjrs/www/AFV_Files/AFV_Transition_Appendix1.pdf) and Struben (2004) treat age dependent discards and initial purchases. For now, let the fleet growth rate $g = 0$, implying a constant total fleet N. Then, since $V_2 = N - V_1$, fleet dynamics are completely characterized by the evolution of the alternative, which, from eq. 1 and 2, is

$$\frac{dV_2}{dt} = \left(\sigma_{22}V_2 + \sigma_{12}(N - V_2)\right)/\lambda - V_2/\lambda. \tag{11}$$

By eq. 3 and 4, the fraction of drivers purchasing an AFV is

$$\sigma_{i2} = F_{i2}a_{i2} / \left(F_{i1}a_{i1} + F_{i2}a_{i2}\right). \tag{12}$$

As before we assume AFV drivers are fully familiar with its attributes, and that everyone is familiar with ICE. Assuming for now that the perceived affinities a_{ij} are also constant, σ_{22} is constant at $a_{22}/(a_{22} + a_{21})$ and

$$\sigma_{12} = F_{12}a_{12} / \left(1 \cdot a_{12} + F_{12}a_{12}\right). \tag{13}$$

With the equation governing familiarity, the system reduces to a pair of coupled differential equations with state variables V_2 (the AFV fleet) and F_{12} (the familiarity of ICE drivers with AFVs).

Figure 5 shows the phase space of the system for several parameter sets, plotting familiarity with the alternative, F_{12}, and the installed base share of the alternative, V_2/N. Because the system now involves only these two state variables, each point in the phase space (F_{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 locus 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 the AFV purchase share is 0.5 when drivers are fully familiar with both. Therefore (*1, 0.5*) gives one stable equilibrium (full familiarity with the alternative, which then receives half the market (since consumers are indifferent between ICE and the AFV). Table 2 shows other parameters. With moderate marketing and no nondriver word of mouth (Figure 5a) there are three 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). For small initial alternative fleets, familiarity and the fleet decay to low levels, even if initial familiarity is high. On the other side of the separatrix dividing the basins, familiarity rises and more ICE drivers switch to AFVs, further increasing familiarity and triggering still more switching. Figure 5b shows a case with no 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 5c marketing and nondriver word of mouth are large enough so that there is only one fixed point: any initial condition will lead, ultimately, to the high familiarity and diffusion equilibrium.

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 with a set of simulations beginning with no familiarity or installed base for the alternative. An aggressive promotion campaign (including advertising and subsidies, α_2=0.025), begins at t=0. In each simulation the campaign ends after T years, $0 \leq T \leq 50$ years. In each simulation the AFV share of sales increases rapidly, even when familiarity 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, familiarity and market share drop back despite initial success: the campaign does not move the system across the basin boundary. Such collapse has been observed. For example, attempts to introduce CNG vehicles in Canada, Italy, and New Zealand faltered after initial subsidies expired, despite some 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 familiarity out of the low-adoption basin of attraction so that adoption proceeds to the high market share equilibrium. With the assumed, optimistic parameters the critical promotion duration is 20 years, and it takes 30 years for AFVs to reach 15% of the installed base.

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

Sensitivity to parameter choice and fleet growth

The technical characteristics of AFVs are subject to large uncertainties, including attributes such as performance, range, fuel efficiency, and cost. 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, build intuition regarding the dynamics of AFV diffusion, and examine the robustness of policies.

Base case values for the main behavioral parameters conditioning familiarity and consumer choice are based on estimates from the marketing literature including durable consumer goods such as microwaves, color televisions and electric refrigerators (e.g. Bass 1980; Easingwood et al 1983; Mahajan 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 to 0.02 for marketing effectiveness and 0 to 0.3 for contact effectiveness, while the role of non-adopters (in our context, non-drivers generating word of mouth about AFVs) is not considered. We selected marketing effectiveness of 0.025 and 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 to typical estimates from the marketing literature. Second, most diffusion models do not distinguish the multiple positive feedbacks that stimulate 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, causing the estimated contact effectiveness to be overestimated. Third, empirical marketing research tends to report estimates for successful products as failed products do not generate sufficient data to estimate diffusion model parameters, introducing selection bias favoring high estimates. Finally, automobiles are more expensive and durable, and the purchase decision more complex and emotionally laden, than 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 and subsidy programs to promote AFVs are maintained for 20 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 30 and 45 years respectively). First consider the sensitivity of AFV diffusion to the parameters governing the growth of familiarity and awareness: 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 impact of social exposure to AFVs cuts the time required to reach 15% of the fleet from 30 to about 20 years. The patterns for the impact of non-driver 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 $a_{i2}^* = a_{i2} \exp\left(\mu * u_2^0\right)$, from $0.5 \le u_2^0 \le 2.5$, that is, from half the ICE value to 250% of ICE (see eq. 14 below). Naturally, inferior technologies (AFVs with utility less than that of the ICE ensemble, i.e. u_2^0 <1) do poorly. But somewhat surprisingly, 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. Such familiarity and comfort grows only slowly, due to the small initial AFV fleet. Second, the long life of vehicles means the fleet turns over only slowly even if the share of purchases going to AFVs is high.

As the logic above suggests, Figure 7 also shows that AFV diffusion is highly sensitive to the average lifetime of vehicles. The discard time has a significant impact on the tipping dynamics. For very fast moving consumer goods, intensive marketing programs can easily 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 the fleet is very large relative to new vehicle sales, particularly in developed economies where the fleet 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 (US Department of Energy 2004; Heavenrich 2006). Even if AFVs suddenly gained 50% of sales of all new cars and light trucks, the AFV share of the fleet would be only 3.5% after 1 year and roughly 18% after 5 years. Figure 7 shows, however, that reductions in the average life of vehicles strongly speed diffusion. The sensitivity of AFV diffusion to average vehicle life suggests that high-leverage policies may consist of accelerating retirement and scrappage of older, less efficient ICE vehicles.

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. In developed economies car parc growth is low, for example, about 1.5%/year in the US between 1990 and 1997 and 1.8%/year in Europe, Countries that developed more recently show higher growth, for example, 4.7%/year in Japan, and parc growth in developing economies is much faster, e.g. about 18%/year for China (United Nations 1997). Car parc growth comprises growth in both population and in ownership per household, 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%/year in China and the US and approaching zero in Europe and Japan (United Nations 1997), is far lower than growth in the total parc in these countries. Figure 7 shows the sensitivity AFV diffusion various rates of growth in the number of vehicles per household, from $-0.02 \leq g \leq 0.18$/year, holding the population constant. Declining fleet size dramatically slows AFV diffusion—with total sales below discards, the fleet 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 far weaker and it is far more difficult to escape the low diffusion basin of attraction. Conversely, faster growth rates speed diffusion as the ICE fleet 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; 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^*:

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

where the expression in the exponent represents the utility and β is the sensitivity of utility to performance.[5] The exponential utility function means the share of purchases going to each platform (eq. 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,

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[5] The sensitivity parameter $\beta = \mu\beta'$ 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, in accordance with standard practice (Ben-Akiva and Lerman 1985).

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

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

Much of the knowledge gained for one platform can spill over to others. Spillovers can be modeled several ways (Jovanovic and MacDonald 1994; Cohen and Levinthal 1989). Since knowledge is multidimensional (e.g., 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 function of the platform's own experience, E_j, and the (perceived) experience of other platforms, E_{ij}^p:

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

where E^0 is the reference experience level, $\rho = (1 - \zeta)/\zeta$ and ζ is the elasticity of substitution between the firms' 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. Note further that the formulation exhibits constant returns to scale.

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}:

$$\frac{dE_{ij}^p}{dt} = \left(E_i - E_{ij}^p \right) \Big/ \tau_{ij}. \tag{17}$$

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:

$$\frac{dE_j}{dt} = s_j \tag{18}$$

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, ζ=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 begin with low experience and immature technology, but high potential, equivalent to that of ICE, 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->AFV" case activates spillovers from ICE to AFVs (but not vice-versa). AFVs quickly benefit from the large experience base of ICE (through transfers of engineers, patents, access to suppliers, and other resources). Performance rises quickly, and diffusion, though still requiring many decades, becomes self-sustaining. The "Spillovers to Both" case allows AFV innovations to spill over to the incumbent (e.g., 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 to AFVs, such as hybrids, that use the existing gasoline distribution system. For others, such as HFCVs, fuel and other infrastructure must be built up together with the fleet. Often stereotyped as "chicken-egg" dynamics, these co-evolutionary dynamics are more complex. The local scale of interactions is paramount. Fuel availability differs for each driver, 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 provides 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 familiarity arising from both global and local effects. For example, national advertising promoting AFVs is a global impact, while social exposure to AFVs is local as 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 increases as fuel availability rises. Effective vehicle range is also endogenous: drivers who perceive refueling effort is high, say because fuel stations are sparse or crowded, will seek to refuel before their tanks near empty. Such topping-off reduces effective vehicle range, requires more frequent refueling stops and increases 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 full familiarity with the AFV. Further, we set the performance of the hypothetical AFV equal to that of ICE. These assumptions are highly optimistic—actual AFVs today face low familiarity and low performance relative to ICE—but isolate the dynamics caused by the interactions among the fleet and fueling infrastructure in a realistic and important geographical region with considerable heterogeneity in human and vehicle population density. The initial ICE fleet 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 fleet 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 10 years.

Figure 9 shows alternative fuel stations and fleet. Despite performance equal to ICE, full familiarity with the AFV and large subsidies to fuel station owners, overall diffusion is slow, and after 40 years has largely saturated. Fuel stations grow roughly with the fleet, though many are forced to exit when subsidies expire in year 10 (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 50 years shows essentially all AFVs 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 fleet, and the resulting availability of fuel induces enough people to drive the alternative vehicle, sustaining the fuel providers. The area with the highest fuel station concentration, roughly covering the greater Los Angeles area, has a station density that is about half of that of gasoline stations. However, though a few AFV fuel stations locate in rural areas when subsidies are available, rural alternative fuel stations are sparse, so rural residents and city dwellers needing to travel through them find AFVs unattractive. Further, urban adopters, facing low alternative 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/adoption interactions. For example, while not considered in the simulation shown, low diffusion limits knowledge accumulation that 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 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 familiarity with the spatial dynamics. In such cases diffusion may be even slower as the dynamics of familiarity 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 identity and social status means purchase decisions involve significant emotional factors.

We 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 familiarity with a platform 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 set. Familiarity 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 familiarity and significant adoption of alternative vehicles, or stagnation with low familiarity and adoption. These fixed points are separated by a threshold, or tipping point. Awareness and adoption must exceed the threshold to become self-sustaining. The existence and location of the tipping 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, due to long vehicle lives that cause the share of alternatives in the fleet to lag significantly behind their share of new vehicle sales, and to the durability of people's emotional attachments to their current vehicle. 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 market 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 whose 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 the share of AFVs in the fleet 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 these old, inefficient ICE vehicles on the road longer (for related cases see Sterman 2000, ch. 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 fleet may have high leverage. Such policies might be implemented through feebate programs (Ford 1995; Lovins 2004; Greene 2005) 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 (e.g., HFCVs). Though AFVs undoubtedly would improve with scale, R&D and experience, these innovation drivers remain weak as long as there is substantial uncertainty, low familiarity, 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 20 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 in conditioning familiarity 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 (Sterman 2000, Ford 1999). The high real oil prices of 1973-1984 led to large improvements in fleet 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 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.

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References

Argote, L. and D. Epple (1990). "Learning-Curves in Manufacturing." *Science* **247**(4945): 920-924.

Abernathy, W. and J. Utterback (1978). "Patterns of Industrial Innovation." *Technology Review* **80**(7): 40-47.

Arthur, W. (1989). "Competing Technologies, Increasing Returns, and Lock-in by Historical Events." *Economic Journal* **99**(394): 116-131.

Bass, F. (1969). "A new Product Growth Model for Consumer Durables." *Marketing Science* **15**(5): 215-227.

Bass, F. M. (1980). "The Relationship between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations." Journal of Business **53**(3): S51-S67.

Bass, F. M., T. V. Krishnan, et al. (1994). "Why the Bass Model Fits without Decision Variables." *Marketing Science* **13**(3): 203-223.

Ben-Akiva, M. (1973). Structure of passenger travel demand models. PhD diss. Massachusetts Institute of Technology.

Ben-Akiva, M. and S. Lerman (1985). *Discrete choice analysis : theory and application to travel demand.* Cambridge, Mass., MIT Press.

Bentham, J. (2005). CEO Shell Hydrogen Testimony to the U.S. Senate Subcommitee on Energy.

Berry, S., J. Levinsohn, et al. (1995). "Automobile Prices in Market Equilibrium." *Econometrica* **63**(4): 841-890.

Brownstone, D., D. Bunch, and K. Train. (2000). "Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles." *Transportation Research Part B-Methodological* **34**(5): 315-338.

Burns, L., J. McCormick and C. Borroni-Bird. (2002). "Vehicle of change." *Scientific American* **287**(4): 64-73.

Cohen, W. and D. Levinthal (1989). "Innovation and Learning — The Two Faces of R&D." *Economic Journal* **99**(397): 569-596.

Dagsvik, J. K., T. Wennemo, et al. (2002). "Potential demand for alternative fuel vehicles." *Transportation Research Part B-Methodological* **36**(4): 361-384.

Dargay, J. and D. Gately (1997). "Vehicle ownership to 2015: implications for energy use and emissions." Energy Policy **25**(14-15): 1121-1127.

David, P. (1985). "Cleo and the Economics of Qwerty." *American Economic Review* **75**(2): 332-337.

Demirdoven, N. and J. Deutch (2004). "Hybrid cars now, fuel cell cars later." *Science* **305**(5686): 974-976.

Domencich, T. A., D. McFadden, et al. (1975). *Urban travel demand : a behavioral analysis : a Charles River Associates research study*. Amsterdam New York, North-Holland Pub. Co. ;American Elsevier.

Easingwood, C., V. Mahajan, et al. (1981). "A Nonsymmetric Responding Logistic Model for Forecasting Technological Substitution." *Technological Forecasting and Social Change* **20**(3):

199-213.

Epstein, R. (1928). *The Automobile Industry - Its Economic and Commercial Development.* Chicago & New York, A.W. Shaw Company.

Farrell, A., D. Keith and J. Corbett . (2003). "A strategy for introducing hydrogen into transportation." *Energy Policy* **31**(13): 1357-1367.

Fiddaman, T. S. (2002). "Exploring policy options with a behavioral climate-economy model." *System Dynamics Review* **18**(2): 243-267.

Flink, J. (1970). *America adopts the automobile, 1895-1910*. Cambridge, Mass.,, MIT Press.

Flink, J. (1988). *The automobile age.* Cambridge, Mass., MIT Press.

Ford, A. (1995). "Simulating the Controllability of Feebates." *System Dynamics Review* **11**(1): 3-29.

Ford, A. (1999). “Cycles in competitive electricity markets: a simulation study of the western United States.” *Energy Policy* **27**(11): 637-658.

Flynn, P. (2002). "Commercializing an alternate vehicle fuel: lessons learned from natural gas for vehicles." *Energy Policy* **30**(7): 613-619.

Geels, F. (2005). *Technological Transitions and Systems Innovations - A Co-evolutionary and Socio-Technical Analysis*. Northampton, MA, Edward Elgar.

Greene, D. (2001). TAFV: Alternative fuels and vehicle choice model documentation. Center for Transportation Analysis, Oak Ridge National Laboratory report ORNL/TM-2001/134.

Greene, D., P. Patterson, et al. (2005). "Feebates, rebates and gas-guzzler taxes: a study of incentives for increased fuel economy." Energy Policy **33**(6): 757-775.

Greene, D. and S. Plotkin (2001). "Energy futures for the US transport sector." *Energy Policy* **29**(14): 1255-1270.

Greenspan, A. and D. Cohen (1999). "Motor vehicle stocks, scrappage, and sales." *Review of Economics and Statistics* **81**(3): 369-383.

Hard, M. and A. Knie (2001). "The cultural dimension of technology management: Lessons from the history of the automobile." *Technology Analysis & Strategic Management* **13**(1): 91-103.

Hauser, J., G. Urban, et al. (1993). "How Consumers Allocate Their Time When Searching for Information." *Journal of Marketing Research* **30**(4): 452-466.

Heavenrich, R. M. (2006). *"Light-Duty Automotive Technology and Fuel Economy Trends: 1975 Through 2006"* U.S. Environmental Protection Agency, Office of Transportation and Air Quality, Advanced Technology Division.

Heywood, J., M. Weiss, et al. (2003). The Performance of Future ICE and Fuel Cell Powered Vehicles and Their Potential Fleet Impact. Working paper, MIT Laboratory for Energy and the Environment. Available at: http://lfee.mit.edu/public/LFEE_2003-004_RP.pdf.

The Horseless Age (November 1896), Volume two, no. 1. New York, E.P. Ingersol.

Jovanovic, B. and G. Macdonald (1994). "Competitive Diffusion." *Journal of Political Economy* **102**(1): 24-52.

Katz, M. and C. Shapiro (1985). "Network Externalities, Competition, and Compatibility." *American Economic Review* **75**(3): 424-440.

Kay, J. (1997). *Asphalt nation : how the automobile took over America, and how we can take it* *back.* New York, Crown Publishers.

Kimes, B. and H. Clark, Jr. (1996). *Standard Catalog of American Cars 1805-1942.* Iola, WI USA, Krause Publications.

Kirsch, D. (2000). *The electric vehicle and the burden of history.* New Brunswick, N.J., Rutgers University Press.

Klepper, S. (1996). "Entry, exit, growth, and innovation over the product life cycle." *American Economic Review* **86**(3): 562-583.

Lovins, A. and B. Aranow (2004). *Winning the oil endgame : innovations for profits, jobs and security*. Snowmass, Colo., Rocky Mountain Institute.

Lovins, A. and D. Cramer (2004). "Hypercars((R)), hydrogen, and the automotive transition." *International Journal of Vehicle Design* **35**(1-2): 50-85.

MacCready, P. (2004). The Case for the Battery Electric Vehicles. *The Hydrogen Economy Transition: Moving Toward the Post Petroleum Age in Transportation.* D. Sperling and J. Cannon (eds.). Amsterdam, Elsevier Academic Press.

MacLean, H. and L. Lave (2003). "Evaluating automobile fuel/propulsion system technologies." *Progress in Energy and Combustion Science* **29**(1): 1-69.

Mahajan, V., E. Muller and F. Bass (1990). "New Product Diffusion-Models in Marketing: A Review and Directions for Research." *Journal of Marketing* **54**(1): 1-26.

Mahajan, V., E. Muller and R. Srivastava (1990). "Determination of Adopter Categories by Using Innovation Diffusion-Models." *Journal of Marketing Research* **27**(1): 37-50.

Mahajan, V., E. Muller and Y. Wind (2000). *New-product diffusion models*. Boston, Kluwer Academic.

McFadden, D. (1978). Econometric Models of Probabilistic Choice. *Structural Analysis of Discrete Data with Econometric Applications.* C. Manski and D. McFadden (eds). Cambridge, MA, MIT Press.

McFadden, D. (2001). "Economic choices." *American Economic Review* **91**(3): 351-378.

McShane, C. (1994). *Down the asphalt path : the automobile and the American city*. New York, Columbia University Press.

Miller, D. (2001). *Car cultures*. Oxford ; New York, Berg.

Moore, J. S., J. D. Maples, et al. (1998). "Light-duty diesels - Consumer perspectives and US energy supply issues." *Energy, Air Quality and Fuels 1998*(1641): 19-26.

Moxnes, E. (1992). "Positive Feedback Economics and the Competition between Hard and Soft Energy Supplies." *Journal of Scientific & Industrial Research* **51**(3): 257-265.

National Academy of Engineering (2004). *The Hydrogen Economy: Opportunities, Costs, Barriers, and R&D Needs*. Washinton D.C., National Academy Press.

National Ethanol Vehicle Coalition (2005) *FYI Newsletter* Volume 10 Issue 11, October 18.

Norton, J. and F. Bass (1987). "A Diffusion-Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products." *Management Science* **33**(9): 1069-1086.

Ogden, J. (2004). Where will the Hydrogen Come From? System Considerations and Hydrogen Supply. *The Hydrogen Economy Transition: Moving Toward the Post Petroleum Age in Transportation.* D. Sperling and J. Cannon (eds.) Amsterdam, Elsevier Academic Press.

Robertson, B. and L. Beard (2004). Lessons Learned in the Deployment of Alternative Fueled Vehicles. *The Hydrogen Economy Transition: Moving Toward the Post Petroleum Age in Transportation.* D. Sperling and J. Cannon (eds.) Amsterdam, Elsevier Academic Press.

Rogers, E. (1962). *Diffusion of innovations.* New York, Free Press.

Romm, J. (2004). "The hype about hydrogen." *Issues in Science and Technology* **20**(3): 74-81.

Rostrup-Nielsen, J. (2005). "Making fuels from biomass." *Science* **308**(5727): 1421-1422.

Schiffer, M. B., T. C. Butts, et al. (1994). *Taking charge : the electric automobile in America.* Washington, Smithsonian Institution Press.

Small, K., C. Winston and J. Yan (2005). "Uncovering the distribution of motorists' preferences for travel time and reliability." *Econometrica* **73**(4): 1367-1382.

Smith, P. (1968). *Wheels within wheels - a Short history of American Motor Car Manufacturing.* New York, Funk & Wagnalls.

Sperling, D. and J. Ogden (2004). "The hope for hydrogen." *Issues in Science and Technology* **20**(3): 82-86.

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

Struben, J. (2004). “Technology Transitions: identifying challenges for hydrogen fuel cell vehicles,” 22nd International System Dynamics Conference, Oxford.

Struben, J. (2006). " Essays on transition challenges for alternative propulsion vehicles and transportation systems." PhD diss,. Massachusetts Institute of Technology.

Sultan, F., J. U. Farley, et al. (1990). "A Meta-Analysis of Applications of Diffusion-Models." *Journal of Marketing Research* **27**(1): 70-77.

Theil, H. (1969). "A Multinomial Extension of the Linear Logit Model." *International Economic Review*.

Train, K and C. Winston. (2005). “Vehicle Choice Behavior and the Declining Market Share of U.S. Automakers” Working Paper, The Brookings Institution.

Urban, G., J. Hauser and J. Roberts (1990). "Prelaunch Forecasting of New Automobiles." *Management Science* **36**(4): 401-421.

Urban, G., B. Weinberg, and J. Hauser (1996). "Premarket forecasting really new products." *Journal of Marketing* **60**(1): 47-60.

Urry, J. (2004). "The 'system' of automobility." *Theory Culture & Society* **21**(4-5): 25-+.

United Nations. Statistical Office. (1997). *Statistical yearbook fourthy-fourth Issue*. U. N. D. o. E. A. S. A. S. Division. New York, United Nations.

US Bureau of the Census (1997). “Historical statistics of the United States on CD-ROM: Colonial times to 1970.” Cambridge University Press, New York.

US Department of Energy (2004). *Transportation Energy Data Book (ORNL-6973)*, Edition 24, Oak Ridge National Laboratory Report, Oak Ridge, TN: October 2004

Figure 1 (a) automobile and horse populations, US (1900-1950) (Source: US Bureau of the Census 1997); (b) Share of auto producers for each platform (ICE, steam, electric), with number of active producers (1876-1942). Source: compiled from Kimes and Clark (1996).

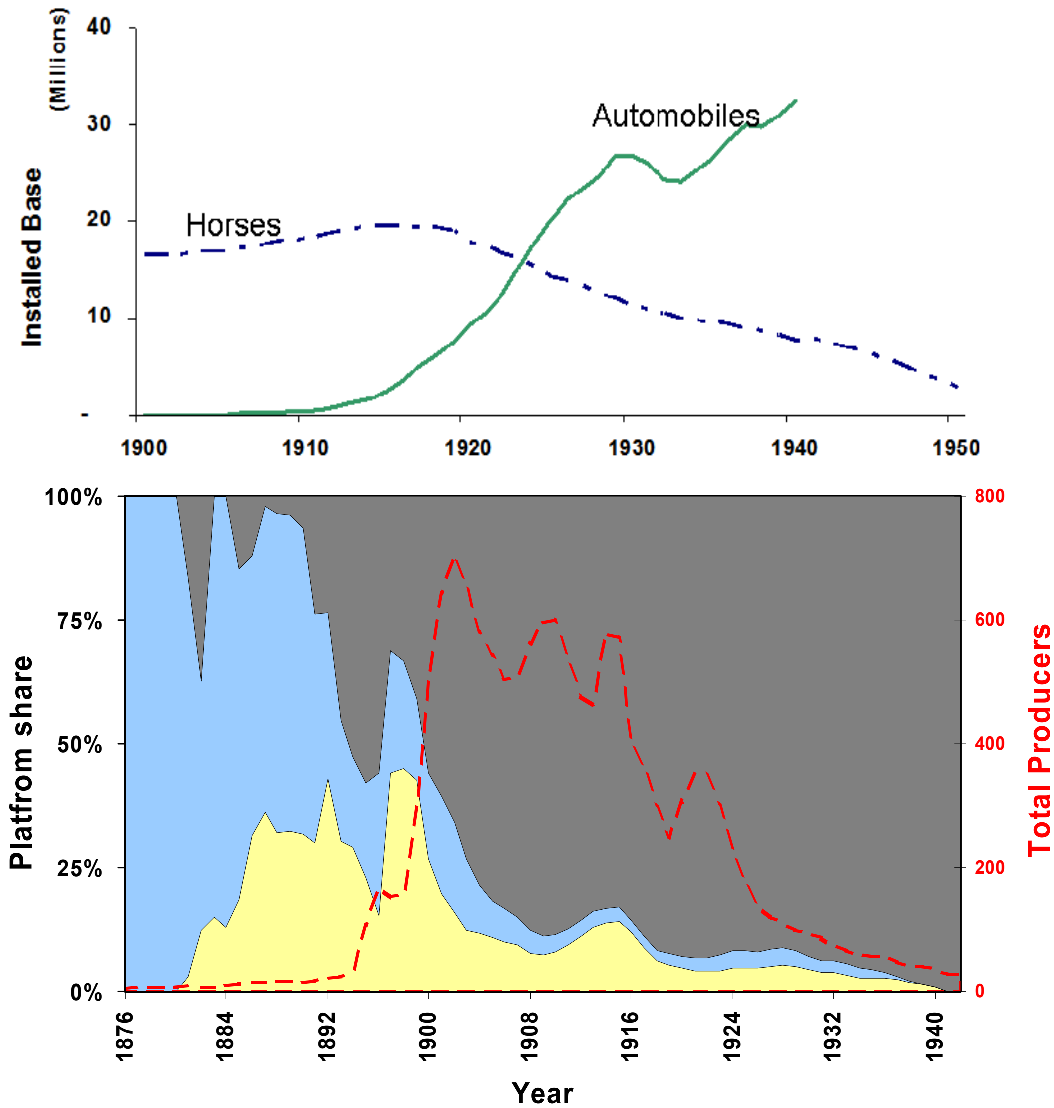

Figure 2 Model boundary, stakeholders, and interdependencies.

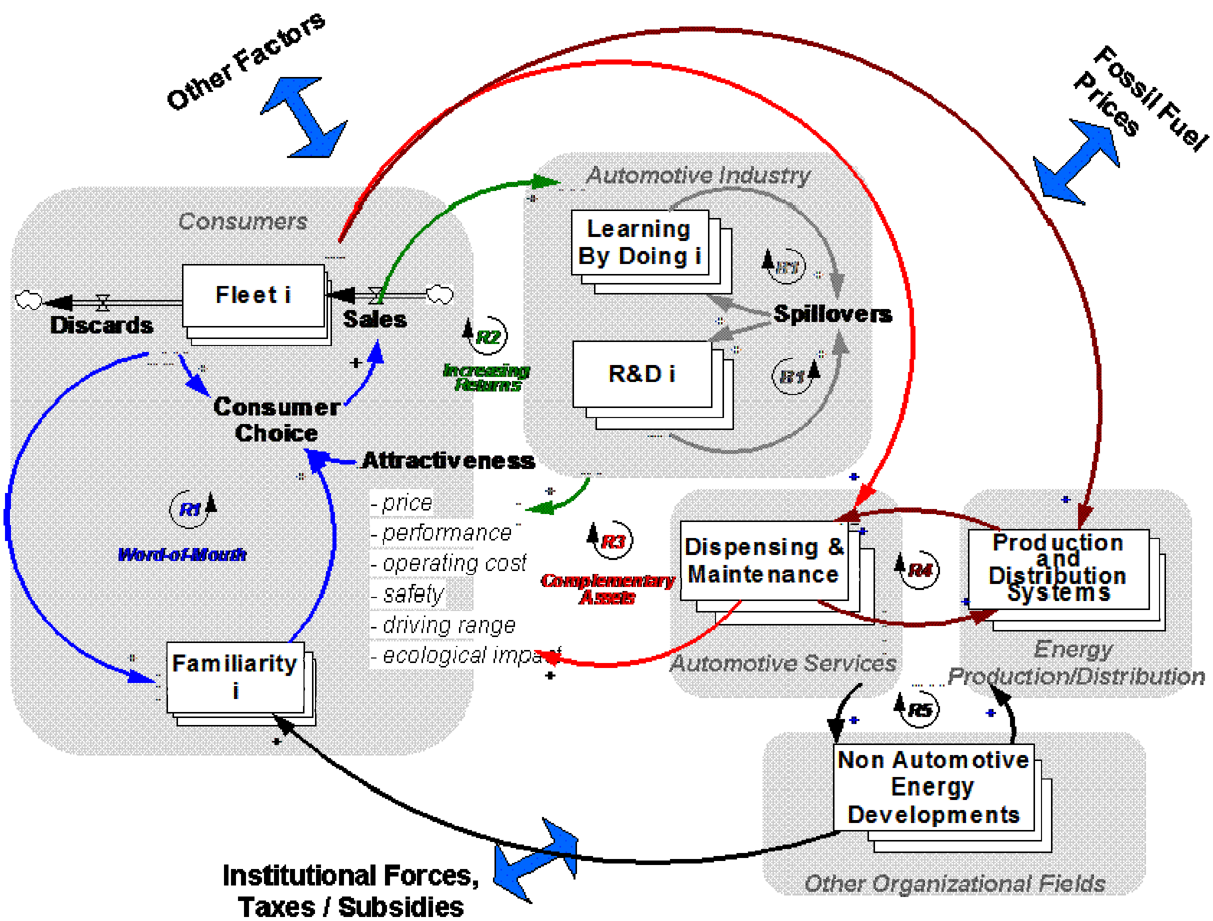

Figure 3 Principal positive feedbacks conditioning familiarity and consumer choice, with expected modes of behavior.

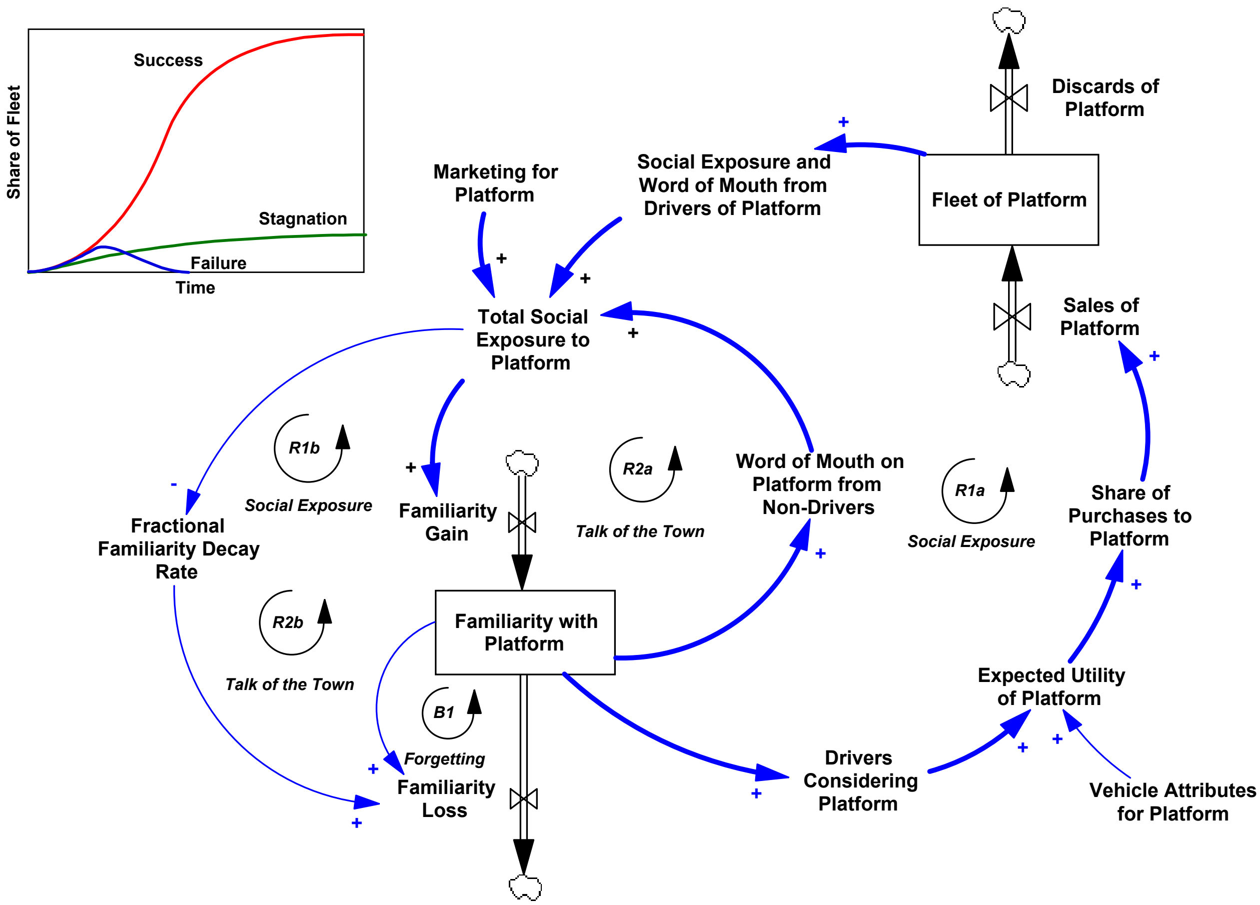

Figure 4 Phase plot for one-dimensional system showing two stable and one unstable fixed points for familiarity of ICE drivers with AFVs (parameters in Table 2).

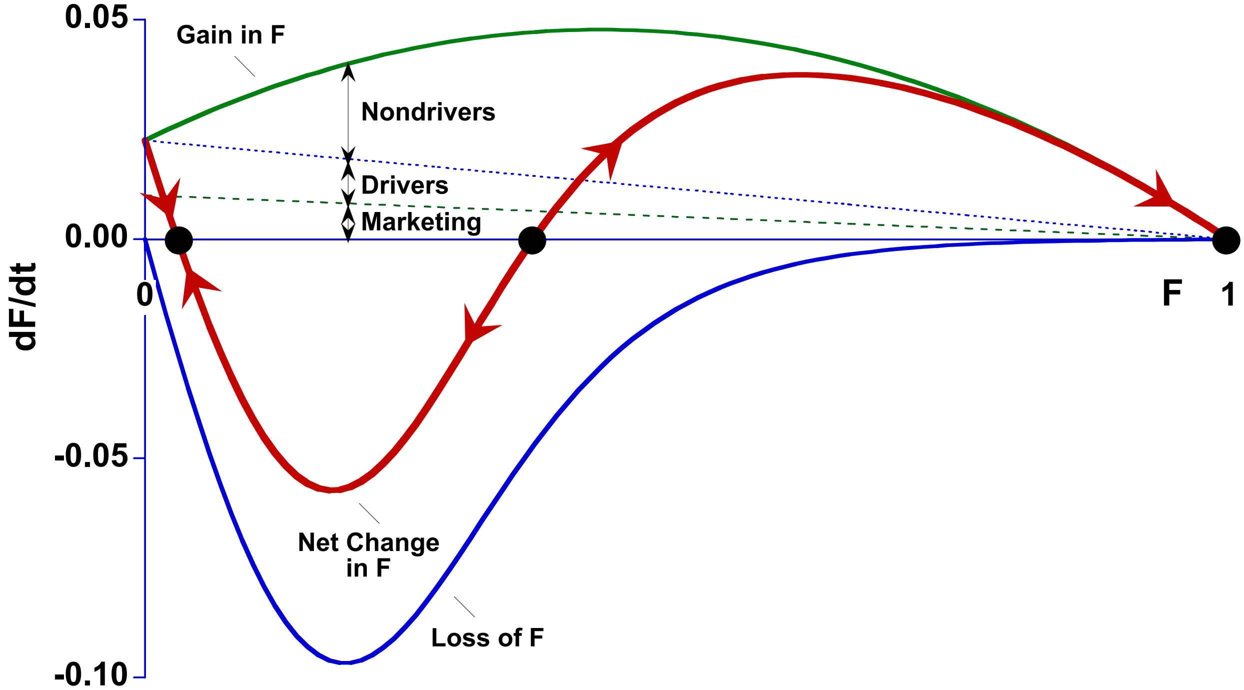

Figure 5 Phase space for two-dimensional system with endogenous familiarity and fleet. Fixed points exist at intersections of nullclines; dots show sample trajectories. Grey area shows basin of attraction for the low-diffusion equilibrium. Strength of marketing and nondriver word of mouth as shown. Other parameters as in Table 2.

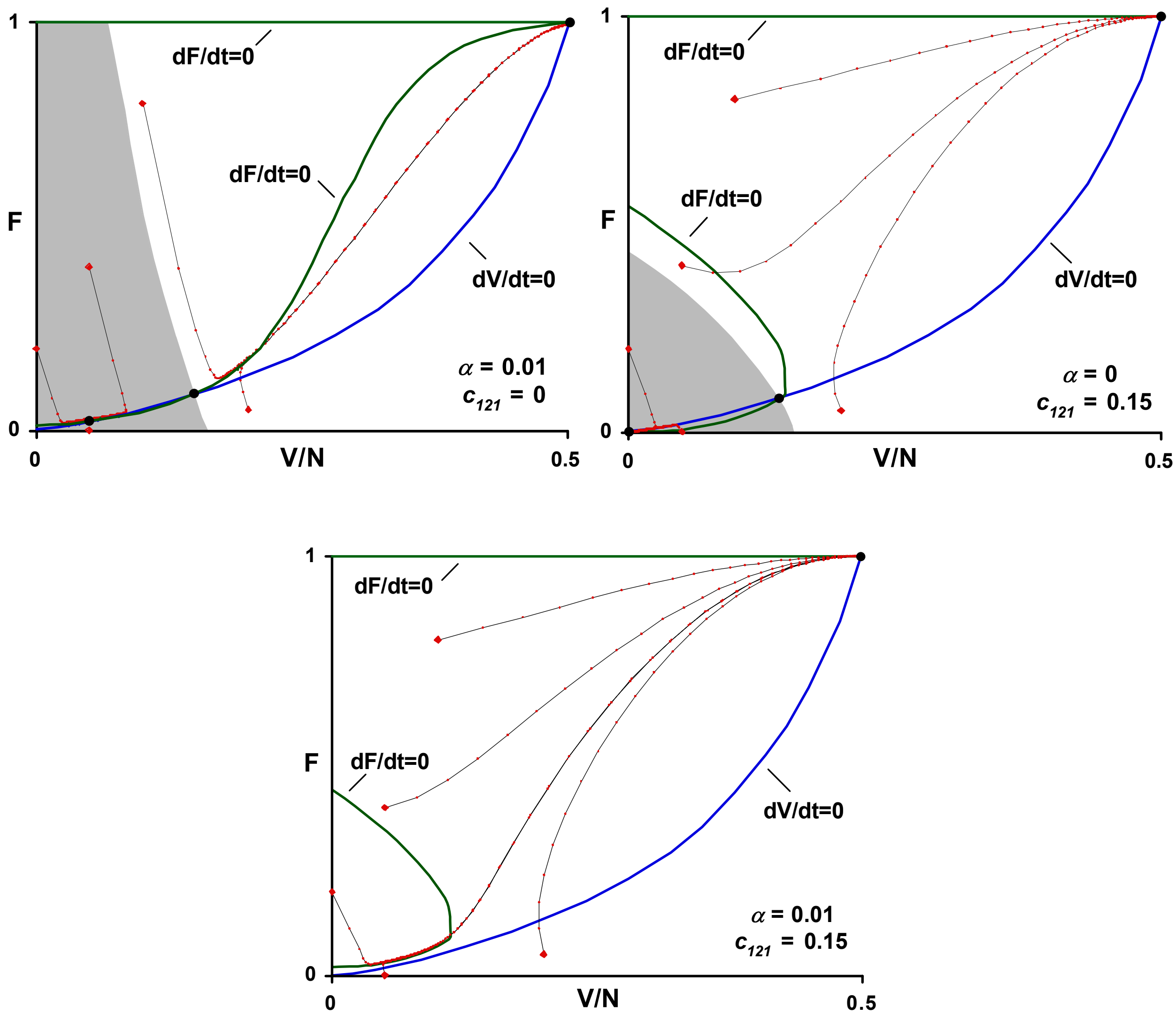

Figure 6 Alternative vehicle familiarity, sales- and installed base share with an aggressive marketing and promotion program. Duration of high marketing impact ($\alpha_2 = 0.025$) varies between 0 and 50 years. Thick lines show the scenario for the critical marketing duration (T^*=20 years), which yields successful diffusion for the shortest marketing duration.

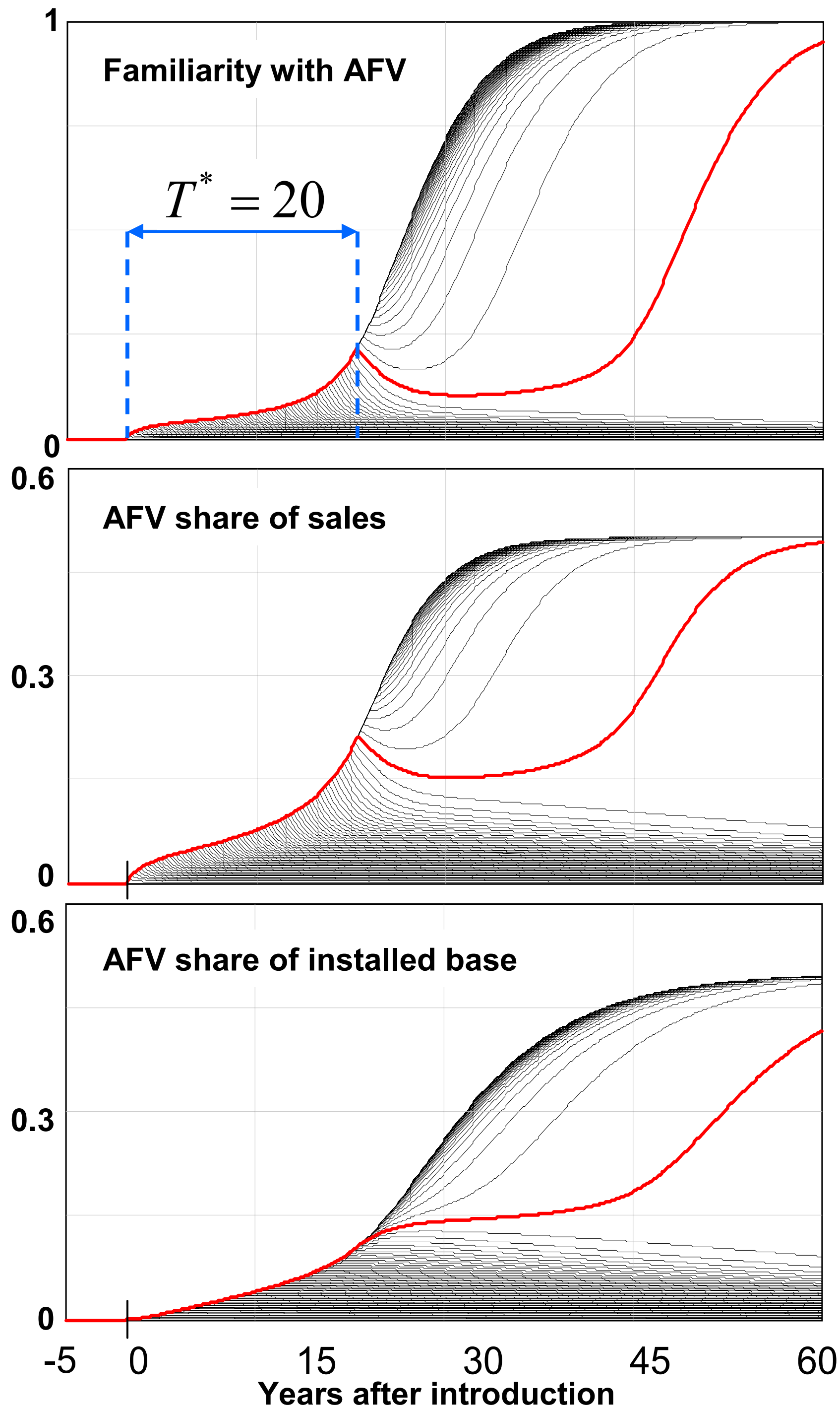

Figure 7 Sensitivity of the AFV installed base share to key parameters. Each panel shows the time required to achieve 15% and 25% share of the total fleet. The reference points (dots for 15% and squares for 25% market share) indicate the values for base run Figure 6 with an aggressive promotion and subsidy program lasting 20 years.

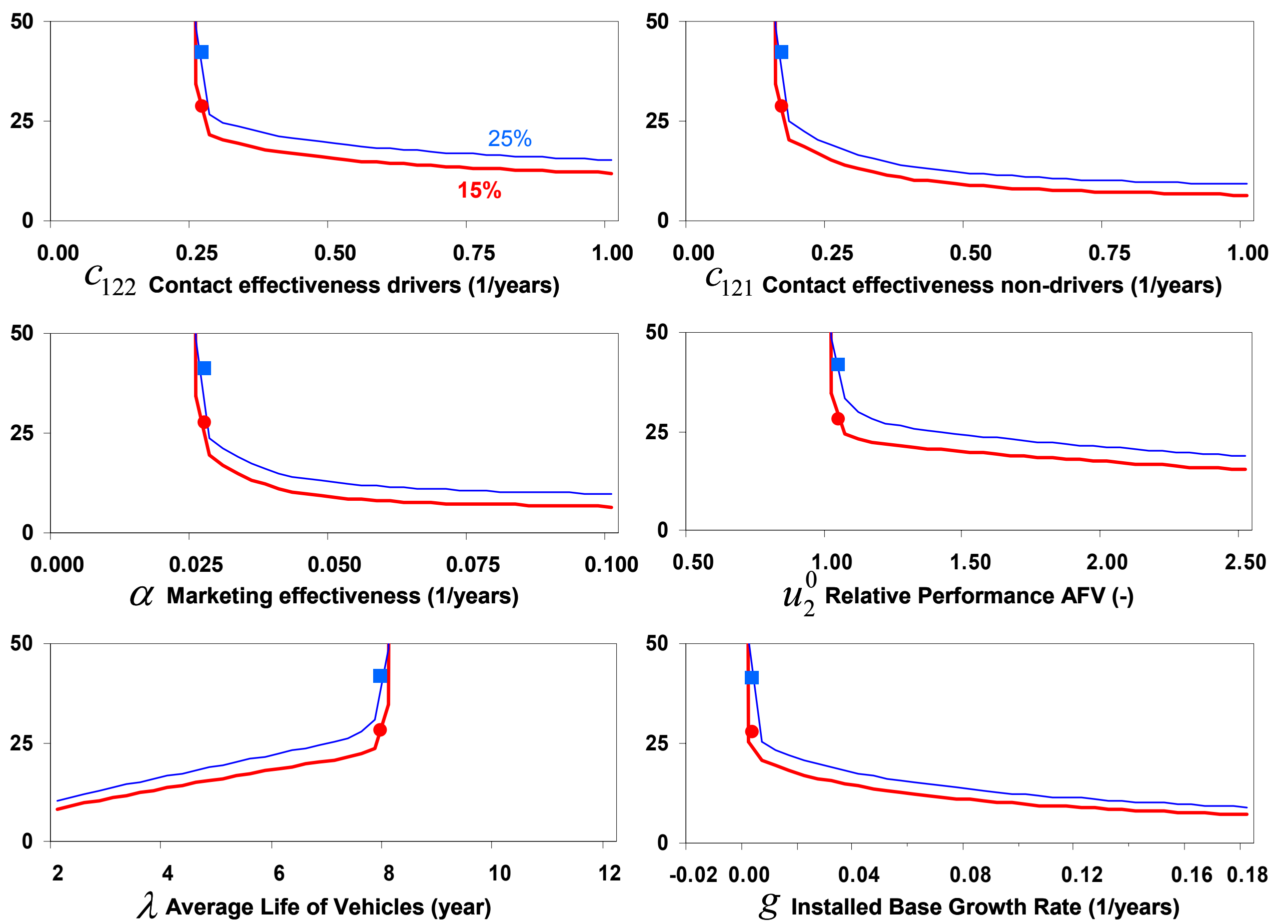

Figure 8 Alternative vehicle familiarity and fleet with endogenous learning and innovation spillovers.

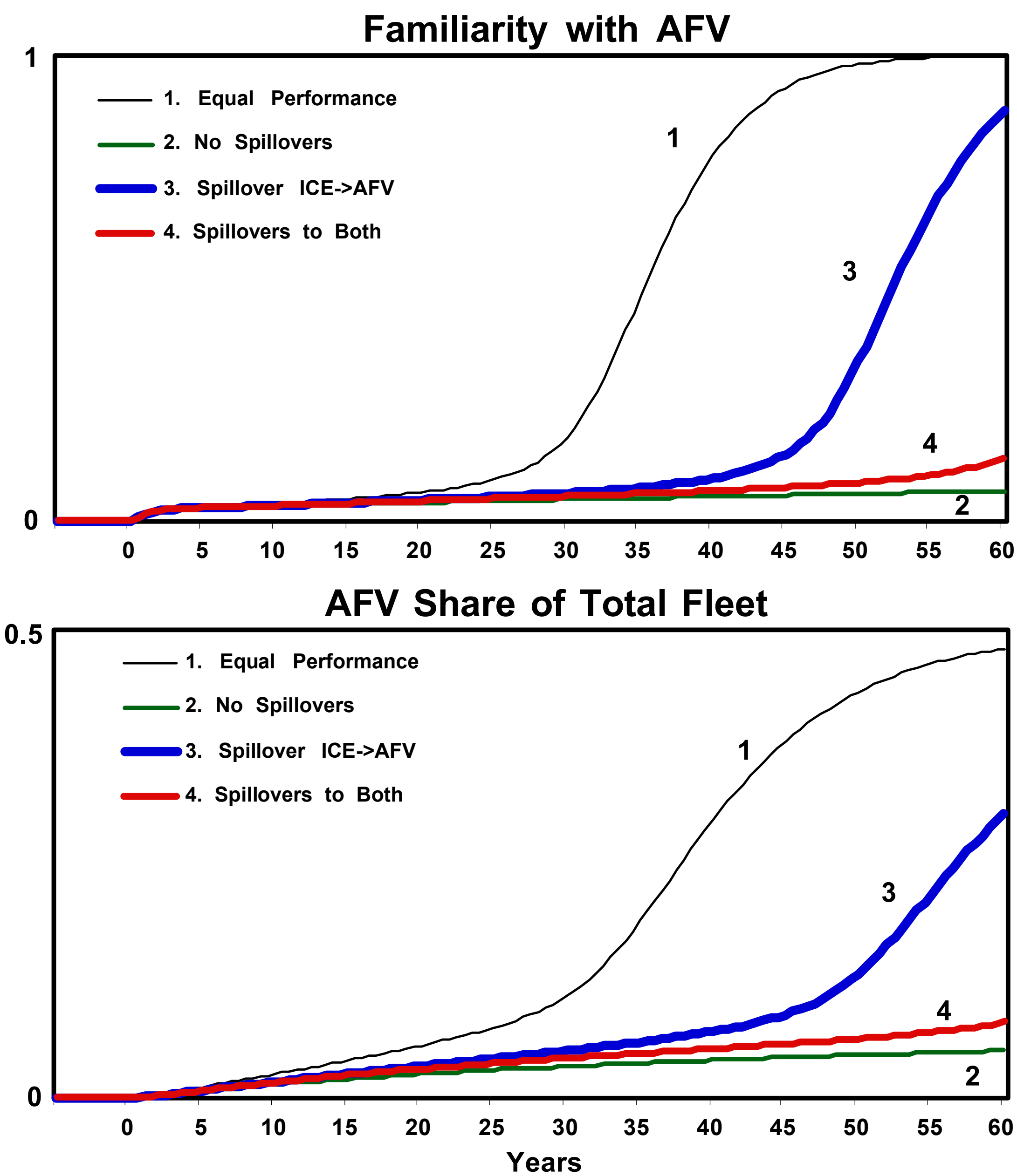

Figure 9 Behavior of spatially disaggregated model calibrated for California.

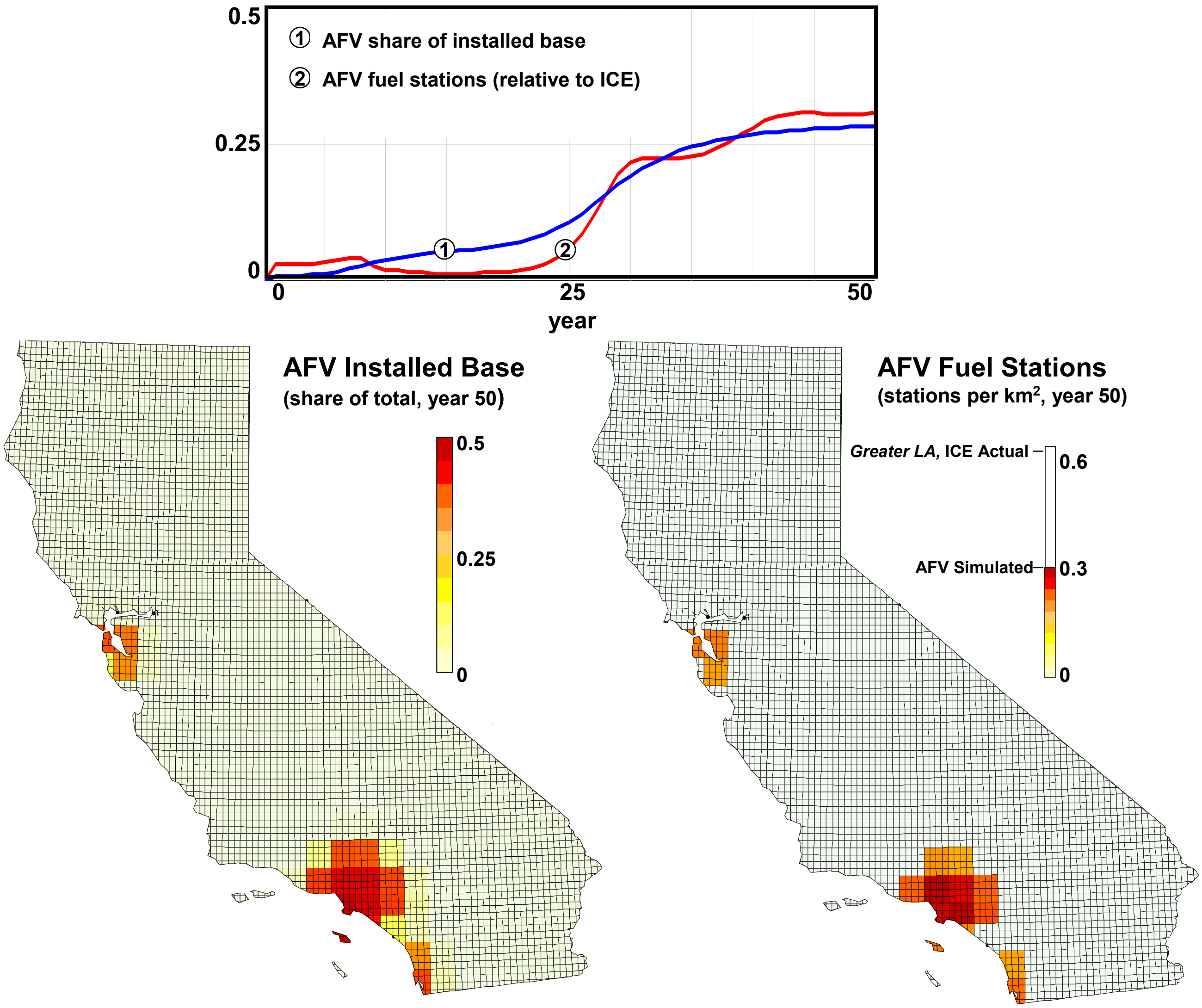

Table 1. Acronyms

Acronym	**Definition**
OEM	Original Equipment Manufacturer (an auto company)
ICE	Internal combustion engine
CNG	Compressed natural gas
HFCV	Hydrogen fuel cell vehicle
AFV	Alternative fuel vehicles

Table 2. Base case parameters.

	Definition	unit	Value	Note
g	Growth rate of the total car parc	1/year	0	See sensitivity analysis
α_2	AFV marketing effectiveness	1/year	0.01	See e.g. Easingwood et al. (1983) and sensitivity analysis
c_{122}	Strength of word of mouth about AFVs for contacts between AFV and ICE drivers	1/year	0.25	See e.g. Easingwood et al. (1983) and sensitivity analysis)
c_{121}	Strength of word of mouth about AFVs for contacts between ICE and other ICE drivers	1/year	0.15	Weaker than that of drivers. See also sensitivity analysis
ϕ_0	Maximum familiarity loss rate	1/year	1	Heuristic (see sensitivity analysis)
η^*	Reference rate of social exposure	1/year	0.05	Heuristic – implies that inflection point for forgetting is at 10% of adoption
ε	Slope of familiarity decay rate at reference rate	years	$1/\eta^*$	Normalizes elasticity of familiarity decay to exposure at 1.
λ	Average vehicle life	years	8	Conservative: Greenspan and Cohen (1999) estimate over 12 years. See sensitivity analysis
β	Sensitivity of utility to performance	dmnl	0.3	Conservative heuristics, e.g. Brownstone et al. (2000)
ζ	Elasticity of substitution between platform internal and external experience	dmnl	1.5	Heuristic – argued in paper
γ	Learning curve strength	dmnl	0.379*	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

* 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 γ=0.379.