Strategies for Transportation Electrification: Overcoming Thresholds, and Overly-Optimistic Forecasts

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Abstract

With increasingly volatile oil prices, unprecedented US dependence on imported petroleum, and growing environmental concerns, the creation of economically sustainable markets for alternative fuel vehicles (AFVs) is vital. In particular, electric drivetrain vehicles (EDVs) offer potential to develop a more sustainable transportation system. However most efforts to supplant the current transportation system, dominated by the petroleum-powered internal combustion engine have failed or had limited success. The diffusion of EDVs is complex, being both enabled and constrained by powerful positive feedbacks arising from scale and scope economies, experience curves, network effects and complementary assets. These positive feedbacks link automakers and their supply chains, fuel suppliers and their supply chains, consumer purchase and driving behavior, and public policy at multiple levels. While such feedbacks are sometimes discussed, dominant mental models among both policy makers and academics may underestimate the strength of these feedbacks and the fact that they also operate to advantage the current dominant technology. The result has been a series of overly-optimistic forecasts for the extent and speed of diffusion for AFVs and EDVs, and insufficient investment in standards and policies to help such vehicles over the tipping point to self-sustained adoption. For example, it is widely believed that higher gasoline prices (either through market forces or carbon policy) will push EDVs over the tipping point to self-sustained adoption and significantly speed the transition. To develop an in-depth understanding of the major challenges and identify high-leverage strategies in transitioning away from a fossil fuel and carbon based transportation system we have developed a suite of behavioral dynamic, spatially disaggregated models with a broad scope. Key actors in the models include consumers, automotive OEMs, infrastructure providers, fuel suppliers and policy-makers. In this paper we describe the model and carry out simulation experiments designed to examine barriers to self-sustaining EDV adoption under a variety of scenarios. In particular, we show that higher oil prices, while important in speeding EDV adoption, are less effective than many expect, due to a range of compensating feedbacks that enable internal combustion-gasoline technology to adapt.

Introduction

The current transportation system does not scale: if the projected world population of 9 Bilion people in 2050 lived the way Americans do today, world oil production would increase 5 fold to 440 million barrels per day, and CO_2 emissions would increase by a factor 2.5 (MIT Transportation Initiative 2009). In particular, light-duty vehicles powered by fossil fuels contribute disproportionately to climate change, US dependence on imported oil, and other harmful environmental and public health problems. With increasingly volatile oil prices, unprecedented US dependence on imported petroleum, and growing environmental concerns, the creation of economically sustainable markets for alternative fuel vehicles (AFVs) is vital to the success of automakers and fuel and energy suppliers, and to the health of the US, and global economies (Sperling and Gordon 2009). In this paper we examine the transition strategies for alternative fuel vehicles, and plug-in electric vehicles in particular.

Of the many possible alternatives to an oil-based automotive transportation system, electricity is particularly promising as part of the bigger transition. Electricity can be generated from renewable sources such as wind and solar to minimize environmental impacts, can be generated domestically to address global security concerns and can take advantage of existing grid infrastructure. Indeed, Electric Drive Vehicles (EDVs) connected to the electricity grid can be seen as a complementary technology to intermittent renewable energy technologies. Renewable electricity minimizes the environmental impact of EDVs, while EDV batteries connected to the grid have the potential to provide storage and buffer the intermittency of electricity generated from renewable sources. These technologies provide a vision for a distributed electricity grid, and an indeed energy system that is vastly less polluting, more efficient and more robust.

It has been well-recognized that the diffusion of AFVs is complex, being both enabled and constrained by powerful positive feedback arising from various scale and scope economies and experience curves throughout the automotive and fuel supply chain, and from consumer behavior and word of mouth. The presumed mechanism by which the EDVs may overcome such chicken and egg problems is through diffusion accelerating investments to improve battery density, and fleet deployment. Says Burgelman and Grove (2009): "*the overarching aim for all participants should be to develop an equivalent to Moore's Law in battery technology*". In line with this, several models exist to examine the long-run benefits from such investments. AFV transition models in general (Alkemade Frenken et al 2009; Van Vliet et al. (2010) and for PHEVs in particular (Lemoine 2008, 2010; Yeh et al. 2010) examine the scenario's offering more success. Models have been developed with focus on respectively benefit-cost (Offer et al 2011), long-term carbon emission reduction impact (Yeh et al. 2010), on minimizing integration with the grid (Lemoine et al 2008), or maximizing the adoption rate (Lemoine 2010).

However, while an effective electricity grid-based transportation system can be envisioned, the process by which such a self-sustaining market gets established is far from clear. In such a multi-faceted system, many pathways may fail or stall and it remains an open question whether desirable scenarios can actually be achieved. Historically, most efforts to transition away from a transportation system dominated by the gasoline fueled internal combustion engine have failed or had very limited success (Yeh 2007; Struben2006). Diffusion outcomes are strongly conditioned by decisions of energy companies, governments, automotive OEMs and their suppliers, and consumers. Moreover, a successful transition to a self-sustaining AFV market requires intensive coordination between key decision-makers. In addition, for EDVs, not all scenarios lead to sustainable solutions. Then, pointing to the path-dependent nature of transitions (researchers have called for dynamic behavioral models that give insights in the transition strategies and the conditions under which they are successful (Geels 2005; Alkemande et al. 2009). While a transition will play out over decades, mobilization of resources within the next few years has long run consequences. Effective strategic pathways for pursuing the electrification opportunity need to be identified. We address critical questions such as: what are robust, high leverage policies to achieve an effective transition? For the successful policy portfolio's, what is the likely burden on each of these actors? Robust scenarios are those whose leverage holds under a wide range of economic and technology uncertainty scenarios, as well as to various forms of competition from conventional and other alternatives.

Building on earlier AFV transition analysis, this paper examines how adoption of AFVs is affected by external shocks. Specifically, we focus on the diffusion dynamics for PHEV and how this pattern is affect by a one-time oil-price increase. We examine how this scenario affects the rate of adoption of PHEVs. In conclusion we discuss how the model we develop here is part of a family of models that can help guide stakeholders and policymakers create markets for alternative fuel vehicles that are sustainable environmentally and economically. Our results show successful PHEV diffusion scenarios. However, it takes a consistently long period before significant reductions in petroleum consumption or carbon emissions are achieved. Even under aggressive carbon policies and optimistic technology scenarios, such as early and successful commercialization of carbon sequestration and storage. We demonstrate that high oil prices while accelerating adoption, many of the benefits f.

Mental models of accelerating alternative fuel vehicle diffusion

Consider the impact of higher oil prices on the diffusion rate of PHEVs. A likely response is that such prices will greatly spur the adoption of PHEVs. Underlying this is the realization that higher oil prices increase market share of PHEVs, this in turn accelerates their growth. In other words, higher oil prices strengthen the positive learning curve feedback of PHEVs, as well as others. Indeed higher oil prices increase the cost of driving petroleum, increasing the cost of driving of conventional internal combustion (ICE) vehicles, and thus reduce their attractiveness (Figure 1).

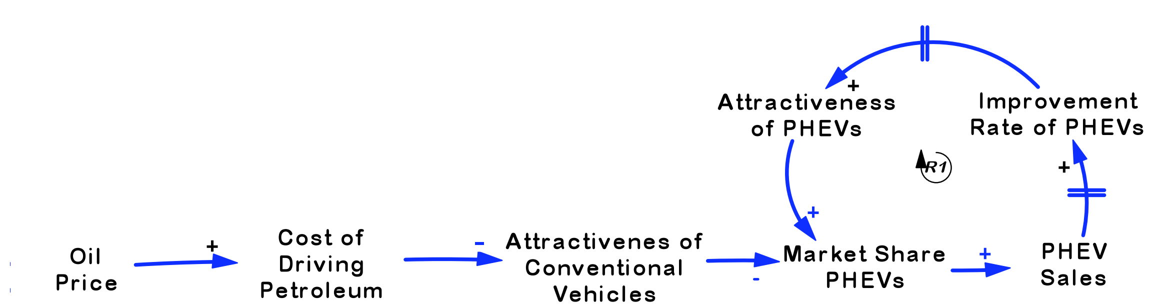

Figure 1 – Higher oil prices strengthen the positive learning feedback of PHEVs.

Reduced attractiveness of ICE vehicles improves the relative attractiveness of PHEVs, providing them a larger market share. Consequently, increased sales compared to the case of lower oil prices speeds up learning, allowing for more rapid improvement of cost, battery storage, take-up and charging infrastructure. Thus, oil prices act to improve the gain of the learning curve. Thus, according to this mental model we should expect a significant and accelerating impact of oil prices on PHEV diffusion.

However, empirical evidence shows that this mental model, while powerful may be incomplete in a problematic way. The market response to shocks is much more complex. In response to oil shocks, consumers adjust their behavior to mitigate the effect. Consumers, when expecting that oil prices remain high, adjust their drive behavior, shift to smaller and more efficient cars (Figure 2). In turn, producers of conventional vehicles may adjust their portfolios to alter the weight, performance efficiency tradeoffs, or increase R&D to improve efficiency technologies.

See appendix due to file size restrictions

Figure 2 Consumer and automotive responses to oil price shocks: Clockwise: car and light truck sales, consumer vehicle miles traveled, and marginal vehicle curb weight and performance. Sources: Data: US Census; http://www.greencarcongress.com/, accessed June 2008; Transportation Energy Data Book, Ed. 26-2007 Table 4.6, Autodata and Ward's

Indeed over the last 25 years, under low oil prices, virtually all progress on fuel efficiency has benefitted vehicle performance rather than fuel economy (Heywood et al. 2004). Thus, much underutilized and latent potential in fuel economy improvement exists in the conventional vehicles. In this paper we examine the dynamics of dominant (ICE) and alternative (PHEV) technology in the context of an environmental (oil price) shock. By focusing on the technological competition dynamics, we contribute to the literature of technology strategy.

Theory on the resolution of technological uncertainty

The question of the degree to which an established market may respond, effectively or not, to competitive and environmental pressures, is a central and unresolved debate in the literature of radical and disruptive innovations. From one view, disruptive innovations are hard to establish in a mature and oligopolistic market. Barriers to change are formed: first, because incumbents can deter entry through preemptive patenting out of fears of cannibalization of existing market share (Gilbert and Newbery 1982, Arrow 1962); and, second, because of the existence of various increasing returns to adoption economies (Arthur 1988). Others describe industry structure-related conditions under which disruption is possible, for example, under sufficient uncertainty of the timing and impact of the innovation (Reinganum 1983). The dominant focus in the literature is however on whether the entrant or incumbent firms are more likely to successfully navigate periods of technological uncertainty. For example, Tushman and Anderson (1986) distinguish capability-enhancing and capability-destroying disruptions: that is, cumulative experience and scale can either help or hinder incumbents producing the old technologies, but not entrants. The dominant argument is that incumbents have inertia because of cost in adjusting their channels (Henderson and Clark 1990) or because of cognitive biases (March 1991; Tripsas and Gavetti 2002). Christensen (1997) notes that disruptive technologies can emerge in a neighboring market and compete on dimensions of merit previously ignored. For the incumbent it is not attractive to invest in a small infant market product, but they can fend off threats by shifting upward in the market. Then, as the experience of the entrant grows, its superior performance in the new attributes allows the entrant to outplay the incumbent.

However, the image of an ex-post technology breakthrough obviates sensitivity to how the resolution of technological uncertainty itself contributes to industry evolution and firm success. During periods of ferment, promising technologies exhibit a wide variety of diffusion patterns including failure and saturation at low penetration levels (Utterback and Suarez 1993; Gelijns et al. 2001; Garud and Karnoe 2001; Danneels 2004; Ansari and Garud 2008), technology succession often occurs in waves (Christensen 1993), dominant technology revival (Henderson 1995; Snow 2006), diffusion paths of rival technologies often crossing multiple times (Sood and Tellis 2005). As has long been acknowledged, a technology's pathway is not merely conditioned by its objective performance across intrinsic dimensions of merit (Rosenberg, 1972; Arthur 1989; Nelson and Winter, 1982). Hence, early organizational commitment has long-run implications for technology pathways.

As a consequence, dominant technologies may offer latent potential that get's exploited once under threat (Henderson 1985). Whether innovations of a potential entrant will generally trigger increased R&D activity and performance increases of incumbents, the so-called sailing-ship effect (Rosenberg 1976), has also been observed in the automobile industry (Snow 2004). Resource allocation decisions are however further complicated as technologies not only act to compete, but also evolve and coevolve. The technological change literature offers overwhelming empirical evidence of diverse and evolving technological choices during periods of ferment (Mitchell 1989; Tushman and Rosenkopf 1992; Christensen 1993; Ansari and Garud 2008). Hence, knowledge spillovers (Romer 1986; Klepper 1996; Owen-Smith and Powell 2000) govern the direction of technology pathways (Yates 2003, Helfat and Raubitscheck 2000; Lewin Long and Carroll 1999), in particular when technological knowledge is heterogeneous (Jovanovic and MacDonald 1994).

Taken together, examining the resolution of technology uncertainty demands capturing the mechanisms at work when technologies respond to changes in the competitive and external environment, including those involving the dominant technologies. Learning occurs through diverse channels: product innovation through R&D, learning by doing (often equated with process innovation) (Arrow 1962; Zangwill and Kantor 1998), learning by using (Mowery and Rosenberg 1989), and spillovers (e.g., Cohen and Levinthal 1989). Technological innovations spill over between technologies (Jovanovic and Macdonald 1994; Aghion et al. 2001), and with the capability to extract knowledge from the outside (Cohen and Levinthal 1989). At the industry level, competence building is a social, distributed process of bricolage (Garud and Karnoe 2003). This view emphasizes the value of technological diversity as was discussed for the emergence of wind energy by (Karnoe 1999; Kemp 2001; Garud and Karnoe 2003). Moreover, while a technology's fate is surely linked to the organizations that sponsor it (Christensen and Rosenbloom 1993), technology dynamics are far from epiphenomenal to organizational and industry dynamics.. The relevance of the various mechanisms, and how they play out, depends on industry specific parameters. In this paper we address one such issues, examining how distinct technologies respond differently to external shocks.

Model Overview

We develop an empirically grounded dynamic simulation model with a broad scope, grounded in economic, social-behavioral, operations management, and consumer demand theory. This work builds 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 - automotive R&D and marketing resource allocation decisions – conditioned by productive benefits, scale economies, learning and R&D and experience, innovation spillovers - retail infrastructure decisions (Figure 3). We expand earlier work that focused on vehicle adoption dynamics including consumer acceptance of AFVs and changes in driver behavior in response to fuel cost and availability, the development of fueling infrastructure, and the evolution of vehicle attributes and auto OEM portfolios (**ref omitted). In particular, we expand the factors that contribute for endogenous vehicle improvements and the distinction between vehicle classes within alternative platform choices.

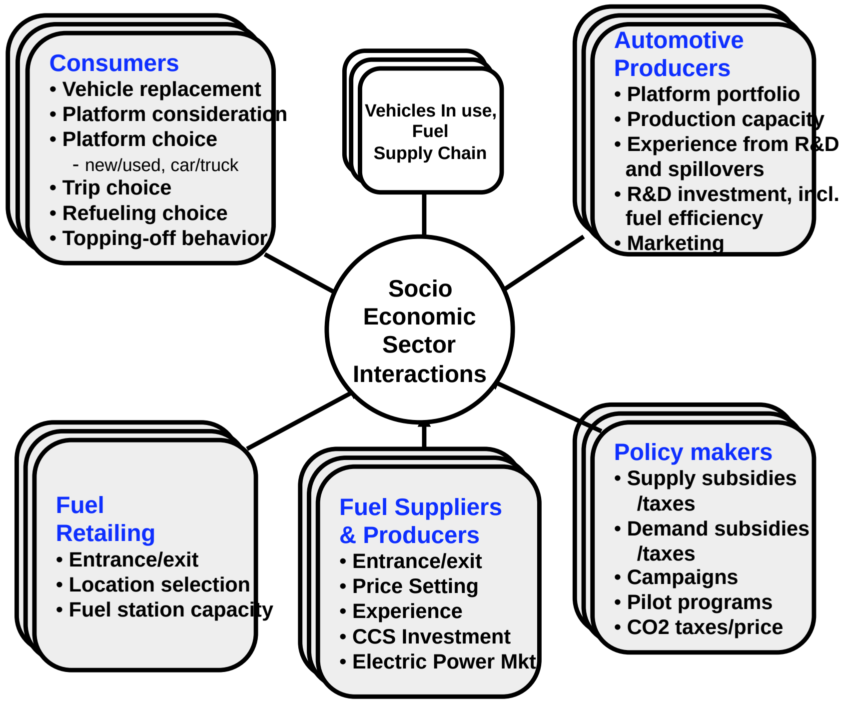

Figure 3 Model boundary and main actors

The fuel supply chain includes fuel markets, entry and exit of plants, installation and operating costs, and traces life cycle carbon- and energy intensities for each pathway. The model captures not only factors involving increasing returns, such as production learning and scale economies, but also diminishing returns, such as from land constraints on biofuel production. Model confidence building process is supported by a rich data set with a variety of sources. We draw among others on media such including major auto and energy companies (especially Ford and Shell), the USDA, EIA, GREET, the US Census, and related academic studies from MIT and other universities. There is substantial uncertainty in many aspects of the market transition (political, technological, behavioral). We further used calibration, extensive sensitivity analysis, and partial model testing to build further confidence in the model. 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). In the following section we discuss in detail the sections of the model most relevant for the purpose of this analysis.

Selected Model specification

The share of consumers switching between vehicle choice *i* to *j* depends on the expected utility of platform *j* as judged by the driver of vehicle *i*. Further, in their choice, drivers have a range of options available. First, they consider buying a vehicle at all. Further, they must decide whether to purchase a new and used vehicle. Next, multiple platforms are available ICE, HEV, PHEV, or BEV, and within that, consumers can consider different sizes. The basis for formalizing these multidimensional choices is a classic nested logit formulation (Figure 4).

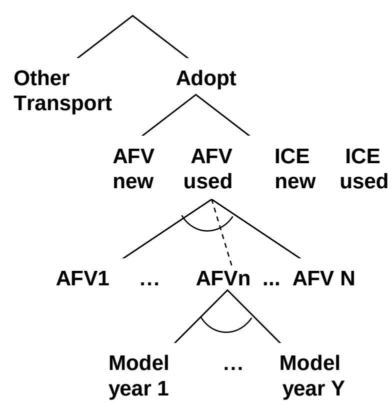

Figure 4 Nested decision-making structure for consumer choice between vehicle options.

In formal terms, the share that drivers of platform *i* replacing their vehicle allocate to platform *j*, σ_{ij}^{d}, involves a nested decision process (Ben-Akiva 1973). A share of the discarded vehicles from platform *i* is replaced by *j*, σ_{ij}^{r}, conditional upon an earlier choice of replacing the vehicle at all σ_{i}^{r}:

$$\sigma_{ij}^{d} = \sigma_{i}^{r}\sigma_{ij}^{r} \qquad (1)$$

For a replacement decision, all vehicle platforms form a "nest" whose utility is compared to an unspecified alternative:

$$\sigma_i^r = \frac{u_i^{ve}}{u_i^{ve} + u^{oe}} \tag{2}$$

An increase in the variety of models does not necessarily increase aggregate utility of "the vehicle nest" proportionally. That is, utility of the nest depends on the correlation (or substitutability) of preference across a range of products in the choice outcome (not necessarily in direct relation to the different platforms). To capture this we introduce a scaled parameter $\mu \equiv 1/(1-\chi)$ with $\chi,\ 0 \le \chi \le 1$, being the correlation parameter for consumer choice with respect to the platforms within the nests (further intuition is provided following equation **Error! Reference source not found.**, the nest utility is:

$$u_i^{ve} = \left[\sum_j u_{ij}^{ve}\right]^{1/\mu} \tag{3}$$

While the effective utilities for the various platforms u_{ij}^{ve} are the perceived utility with each platform u_{ij}^{v} adjusted for their correlation, multiplied with familiarity F_{ij} of the population with the various choices:

$$u_{ij}^{ve} = \left(F_{ij} u_{ij}^{v}\right)^{\mu} \tag{4}$$

Utility, u_{ij}^{v}, depends on vehicle attributes for platform j, as perceived by driver i. For an aggregate population average familiarity F_{ij} varies over the interval [0, 1]. The correlation parameter can now be interpreted as follows, with $\chi \to 0$, the case of no correlation, platforms are perceived by the consumers as fully distinct and overall "vehicle utility" rises linearly with number of platforms. For $\chi \to 1$, full correlation, vehicle platforms are perceived to be identical, and the perceived utility equals that of the most superior. For instance, in the case of n identical products, with only different prices, all demand goes to the cheapest product. Lowering price for a more expensive product, while still being above the most affordable, has no effect on market shares, nor on the overall demand. Neither extreme is behaviorally appropriate. Further, dynamically, χ controls a potentially very strong feedback, between demand and the introduction of new platforms (with maximum strength at the default, no correlation, case $\chi = 1$). In addition, χ is arguably a function of the technological heterogeneity of products on the market. That is however not the point we want to make here. In this paper we assume that the consumer only cares about performance, not so much about distinctiveness between them. Thus, in this model, χ is constant between 0 and 1.

The above formulation is equivalent to the compact general nested formulations (Ben-Akiva and Lerman (1985), Ben-Akiva 1973), frequently used in transportation decision making models (e.g. Brownstone and Small (1989)), industrial organization literatures (e.g. Anderson and Palma (1992) regarding multi product firms, Berry et al. (1995) regarding the automobile industry). We can write σ_{ij}^{d} as:

$$\sigma_{ij}^{d} = \sigma_{ij}^{r}\sigma_{i}^{r} = \frac{u_{i}^{ve}}{u^{oe} + u_{i}^{ve}}\frac{u_{ij}^{ve}}{u_{i}^{ve}} = \frac{F_{ij}\left(u_{ij}^{ve}\right)^{\rho}}{\left[\sum_{j} F_{ij}\left(u_{ij}^{ve}\right)^{\rho}\right]^{1/\rho} + u^{oe}}$$

In the nested logit model, $1 \le \mu \le \infty$ is the scale parameter for the MNL associated with choice between alternatives within the nest (in our case the vehicles). For $\mu \to 1$, corresponding to $\chi \to 0$, the function converges to a standard MNL, while for $\mu \to \infty$, or $\chi \to 1$, the model is a perfect nest. In the model χ is set to 0.5 throughout.

For arguments of consistency, the model must explicitly capture those attributes that are affected by parameters that vary supply and demand elsewhere in the model. For example, the maximum action radius of a vehicle (which correlates with, but is not identical to, trip convenience), influences not only a consumer's purchase decision, but also influences the number of fuel station visits by drivers, and thus utilization; supply is affected in a non-trivial way. For the same reason, we capture operating cost (which is a function of fuel price that also affects supply) and fuel economy (which affects demand, as well as fuel station visits). We capture these under attributes a_{jlz}. All other attributes, by which AFVs may differ, such as vehicle power and footprint, are aggregated under the vehicle-specific term u_{jz}^{0}. Using the standard multinomial logit formulation we can now state:

$$a_{jz} = a_{jz}^{0} a_{jz}^{t} \exp\left[\sum_{l} \beta_{l} \left(x_{jlz} / x_{l}^{*} \right)\right] \quad (1)$$

where β_l represents the sensitivity of utility to performance of attribute *l*.

OEM Profits and Capabilities

For platform economies we use a simple model of cost, volume and profits. Aggregate profits earned by producers of platform type *j,* $j = \{1,...,n\}$, depend on the net profits π_j^n minus capital cost, C_j^k, and investments in R&D, C_j^{RD}:

$$\pi_j = \pi_j^n - C_j^k - C_j^{RD} \quad (2)$$

The price equals unit cost plus markup $p_j = (1+m_j)c_j$. Then, net profits equal the markup multiplied by unit cost c_j and total sales s_j,

$$\pi_j^n = (p_j - c_j)s_j = m_j c_j s_j \quad (3)$$

A key structure in the model is how experience and revenues feedback to improve knowledge, technology and then consumer choice and sales. The chain is comprised of three main segments: consumer choice (discussed above), effective technology and knowledge accumulation, and resource allocation. We discuss the other two in the following sections. The technology frontier moves with an increase in the effective knowledge, with diminishing returns. Effective knowledge aggregates knowledge from all sources *i* that contribute to the state of the technology and that are associated with activity *w*, this is done through a constant elasticity of substitution (CES) function. Knowledge of platform j accumulates, through internal learning-by-doing and product improvement $(i = j)$, or through spillovers $(i \neq j)$.

Vehicles comprise different intrinsic attributes (powertrain, body, brake-system, electrics). It is at this level that spillovers and improvements are captured, and the learning curve exponents, and potential, depend on the specific module. Importantly, also the vehicle efficiency improvement occur at those levels.

The vehicle attributes are linked to the choice attributes. Cost have a fixed component c^f and a variable component that decreases with the advance of relative process technology θ_{j2} (index w=2, $\theta_{jw} \equiv T_{jw} / T_w^0$). The variable costs are equal to c^v when relative technology is equal to the reference technology T_2^0:

$$c_j = c^f + c^v / \theta_{j2} \tag{4}$$

Technology, T_{jw}, adjusts to its indicated level T_{jw}^* with adjustment time τ^t , while technology exhibits diminishing returns in accumulation of effective knowledge K_{jw}^e.

$$T_{jw}^* = T_{jw}^0 \left(K_{jw}^e / K_w^0 \right)^{\eta_w^k} \tag{5}$$

where T_{jw}^0 represents the quality of a platform, or its technology potential. The state of technology adjusts to T_{jw}^0 when internal knowledge equals the mature knowledge K_w^0. η_w^k is the diminishing returns parameter, $0 \le \eta_w^k \le 1$.

Knowledge accumulates through four distinct processes: product improvement through R&D, process improvement through learning-by-doing, and spillovers of both product and process knowledge. Much of the knowledge that is accumulated within one platform can spill over to others. 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, the knowledge base for each platform is a constant elasticity of substitution (CES) function of the platform's own knowledge K_{jjw}, and the knowledge, spilled over from other platforms, K_{ijw}, depending on the spillover effectiveness κ_{ijw}:[1]

$$K_{jw}^{e}=\left[\kappa_{jjw}\left(K_{jjw}/K_{w}^{0}\right)^{-\rho_{jw}^{k}}+\sum_{i\neq j}\kappa_{ijw}\left(K_{ijw}/K_{w}^{0}\right)^{-\rho_{jw}^{k}}\right]^{-1/\rho_{jw}^{k}} \tag{6}$$

We separate the contribution from internal knowledge to emphasize the different process (see below). The spillover effectiveness is not identical across technologies. For instance, the fraction of the knowledge of a HEV powertrain that is relevant to ICE vehicles differs from the fraction relevant from a biodiesel powertrain. 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, which radically alters most design elements. We specify this spillover potential between two technologies, with respect to activity *w* as $\kappa_{ijw}, 0\leq\kappa_{ijw}\leq 1$ and, by definition, for internal knowledge there is full spillover (carry over) potential, $\kappa_{jjw}=1$.

Further, $\rho_{jw}^{k}=\left(1-\varsigma_{jw}^{k}\right)/\varsigma_{jw}^{k}$ is defined as the substitution parameter, with its transformed value ς_{jw}^{k} being a measure of the elasticity of substitution between the various knowledge sources for platform *j*.[2] For such technologies $1<\varsigma_{jw}^{k}<\infty$. Further, we see that one way for the effective knowledge to be equal to the normal knowledge is when internal knowledge equals the mature knowledge K_{w}^{0} in absence of any spillover knowledge.

[1] This expression is a natural generalization of McFadden's (1963) multiple input CES function. This significantly increases the production possibilities. For instance the elasticity of substitution does not have to be identical for all inputs (see also Solow 1967). See the analysis for an explanation of how this function behaves naturally with accumulation of knowledge.

[2] In a two platform context, ς_{jw}^{k} would measure exactly the elasticity of substitution between spillover knowledge and internal knowledge. In a multiple platform situation the definition of elasticity of substitution is not well defined.

In the model we repeat Equation (6) to specify effective knowledge as a non-linear sum of OEM knowledge (as specified in equation (6) and generic knowledge. Doing this, allows capturing a richer knowledge improvement pattern than when using standard learning curve. For example, electric vehicles at the system integration can make a significant of improvement even though experience with electric vehicles is scarce. This is so, because non-automotive knowledge exists and can be tapped.

Knowledge Accumulation

Knowledge accumulate at a rate Γ_w when resources are equal a normal value R_0. The accumulation rate increases with allocation of resources, an endogenous productivity effect ε^i_{jw}, and relative resource allocation:

$$\frac{dK_{jjw}}{dt} = \varepsilon^i_{jw}\left(R_{jw}/R_0\right)^{\eta^i_w}\Gamma_w \tag{7}$$

Benefits to resource allocation exhibit diminishing returns: $0 \le \eta^i_w \le 1$.

For product improvement the productivity effect is constant, $\varepsilon^i_{j1} = 1$. Process improvement is subject to learning-by-doing effects and the effectiveness is a concave function of the relative resources per volume produced:

$$\varepsilon^i_{j2} = \left(s_j/s_0\right)^{\eta^s} \tag{8}$$

with $0 \le \eta^s_j \le 1$.

Knowledge can spill over to other technologies. Imitation, reverse engineering, hiring from competitors and other processes that enhance spillovers take time and resources. Further, spillovers close the gap between the *perceived* knowledge of platform *i* as perceived by platform *j*, $K^{\sim}_{ijw}$, and the knowledge that has already spilled over K_{ijw}. Further, spillover increases with resource allocation, and fractional growth rate g_w^o:

$$\frac{dK_{ijw}}{dt} = g_w^o \left(K_{\tilde{ij}w} - K_{ijw} \right) \left(R_{jw} / R_0 \right)^{\eta_w^o} \qquad (9)$$

Note that the model exhibits diminishing returns in the accumulation of technology, in relation to effective knowledge, but that there are constant returns to the accumulation of knowledge itself. In real life, the exact locus of diminishing returns is not always easy to measure. For instance whether aggregate diminishing returns are the result of constraints at knowledge collection, effectiveness of knowledge, or transforming knowledge into technology is not easily to observe. Moreover, all will be true in reality, in the long run. In appendix 3b I show that we can be indifferent to where we impose diminishing returns, as they are mathematically interchangeable. Therefore I collapse all sources of diminishing returns into one parameter.

The fuel economy related benefits that can e accrued, depends on the module. For example, the module "body" has a large potential effect on reducing weight and therefore on improving fuel economy. In contrast, improvements in gasoline storage improve much more benefits. An increased attention to fuel economy, induced by the oil shock, reduces the improvement rate of other parts of the vehicle.

OEM Resource allocation

We now describe how the resource allocation process is captured. Upfront investment in R&D can increase total profits in the long run, either by improving performance or by lowering costs (and subsequently price). Both have a positive effect on attractiveness and sales. Actual resource allocation decisions then depend on expected demand elasticity under the existing market structure, and effectiveness in improving platform performance, as compared to reducing its cost.

Decision makers within organizations are bounded rational (Cyert and March 1963; Forrester 1975; Morecroft 1985). They learn about relevant knowledge and productivity over time and resources are allocated based on the relative perceived marginal returns (Nelson and Winter 1982). Further, decisions are made locally. Managers push projects by pushing those allocations that are perceived most beneficial, modules that are outsourced are optimized at the module level. This concept is used here for the resource allocation decision. While the key findings of this paper do not rest on the concept of local decision making, it is robust as compared to globally optimal decision making, but also mathematically convenient, for the same reason that actual decision making is local.

Resource allocation decisions include: i) allocation of a share of total revenues going to R&D, σ_j^r; ii) the share of total R&D resources of platform *j* that the chief engineers dedicates to process or product improvement, $\sigma_{jw}^r, \sum_w \sigma_{jw}^r = 1$; iii) the share of total R&D resources of platform *j* activity *w,* that managers dedicate to internal knowledge accumulation, σ_{jjw}^r, as opposed to spillovers $\sigma_{\sim jjw}^r = 1 - \sigma_{jjmw}^r$; and finally, iv) the share of total R&D spillover resources of platform *j*, activity *w*, that engineers dedicate to extracting knowledge from platform $i \neq j, \sigma_{ijw}^r, \sum_{i \neq j} \sigma_{ijw}^r = 1$.

We will discuss one resource allocation decision here, others follow the identical structure. Resources that are dedicated by platform *j* to spillovers, $R_{\sim jjw}$, need to be distributed to capture spillovers from the various platforms. The distribution results in resources $R_{ijw} = \sigma_{ijw}^r R_{\sim jjw}$, going to platform *i,* with σ_{ijw}^r being the share of the total budget going to *i*. The share adjusts over resource adjustment time τ^r to the desired share for platform *i*, σ_{ijw}^{r*}, which equals desired resources R_{ijw}^* divided by the resources others bargain for:

$$\sigma_{ijw}^{r*} = R_{ijw}^* \Big/ \sum_{i' \notin j} R_{i'jw}^* \tag{10}$$

Desired resources for platform *i* increase with expected return on effort ς_{ijw}^{r*} relative to the reference returns ς^k in knowledge generation.

$$R_{ijw}^{*} = f\left(\varsigma_{ijw}^{r*} / \varsigma^{k}\right) R_{ijw}^{r};\ f' \geq 0;\ f \geq 0;\ f(1) = 1 \qquad (11)$$

Returns are measured in relation to the relevant lowest level performance indicator that is perceived to be fully influenced by the decision, capturing the essence of local decision making. The planning horizon over which the expected performance is estimated is τ^{p}. In the case of resources for spillovers across platforms, the reference indicator is total spillover knowledge, $K_{\sim jw}$, with

$K_{\sim jw} \equiv \left[\sum_{i \neq j} \kappa_{ijw} \left(K_{ijw} / K_{w}^{0}\right)^{-\rho_{jw}^{k}}\right]^{-1/\rho_{jw}^{k}}$, which follows from equation (5).

Results

As in earlier analyses, we launch our platform in California (see Struben and Sterman 2008). For the parameter settings related to ICE vehicle PHEVs, and fuel supply chain we rely upon established data sources, from among others Ford and Shell Hydrogen. the base case we specify a scenario of successful PHEV diffusion. Earlier analysis shows that such scenarios are feasible. This is so, even for HFCVs, that are much more infrastructure constrained than PHEVs. Nevertheless, successful PHEV diffusion requires policy commitment. Initial PHEV costs are realistically high, but, we assume, optimistically, a charge-at-home capability for all adopters. Further, extensive resources are deployed to improve PHEV, through R&D, and make people familiar with these vehicles, through marketing and education. For illustrative purposes, electricity predominantly derived from fossil inputs (coal, natural gas). In the scenarios below we do not focus on the carbon price. We now perform and analyze 4 different scenarios (Table 1).

Table 1. Scenarios analyzed (the cases without PHEV are for reference)

Scenario	Oil Price: $60/barrel throughout	Oil Price: $60/barrel until 2010; $120/barrel as of 2010
ICE Vehicles only	Base	Oil Shock
Introduce PHEVs in 2010	PHEVs	PHEVs + Oil Shock

Simulation results for the PHEV case (Figure 5) show a viable path to widespread, self-sustaining PHEV diffusion. A positive feedback allows learning in PHEVs, improving their market share over time (Figure

5, thick lines). PHEVS have infrastructure advantages over other AFVs such as HFCVs and pure BEVs. A fueling infrastructure already deployed;. Self-sustaining diffusion much easier to achieve. PHEVs offer thus a transition path to carbon-neutral via biofuels. Nevertheless, diffusion is slow, consistent with history of other automotive technologies. Note that the installed base grows at an even slower pace than the market share. Thus, significant investment still required to pass tipping point, including on marketing to achieve consumer acceptance, cost reduction and reliability improvement through learning, R&D, and scale.

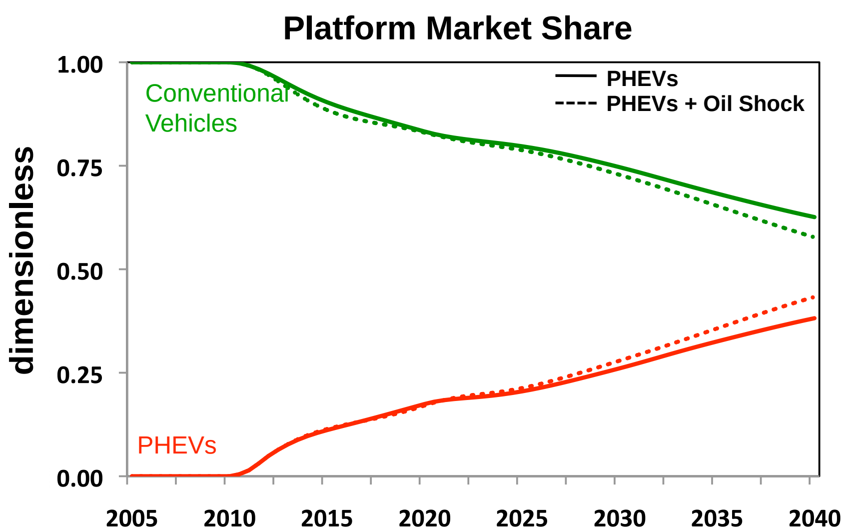

Figure 5. PHEV adoption rate with and without oil shock

Figure 5 also shows the market share of PHEVs under the oil shock scenario. While the introduction of an oil shock in 2010 with the PHEV introduction improves the PHEV market share, the effect is very surprisingly limited. Tracing a subset of underlying variables helps explain why (Figure 6). Figure 6 shows the evolution of the ICE vehicle installed base, decomposed by car and trucks, their respective fuel economy improvements over time, and the vehicle miles. The fastest response comes from adjustments in vehicle miles traveled. Vehicle miles have the effect to reduce the operating costs, and with that they also lower the relative advantage of switching to PHEVs. Second, consumers switch to smaller vehicles and more fuel-efficient vehicles. This effect is somewhat slower, as vehicles are replaced on average every 5-8 years. Finally, fuel economy of the conventional vehicles improves above levels that would have been the case otherwise. This response, while much less responsive, is relatively large compared to the others. Note that the fuel economy of the PHEV only scenario is also improved compared to the base scenario, which is due too spillovers, which dominates the reduced the effect of reduced sales. Note further the classic rebound effect at work, when, a result of the fuel economy improvements through a combination of smaller vehicles and fuel-efficient vehicles, the vehicle miles increase after the initial decline.

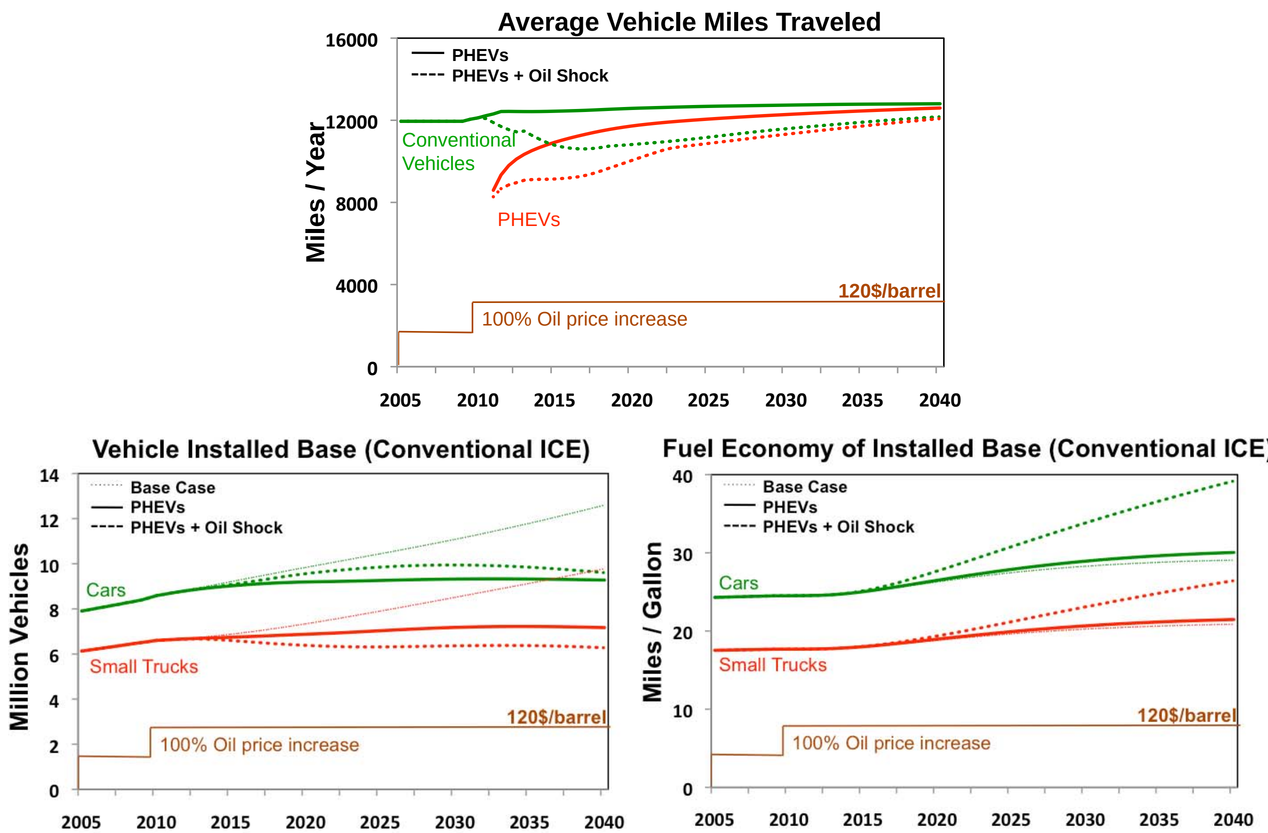

Figure 5. vehicle installed base, fuel economy, and vehicle miles traveled under the various scenarios

Interpreting results: feedback rich versus reduced feedback models.

As Figure 5 illustrates, the degree to which PHEV diffusion benefits from consistently high oil prices, can be explained by the working of several feedbacks (Figure 6). Consumer responses (in blue) involve reduction of vehicle miles, switching to smaller and more fuel-efficient vehicles. Automotive industry (green) responds by offering more efficient vehicles and, through a slower R&D process, improves efficiency of new vehicles.

See appendix due to file size issues

Figure 6. Broader feedback structure capturing oil shock responses and implications for PHEV diffusion

Yet there are other responses: with structurally high oil prices, households and industry may switch some stationary applications to those that are electricity based, adjusting the relative price advantage for PHEV driving. Moreover, cost of producing electricity increases as well. Further, as petroleum-based vehicle miles and petroleum cars on the road reduce, the world oil demand decreases as well (transportation making up 67%), the oil shock itself is suppressed. Then, the broad view of Figure 7 contrasts sharply with the mental model of Figure 1. In sum, while the learning curve feedback for PHEVs may be accelerated by oil shocks, this effect is partially undone by a combination of fast (vehicle miles).

Figure 7 compares the impact of oil shock on PHEV installed base accorsss two different models: the feedback rich model that we used for the analysis above, and a reduced feedback version, in which three critical feedbacks are switched off. That is, we now capture a single vehicle size for each alternative (we select average of the 2040 size distribution for both alternatives), we do not allow for increased attention to fuel efficiency, and finally, we hold the electricity price constant.

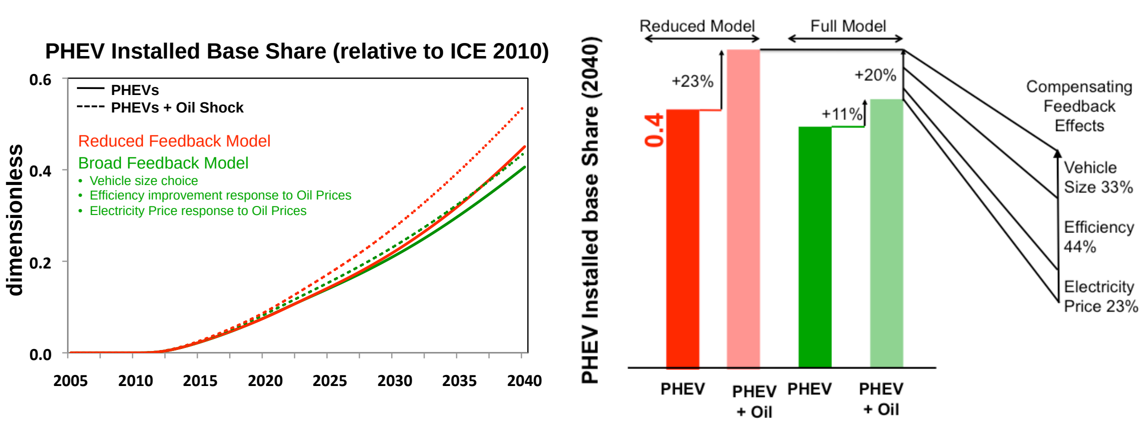

Figure 7. The impact of behavioral feedback on variation between oil and non-oil scenarios

The reduced feedback model estimates higher PHEV adoption than the feedback rich model. More importantly, we observe that the reduced feedback model overestimates how PHEVs benefit from the oil shock. That is the gap between the PHEV and the PHEV + oil shock scenarios is more than 50% larger.

While high gasoline prices have limited effect on PHEV diffusion, this does not necessarily mean that under those scenarios gasoline consumption is not importantly reduced. In fact, while the reduced feedback model overestimates how PHEVs benefit from the oil shock, the reduced feedback model also overestimates the resulting oil consumption. This may be surprising as a larger share of PHEV has the direct consequence that gasoline consumption is reduced. Hence, with this in mind, one would expect that the reduced model estimates lower gasoline consumption than the behavioral feedback rich model. However, as the reduced model fails to capture the consumer and producer responses that act to reduce the appeal of PHEVs, it ignores precisely those behavioral responses within the broader system that act to reduce gasoline consumption.

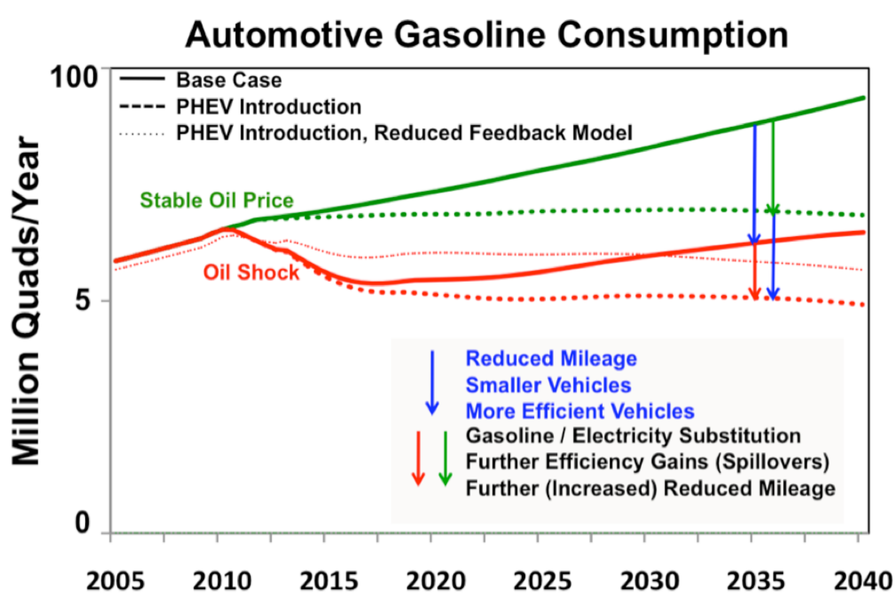

Figure 8. Gasoline consumption under the relevant scenarios

Expanded Discussion

Results suggest that technological spillovers across AFV platforms, and within and with ICE conventional vehicles, can strongly condition the dynamics of adoption (e.g., improvements in materials, software and battery technology developed for plug-in hybrids may benefit hydrogen fuel cell vehicles; hybrids and HFCVs could be powered by biofuels). Results also suggest that higher gasoline prices (whether caused by the market or policies to increase the market price of carbon) do not automatically lead to the rapid developing of a viable AFV market: higher fuel prices cause consumers to shift to more efficient conventionals, increasing the threshold AFVs must meet to become competitive. We demonstrate how the model can be used to examine how alternative fuel pathways and policies affect the viability of different strategies for the development of the AFV market and their impact on automakers, fuel suppliers, consumers, government, and the environment. Other pathways we can include for example Biomass + Coal to Liquid (BCtL) or biomass to hydrogen (BtH), under varying policy and technology success climates, involving factors such as carbon pricing, carbon capture and sequestration (CCS), and the oil price.

Conclusions

Transitions to alternative energy in the transportation sector take long and are prone to failure. Achieving success requires an understanding of the detailed processes conditioning the dynamics, including alternative fuel pathways and their broader impact. Behavioral, dynamic models with broad scope can aid in this, as well as in strategizing for the development of the AFV market. Dethroning gasoline is difficult: A century of learning, cost reduction, infrastructure development create lock-in to existing system and cause "sizzle and fizzle" in AFV diffusion. Multiple interacting reinforcing feedbacks cause strong "tipping" behavior – but also a high threshold.

Creating an economically sustainable AFV market requires aggressive, consistent, sustained policies to drive consumer awareness and adoption, vehicle costs and performance, and fuel infrastructure over the tipping point. These markets are characterized by strong Worse-Before-Better dynamic: short run costs, long run gains – environmental and economic. Strong reinforcing feedbacks create win-win-win-win for the public, government, auto OEMs and fuel providers. While simulations suggest a viable path to widespread, self-sustaining PHEV diffusion, nevertheless, diffusion is slow, consistent with history of other automotive technologies. Thus, significant investment still required to pass tipping point, including on marketing to achieve consumer acceptance, cost reduction and reliability improvement through learning, R&D, scale. The oil shock scenario demonstrates that accelerating PHEV take-up may be difficult. Further, nontrivial risks remain: Technical (e.g. battery reliability), Economic (cost), as well as social (willingness to consider). However, such successful scenarios only work if all actors participate. No one actor can do it alone.

Moreover, actors need to anticipate policy resistance from within the broader transportation system. In particular, we showed here that higher oil prices, while important in speeding EDV adoption, are less effective than many expect, due to a range of compensating feedbacks that enable internal combustion-gasoline technology to adapt. The view of Figure 7 contrasts sharply with the mental model of Figure 1. In sum, while the learning curve feedback for PHEVs can be accelerated by oil shocks, this effect is partially undone by a combination of feedbacks involving consumers within and outside transportation, automotive producers, energy players, governments and regulators. While such feedbacks are sometimes discussed, dominant mental models among both policy makers and academics may underestimate the strength of these feedbacks and the fact that they also operate to advantage the current dominant technology. Analysis need to address potentially overly-optimistic forecasts for the extent and speed of diffusion for AFVs and EDVs, and insufficient investment in standards and policies to help such vehicles over the tipping point to self-sustained adoption. To understand to what extend such a broader view is critical to know more about the degree of inertia and elasticity in the various feedbacks.

Selected References

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

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.

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

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.

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.

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.

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.

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

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.

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.

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

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.

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

Struben, J. and J. Sterman, (2008). "Transition Challenges for Alternative Fuel Vehicle and Transportation Systems". *Environment and Planning B.* **35**(6): 1070-1097.

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

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