Managing the Transition toward Self-Sustaining Alternative Fuel Vehicle Markets: Policy Analysis Using a Dynamic Behavioral Spatial Model

by

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Submitted to the Engineering Systems Division
in Partial Fulfillment of the Requirements for the Degree of

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Abstract

Designing public policy or industry strategy to bolster the transition to alternative fuel vehicles (AFVs) is a formidable challenge as demonstrated by historical failed attempts. The transition to new fuels occurs within a dynamically complex system with many distributed actors, long time delays, several important feedback relationships, and multiple tipping points.

A broad-boundary, behavioral, dynamic model with explicit spatial structure was previously developed to represent the most important AFV transition barriers. Using California as an illustrative testing region, the model simulates the spatial diffusion of entrant vehicle/fuel technology pairs individually or in competition with other entrants. In this work, the integrated model is carefully parameterized for various specific alternative vehicle technologies. Structural and parametric sensitivity analyses are used to build understanding of system behavior and to identify policy leverage points or the need for further model calibration. The qualitative impacts of policies are tested individually and then in multi-policy combinations to find synergies.

Under plausible assumptions and strong policies, AFVs can achieve successful diffusion but this process requires long time periods. Findings indicate some commonly suggested policies may provide little leverage and be very costly. The analysis reveals the importance of designing policy cognizant of the system structure underlying its dynamic behavior. Several examples demonstrate how policy leverage varies with context such as key attributes of the alternative vehicle technology.

Broadly, coordinated portfolios of policy instruments should be designed to simultaneously develop consumer familiarity, well distributed fueling infrastructure, and manufacturer knowledge at similar rates and over long enough duration to surpass thresholds in these complementary assets before alternative fuel and vehicle markets become self-sustaining. Further, policy should dynamically adapt to observed conditions to lessen the transition constraints dominant at the time. Policy and strategy makers must recognize from the outset that incentives must be stable over long durations for AFV transitions to succeed.

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List of Acronyms

AEO	Annual Energy Outlook, Energy Information Administration
AFV	Alternative Fuel Vehicle
ANL	Argonne National Lab
AVMT	Alternative Vehicle Market Transition Model
B	Balancing Feedback Loop
BEV	Battery Electric Vehicle
CNG	Compressed Natural Gas
CO2e	Carbon Dioxide Equivalent (Global Warming Potential)
DMNL	Dimensionless
DOE	U.S. Department of Energy
DTW	Dealer Tank Wagon
E85	High concentration ethanol blend (~85% ethanol, 15% gasoline)
EIA	Energy Information Administration, U.S. Department of Energy
EPACT	Energy Policy Act of 1992
ENT	Hypothetical entrant alternative fuel vehicle equivalent to ICE
FFV	Flex Fuel Vehicle, able to run on E85 fuel under warranty
GGE	Gasoline Gallon Equivalent
GREET	Greenhouse Emissions and Energy Transportation Model, Argonne National Lab
H2FSMR	Hydrogen via Forecourt Steam Methane Reformation
H2A	Hydrogen Analysis family of models, U.S. Department of Energy
HEV	Hybrid Electric Vehicle
HFCV	Hydrogen Fuel Cell Vehicle
HICE	Hydrogen-compatible Internal Combustion Engine
HyTRANS	Hydrogen Transition Model, Oak Ridge National Lab
ICE	Internal Combustion Engine
IEA	International Energy Agency
KG	Kilogram
LDV	Light Duty Vehicle
MARKAL	Market Allocation Models
MIT	Massachusetts Institute of Technology
MNL	Multinomial Logit equation
MSRP	Manufacturer Suggested Retail Price
NRC	National Research Council
OEM	Original Equipment Manufacturer
OTH	Hypothetical entrant alternative fuel equivalent to gasoline (for use in ENT vehicles)
PHEV	Plug-In Hybrid Electric Vehicle
R	Reinforcing Feedback Loop
SD	System Dynamics
TAVF	Transitional Alternative Vehicles and Fuels Model
VCL	Vehicle
WBCSD	World Business Council for Sustainable Development

Introduction

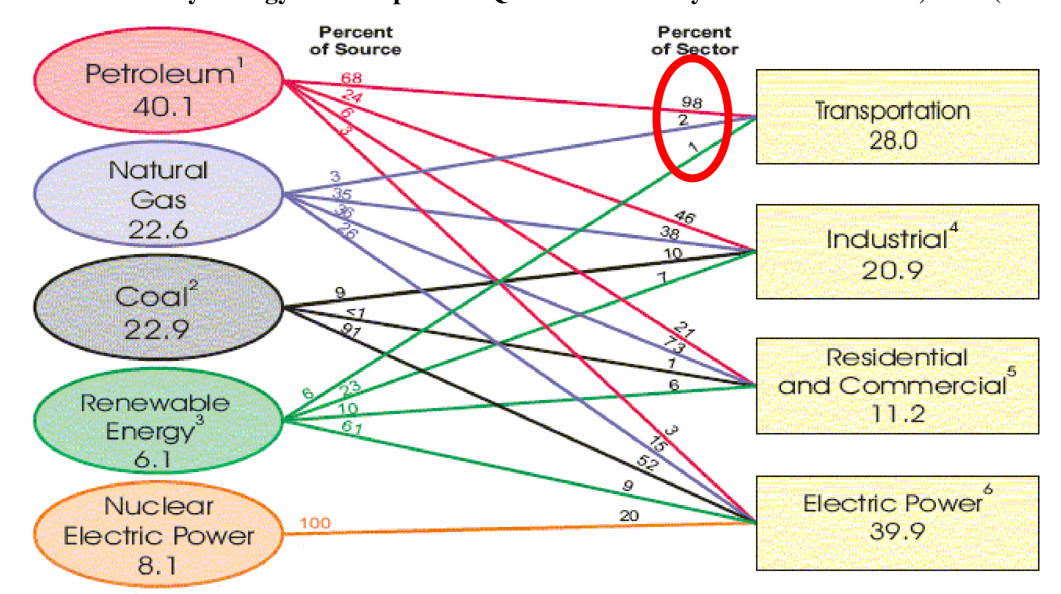
This thesis addresses the challenge of designing policy to most effectively stimulate the transition to less greenhouse gas and petroleum intensive transportation fuels and vehicle drivetrains. Specifically, it illuminates the role of several causal feedbacks governing such transitions and suggests policy cognizant of the system structure behind its dynamic behavior.

Motivation

The future development of transportation energy systems is arguably the most difficult challenge society must confront in the quest for sustainable development. The steam engine, internal combustion engine, and turbo-jet have enabled a level of mobility unimaginable in prior human history. Mobility is vital to economic health and political stability. It enables global trade and provides access to employment, goods and services, health care, education, and recreation. Not surprisingly, motorization and personal travel growth rates continue to reach record highs worldwide (IEA 2006). The current global stock of 800 million light duty vehicles in use in the world today is projected to reach 2 billion by 2050 (WBCSD 2004).

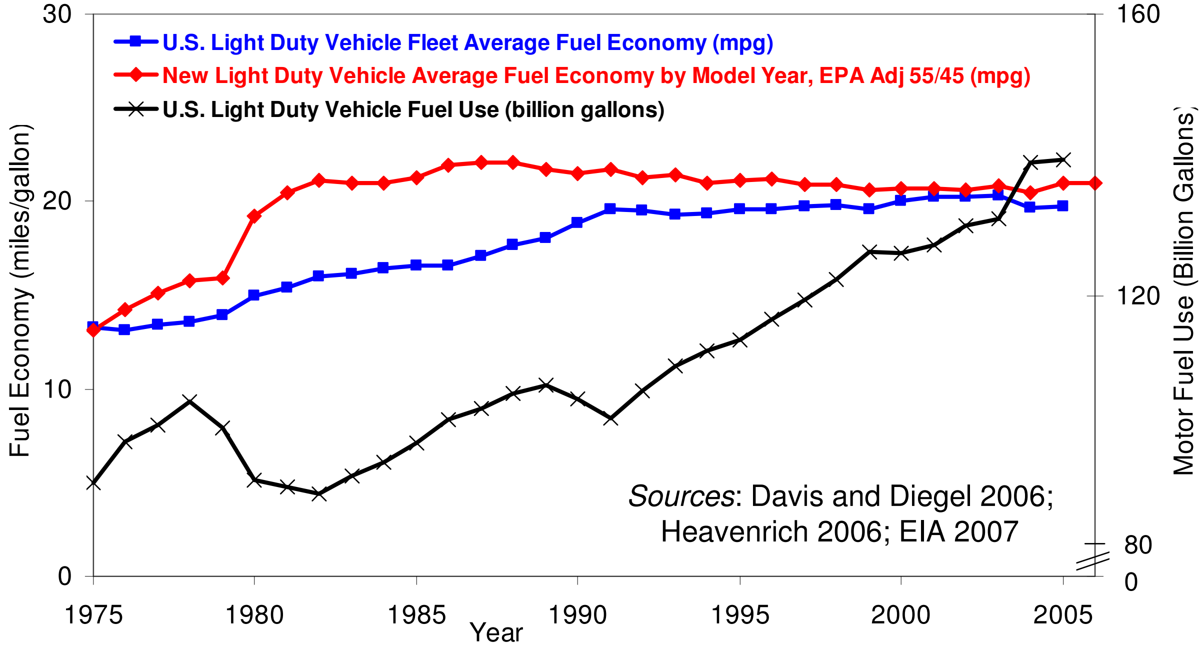
Not unlike the rest of the world, the United States' system of transportation today is all but entirely dependent on petroleum as a primary energy source.

Figure 1: U.S. Primary Energy Consumption in Quadrillion Btu by Source and Sector, 2005 (EIA 2006b)



Although versatile and cheap petroleum-based fuels have been a great enabler of today's unprecedented levels of mobility and quality of life, society's oil dependence is destabilizing economies, geopolitical relationships, and the global climate. Yet while energy efficiency and renewable energy are making modest strides in the electric and heating sectors, the transportation sector continues to explode while fuel economy remains stagnant (Figure 2). Reducing fossil-fuel dependence and environmental impact of transportation systems is a colossal challenge with no simple technological solution. Substitution of renewable transport fuels must be complemented in a comprehensive and integrated fashion by several other strategies to reduce the oil intensity of the economy including: urban and regional planning to reduce necessary vehicle miles, increasing passenger and parcel vehicle occupancy, improving driving and vehicle maintenance behavior, and shifting to more fuel efficient vehicle designs.

Figure 2: Light Duty Vehicle Fuel Consumption Trends



This work focuses on the alternative fuel substitution component of the integrated strategy. It supports the literature suggesting that the market diffusion of alternative fuels and advanced vehicles capable of using such fuels is a *complex system transition* governed by the interplay of many distributed agents and several feedback effects (Metcalf 2001; Cahill 2002; Sperling and Cannon 2004; Janssen 2005; Struben 2006; Struben and Sterman 2006; Welch 2006).

Audience

This work is intended for a broad audience of folks working to support the introduction of hydrogen, biofuels, electricity, and/or other transport fuels with less fossil fuel-intensive pathways from primary energy source to delivered vehicle mile, or from "well-to-wheel." Business strategy and development managers within firms that are placing bets on alternative fuels and/or vehicle drivetrains are in great need of guidance. Just as important, the analysis should engage agency program managers, policy analysts, and legislative aides to assist them in making public policies and programs to support new fuels more effective.

Research Question

In general system dynamics practice, one's research hypothesis takes the form of an evolving model intended to represent the most important system structure of the problem of interest at the most appropriate level of aggregation or detail. Although this thesis work helped to test and to extend such a model, the research focus is primarily to build intuition and infer policy guidance from a very large, substantially developed model. The central research question is: what new and unintuitive policy insights for supporting transitions to less carbon intensive fuels can be gained from a dynamic and behavioral simulation model that would not be learned from the more common optimization models and static, end-state analytical approaches?"

Background

System Dynamics Approach: Modeling Feedback

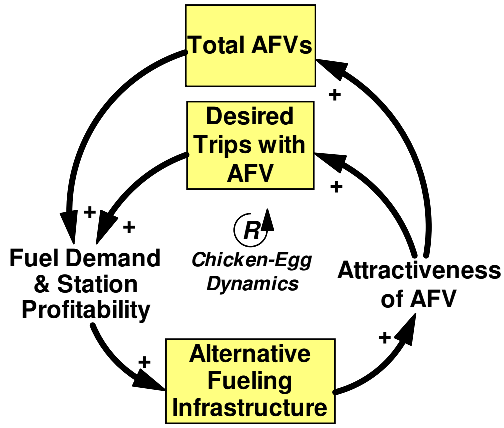
System dynamics is a field of study of the structure and behavior of socio-technical systems to guide effective decision making, learning, and policy in a world of growing dynamic complexity (Sterman 2000). Grounded in the theory of nonlinear dynamics and feedback control, the method was pioneered at MIT in the 1950s by Jay Forrester (1961). The essential conceptual tools of the field include feedback-rich causal diagrams to elicit mental models and computer simulation models to quantify the interrelationships of physical and behavioral processes, information feedback and time delays. Systems are conceptualized as physical and information state variables (stocks) that are accumulated, depleted, and/or updated by corresponding rate variables (flows); all interact through closed chains of cause and effect (feedback loops). Formally, system dynamics models are sets of simultaneous, nonlinear differential equations solved through numerical integration. Generally simulations are implemented with graphical user interface tools useful for visualizing system feedback structure to assist in building an understanding of the patterns of behavior observed in simulation results.

The modeling process is a disciplined experimental approach to gain confidence in the hypothesis articulated by the model--that the model structure is indeed responsible for empirically observed patterns of behavior (Oliva 2003). The process of model creation and testing builds a richer understanding of the problem of interest using computer simulation to compensate for deficiencies in human intuition. Robust models can then be used to guide policy testing, what-if scenario analysis, decision optimization, and to anticipate unintended consequences of policies that could develop in the long run.

As an introductory example of the feedback concept, consider the most commonly cited barrier to the introduction of alternative fuel vehicles (AFVs): the so called "chicken-and-egg" dilemma (Winebrake and Farrell 1997; Wells 2001; Farrell, Keith et al. 2003; Romm 2004; Struben 2005). There is an obvious interdependence between vehicles and complementary assets such as refueling infrastructure. One will not grow without the other. People will neither purchase nor choose to make the majority of their trips with alternative fuel vehicles without access to fueling stations. At the same time, energy companies and retailers won't invest in new fuel production and distribution infrastructure without reasonable certainty of a market demand for fuel. Thus, there is a positive or reinforcing feedback at play in the system (Figure 3).

A causal loop diagram, such as Figure 3, is a system dynamics tool used to map relationships in a system. A + sign at the arrowhead indicates a positive causal relationship. If the variable at the arrow's origin increases (decreases), then the dependent variable will also increase (decrease). A – sign at the arrowhead indicates an inverse relationship, meaning an increase (decrease) in one variable leads to a decrease (increase) in another. Loop identifiers are placed in the center of feedback loops to indicate whether the polarity of an entire loop is positive (denoted R for self-reinforcing) or negative (denoted B for balancing). For a comprehensive introduction to causal loop diagrams, see Sterman (2000).

Figure 3: Chicken-Egg Dynamics - Example of Reinforcing Feedback

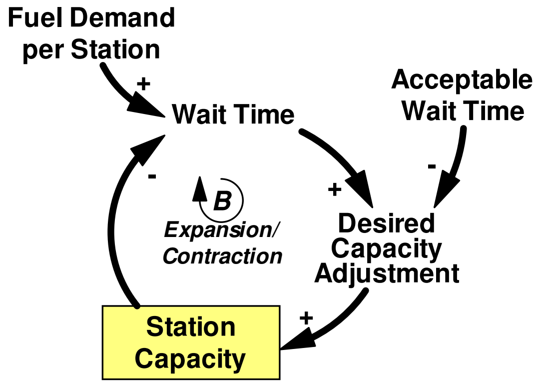


The behavior of a simple reinforcing feedback loop like that in Figure 3 is exponential growth and amplification (Sterman 2000). As the number of one type of AFV increases, there is growing demand for its fuel, more investment in new fueling stations, and consequently, that vehicle platform is more attractive to new buyers. While this complementary infrastructure feedback is often recognized as a growth driver to seed by those designing AFV supportive policies, the role of such reinforcing feedback in destabilizing the system and leading to collapse is overlooked.

What is once a virtuous cycle of growth may also become a vicious cycle of collapse**.** Just as growth in vehicle adoption leads to growth in station availability, a drop in station availability due to other feedbacks in the system leads to decay in vehicle adoption when this reinforcing feedback dominates. Reinforcing feedback can be a source of both explosive growth or of collapse in systems. Historical policy attempts to support alternative vehicle penetration in New Zealand and California are good examples of the potential for this type of collapse (Harris 2000; Flynn 2002; Paine 2006). This chicken-egg fueling infrastructure feedback loop described above is just one example of several reinforcing feedbacks at play. Some of the feedbacks are subtle or “below the waterline.” As a result, the chicken-egg dynamics for AFVs are more nuanced than the simple one-loop market formation process often portrayed by policy analysts.

In addition, systems are also governed by balancing (negative) feedbacks that act to bring the state of the system in line with a goal or desired state (Sterman 2000). To provide another example from the AFV story, consider one feedback governing the size of fuel stations depicted in Figure 4. As station utilization rises and lines begin to form, station owners will invest to expand the number of fueling positions to the extent physically feasible in order to reduce waiting times, increase throughput, and earn more profits. Such expansion occurs with a delay and eventually reduces the difference between the actual wait time and acceptable wait time for drivers, bringing the system into equilibrium (or balance) with a desired goal. There are, of course, several other balancing loops at play in the system to bring waiting times to desired levels, but those will be described later.

Figure 4: Fuel Station Size Adjustment – Example of Balancing Feedback



The understanding of causal feedbacks and which are dominant provides a very useful conceptual framework for understanding dynamically complex problems. Nonlinearities in model relationships allow shifting dominance of feedback loops. Traditional engineering and economic models often make assumptions of linearity and equilibrium to ease mathematical characterization, implementation, and understanding. But the world is fundamentally nonlinear, and disequilibrium is the rule rather than the exception (Sterman 2000). It is then not surprising that the system dynamics approach is becoming more popular to address complex problems.

Theoretical Influences

A very brief summary of the various realms of general theory from which this policy analysis model draws may be useful for communicating confidence to those unfamiliar with broad-boundary system dynamics models. System dynamics modeling is inherently interdisciplinary and builds on theory in a variety of disciplines.

Product Diffusion

Marketing science has a rich tradition of diffusion models that describe the lifecycle of durable good sales (Urban, Hauser et al. 1990). When products have a long lifetime, such as an automobile, replacement purchases are delayed and sales forecasting is equivalent to predicting the adoption rates for a new type of product or innovation.

The diffusion of an innovation is a process by which awareness of an innovation "is communicated through certain channels over time among members of a social system" (Rogers 1983). Frank Bass developed a simple analytical model for the diffusion of innovations (Bass 1969; Bass 1980) by combining the logistic and modified exponential into a single equation, fitting adoption time-series data with a quadratic form. The model has been used widely to reproduce empirical adoption for many new technology introductions (Dodds 1973; Lawrence and Lawton 1981; Sultan, Farley et al. 1990; Bass, Krishnan et al. 1994; Jeuland 1994).

While there are several theories and behavioral interpretations for why the simple Bass model performs so well, Lekvall and Wahlbin (1973) provide the most general and useful definitions for the two drivers at play, renaming the estimated coefficients the "external and internal influences on adoption." In other words, there are clearly strong influences that are internal (or endogenous) to the size of the installed product base. But there are also clearly market seeding influences that are independent of the number of existing adopters.

There are several extensions necessary for applying this theory to the AFV transition challenge. First, while several have applied diffusion models for the automobile market in forms adapted for the intuition of product development managers (Urban, Hauser et al. 1990), an extensive literature review does not turn up published estimations of the Bass model coefficients for new automobile innovations. Sultan, Farley et al.(1990) provides a meta-overview of estimations performed for other comparable durable goods such as refrigerators or electric dryers. Second, most product diffusion models represent how products diffuse over *time* but not how they diffuse over *space*. There may be various types of spatial diffusion (Morrill, Gaile, Thrall 1988).

Behavioral Decision Theory and Bounded Rationality

Extensive evidence from psychology and economics research demonstrates that the rationality of human behavior is bounded (Cyert and March 1963; Conlisk 1996; Simon 1997). Simulation models that conform to actual practice, "warts and all", are more useful for policy testing and anticipating unintended consequences (Sterman 2000).

While the paradigm of neo-classical economics rests on extremely elegant positive theory and mathematics, Simon (1979) argues that the majority of economic practice is too narrow in scope by assuming "omniscient rationality" by actors. From the classic economist's viewpoint, any deviation from utility maximization is "irrational." Yet, theories of utility or profit maximization often fail to predict empirical observations of decision-making on the micro level, especially in situations involving decision making under uncertainty or imperfect competition. Simon's theoretical work was ground-breaking, earning him the Nobel Memorial Prize in Economic Sciences, because behavioral theories of bounded rationality, heuristics, and "satisficing" lead to correct predictions at both the macroscopic and microscopic levels of observed phenomena.

There are limits to knowledge, cognitive capabilities, and time when making decisions in the face of complexity. Thus models should capture theses limitations to represent the system with fidelity. To do this modelers follow two fundamental rules, amongst others. Sterman (2000) provides a comprehensive development of principles for formulating behavioral models. First, modeled decision-making can only use information that is available and known to the agents as inputs. For example, in modeling the utility of alternative fuel vehicles, owners do not know the spatial density of fueling station coverage in real time. Rather, through experience and communication drivers update the perception of the searching and travel time needed to refuel. Second, experiments, interviews, or anthropological field study are conducted to identify rules of thumb, habits, standard operating procedures, subordinate goals, or other common decision rules. A behavioral approach may not only produce a more useful model but also makes the least restrictive assumptions about the human cognitive system (Simon 1979).

Discrete Choice

It is no coincidence that discrete choice analysis has its roots and most common application in forecasting transport demand. Transportation mode choice is one of the more well-suited problems for its application. The most important decision-making that occurs in an AFV transition model is by agents choosing A) which vehicle to purchase and B) with which vehicle or transportation mode to make their trips. A behavioral perspective suggests decisions usually consist of a choice made among a limited and finite set of alternatives. If multiple choices must be made, they normally are made in sequence (e.g. destination, transportation mode, itinerary).

Discrete choice models make assumptions of the decision-making agents, available alternatives, and the attributes of each alternative considered in decision making (Ben-Akiva and Lerman 1985). Because making such simplifying assumptions introduces uncertainty and incomplete information, utility is modeled with a stochastic component to reflect the uncertainty. The deterministic and stochastic components together make a utility function, U, representative of a heterogeneous population that is linear in sensitivity parameters for the attributes of interest. McFadden (1974) demonstrated that, if the error terms of the utility functions are independent and identically distributed, the choice share for alternative υ among *n* different alternatives can be represented by the formulation:

$$Share_v = \frac{e^{\mu \cdot Uv}}{\sum_{i=1}^{n} e^{\mu \cdot Ui}}$$

where U is the utility function and μ is a scaling parameter. This is known as the multinomial logit (MNL) equation. McFadden was awarded the Nobel Memorial Prize in Economic Sciences in 2000 for developing the MNL model. Discrete choice, random utility models have played an important role in transportation planning ever since. An immense amount of useful work has applied this theory to vehicle and alternative fuel vehicle choice (Train 1986; Kurani and Sperling 1988; Bunch, Bradley et al. 1993; Bunch, Brownstone et al. 1996; Ewing and Emine 1998; Brownstone, Bunch et al. 2000). The nested logit model used in this analysis was first derived by Ben-Akiva (1973) and extends the MNL model to capture similarities within subsets of the alternatives.

Survey of AFV Market Penetration and Policy Analysis

There is no shortage of analysis of the alternative policy measures available to reduce motor fuel consumption and its associated externality costs via alternative fuel substitution, more fuel efficient vehicles, and/or less driving. A lot of valuable analyses have been performed on consumer vehicle technology choice preferences, vehicle and fueling infrastructure costs, and requisite fueling station coverage for a fully penetrated market. Little analysis has focused on the endogenous transition dynamics governing the transformation to new transportation systems.

Several areas of previous work inform the development of a broad, integrated dynamic model that is needed for effective policy analysis for the AFV transition challenge:

<u>Modeling Physical Vehicle Stock</u>

The best of these policy analyses recognize the inherent time delays in vehicle stock replacement as a constraint for rapidly reducing motor fuel consumption (Leiby and Rubin 2000; Bassène 2001; Leiby and Rubin 2001; Greene and Schafer 2003; Bandivadekar 2004). While the need may appear obvious, policy analysis scenarios are not always generated under constraints of explicit assumptions in a stock turnover model. The median passenger car lifetime is 16.9 years for the most recent model years tracked by Davis and Diegel (2006) in applying Greenspan and Cohen's (1996) motor vehicle scrappage model to updated historical vehicle registration data.

As demonstrated later, effects of the new vehicle technologies become visible only after 10 to 20 years at best due to the slow rates of fleet turnover. Physical time delays also exist in product development and the development of production capacity. Clearly such representations of physical vehicle stocks are critically important in trying to assess realistic speeds of market penetration that might be achieved through policy.

Static "Near-Term" and "End-Game" Analysis vs. Dynamic Transition Analysis

In the study of alternative fuels such as hydrogen, electricity, and lignocellulosic biofuels, a majority of the research has focused on the optimal requirements for and the implications of "end-game" scenarios in which the alternative fuel has fully penetrated the market. This category includes detailed analysis to estimate the costs and benefits of new vehicles and fueling infrastructure once diffused (Thomas, Kuhn et al. 1998; Mintz, Molburg et al. 2000; Simbeck and Chang 2002; US DOE 2003; Ogden 2004a; US DOE 2004). Because the development of alternative fuels infrastructure is very costly, much work is focused on how it can be done well both initially and in the long term. Notable research includes optimization of fuel production pathways (Thomas, Kuhn et al. 1998; Mintz, Molburg et al. 2000), architecting the lowest-cost delivery mode for geographic and market characteristics (Yang and Ogden 2006), and estimating the number and spatial distribution of fueling stations to sustain large public vehicle fleets (Melaina 2003; Melendez and Milbrandt 2005). In addition, there has been some great work to project well-to-wheel environmental impact under future scenarios of substantial alternative fuel penetration (Wang and Huang 1999; Weiss, Heywood et al. 2000; Heywood, Weiss et al. 2003; Demirdoven and Deutch 2004; Farrell, Plevin et al. 2006). This type of end-state focused work is critically important to inform whether a certain alternative fuel dominated market is even a goal worth realizing.

However, as much, if not more, consideration must be given to the transitional dynamics concerning if and how such end states can be reached and how quickly. In fact, the authoritative National Research Council assessment of the needs for a hydrogen economy suggested that the Department of Energy focus on transition strategies rather than markedly different ultimate visions (NRC 2004). Others emphasize that, because transition barriers matter a lot for the technology's ultimate market success, static equilibrium analysis of the prospects for new vehicle technologies is misleading (Leiby and Rubin 2003). This argument suggests that dynamic models with broad boundaries including the endogenous growth of the AFV fleet and its complementary assets would now be in high demand and thus be plentiful and diverse. However, this is not the case. The universe of this important class of model for vehicle and fuel technology transitions has been slow to develop (Welch 2006).

Alternative fuel vehicle penetration has been represented within several bottom-up, dynamic MARKAL (MARKet ALlocation) models integrated with Climate-Economy models for the purposes of climate policy analysis (Schafer and Jacoby 2006). Such models solve dynamically in discrete time, period by period, for the least cost portfolio of transport technologies that are available in the model to meet the exogenous transport demand from the computable general equilibrium (CGE) economic model. In using linear optimization to specify technology shares and diffusion patterns to satisfy energy and mobility demands over time, these models make very strong perfect rationality assumptions. Thus these models provide a weak treatment of time delays and transition barriers, which may undermine the cost benefit analysis for which they are intended. In addition, MARKAL models assume exogenous scenarios for technological learning and infrastructure rather than using vehicle penetration in prior periods to endogenously model such change.

The most well-known transition model that incorporates dynamic elements such as learning and scale economies in modeling the adoption rates of alternative fuels and vehicles is the Transitional Alternative Fuels and Vehicles (TAFV) model (Greene 2001) and its hydrogen-fuel specific successor HyTRANS (Greene, Leiby et al. 2004). Representation of the dynamics included in the TAFV model has proven very useful for policy analysis to assess the cost and time scales need for such a transition (Leiby and Rubin 2001; Leiby and Rubin 2003). However the TAFV and HyTRANS models do not include the endogenous behavioral entrance and exit of fuel stations in response to market demand. Rather, simulations are run using various infrastructure development scenarios with *optimized* spatial distribution as exogenous inputs to the model. Until Struben (2005), there was no model that *endogenously* modeled the *behavioral* evolution of both supply and demand of vehicles and fuel at the same time.

<u>Coordinated Policy Portfolio Analysis</u>

Policy options to increase the substitution of low carbon alternatives for conventional motor fuels such as renewable fuel standards, alternative fuel tax exemptions, vehicle purchase tax credits, or gasoline taxes are normally assessed individually. (Bandivadekar 2004) reveals that reinforcing combinations of policies that balance cost and responsibility amongst stakeholders will more effectively clear political and institutional hurdles. Not only does such an integrated approach aid the development of political support, but it also aims to harness synergies between policy instruments that make impact greater than the sum of individual policy impacts (Agras and Chapman 1999; Schipper, Marie-Lilliu et al. 2000; Rafaj 2005). This insight calls for more impact evaluation of coordinated sets of policy instruments or *policy portfolios*.

In response to the commonly conceived chicken-egg conundrum, policymakers (Arthur 1989; Energy Policy Act (EPACT) 1992; U.S. Congress 1992) have proposed to harness this feedback to create “momentum” by independently seeding one or the other, particularly via government and private vehicle fleets. More sophisticated approaches advocate for coordinating incentives to closely match the growth rates of both the vehicle stock and fuel stations in order to artificially maintain a stable and economically viable vehicle to fuel station ratio of 1000-2000 vehicles per station (General Accounting Office (GAO) 2000; Kolodziej 2002; Zhao and Melaina 2006).

Overview of Struben AVMT Model

To gain understanding of these transition challenges, several system dynamics models have been developed (Struben 2006; Struben and Sterman 2006). These models, each focused on a critical part of the transition challenge, have recently been joined together into one large integrated model with a broad model boundary (Struben 2007). There are three important attributes of this integrated model that make it unique for addressing the AFV transition challenge: spatial disaggregation, explicit behavioral decision-making, and, most importantly, dynamic system structure. It is titled the Alternative Vehicle Market Transition (AVMT) model.

Spatial

The model is unique in representing how supply and demand evolve endogenously in space, representing important spatial heterogeneities and behavioral implications. The simplified "chicken-and-egg" reinforcing feedback (presented earlier), as widely conceived, leaves out important characteristics of the relationship, calling for a more detailed understanding of spatial interactions. For example, the aggregate number of stations in the region of interest alone does not fully characterize fuel availability. The spatial distribution of fueling stations is very important as drivers consider making trips of various lengths (Struben 2005). Notably, establishing the geographic distribution to maximize early station profitability may not be the distribution that best enables further vehicle adoption. The co-evolution of vehicle adoption and fueling infrastructure for various alternative fuels has historically exhibited clustering behavior near major urban centers. While this clustering can speed initial urban adoption, it counteracts the emergence of sustainable, fully-penetrated fuel market in the long term (Struben 2005).

Behavioral

This model treats decisions of the various stakeholders explicitly. The fields of psychology, economics, and organizational behavior provide strong evidence that humans have cognitive limits and decision making is not perfectly rational. Rather than optimizing with perfectly comprehensive information, people use simple decision rules (heuristics) in the face of uncertainty and situations of even modest dynamic complexity (Sterman 2000). For example, while many current hydrogen market penetration models assume competitive equilibrium in hydrogen prices and retail margins, the AVMT model captures the decision-making process by fuel retailers to set markups in the face of pressures to increase utilization and gain market share as well as pressures to reduce crowding and earn sufficient profit to stay in business. To their credit, the standard microeconomic optimization models usually include extensive monte carlo sensitivity analysis for various parameters or time-series inputs. Yet the attempt to represent how decisions are actually made by agents in the system can yield important insights that would be missed by assuming perfect rationality.

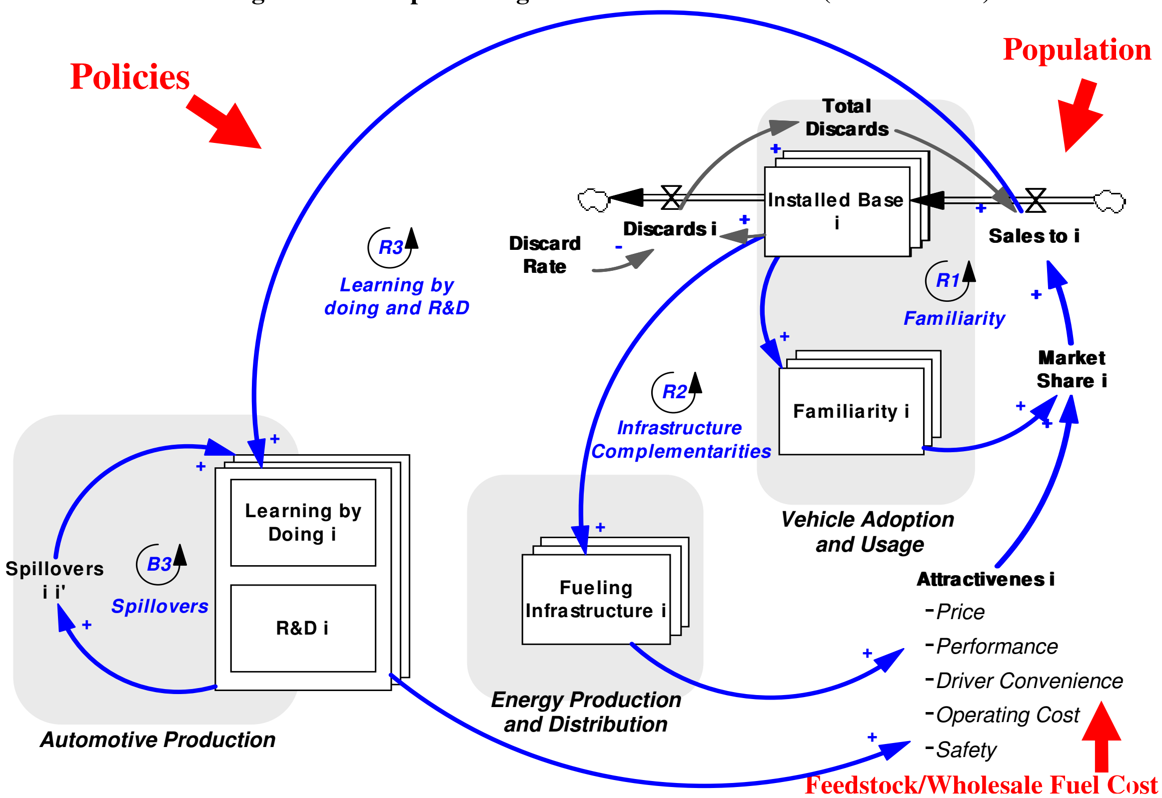
Dynamic

A system's dynamic behavior arises from its structure of stocks, flows, feedback loops and the nonlinear interaction of these basic structures (Sterman 2000). The AVMT model captures the physical evolution of the installed vehicle base, automaker production capacity, relevant vehicle attributes, as well as refueling outlet infrastructure location, size, and age. It also endogenously represents the evolution of awareness, perceptions, and knowledge of various agents such as vehicle buyers, fuel station operators, or automotive companies. Adjustment of the physical assets and decision-maker perceptions introduce crucial time delays into the system. Examples of important time delays in the system include:

- Average vehicle life,
- Average fuel station lifetime,
- Fueling station planning, permitting, and construction delays,
- Station size adjustment delays,
- Time for retail fueling industry to adjust market expectations,
- Time for entrepreneurs to perceive potential market and decide to enter,
- Time fuel station adheres to business plan without adaptation,
- Time for consumers to be exposed to marketing, other drivers, and social contacts,
- Time for consumers to forget and drop a technology from their consideration set,
- Time for drivers to update their perception of station coverage and conception of their effective tank range,
- Time over which manufacturers average sales to inform product development decisions,
- Time to deliver vehicles to consumers, and
- Time to improve vehicle attributes via learning through cumulative production

These adjustments to physical stocks and information states operate as part of a system of several interacting feedbacks that condition the level of difficulty for AFVs to penetrate the market. A high level overview of the model boundary and primary feedbacks is depicted in Figure 5.

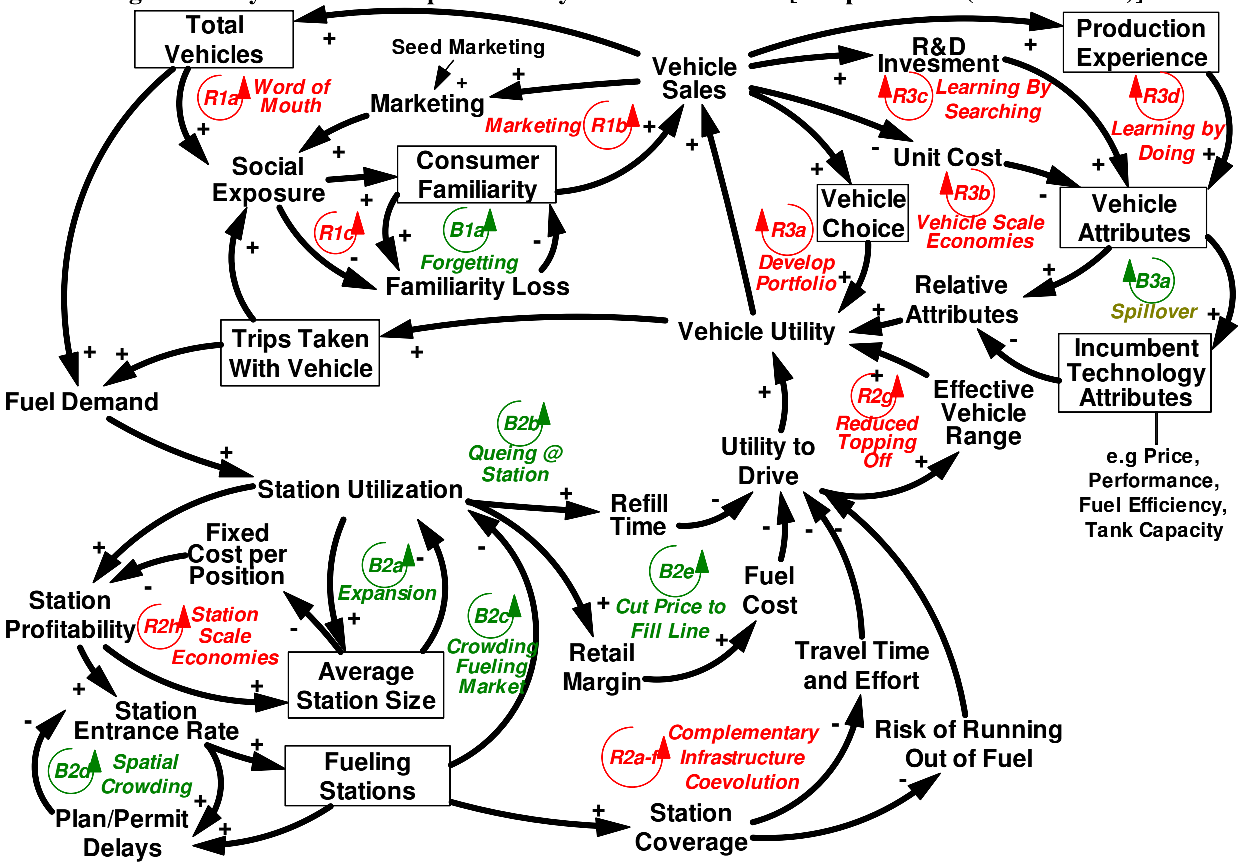
Figure 5: Conceptual Diagram of the AVMT Model (Struben 2006)



Policy may intervene at many points in this system to seed and strengthen the rates of the three major reinforcing feedback groups in order to sustain the installed base beyond various tipping points to form a self-sustaining market. Also outside the boundary of this model are feedstock or wholesale fuel availability and cost, population growth, and vehicle ownership patterns.

A causal feedback map of the feedbacks at play is shown in Figure 6. For simplicity, many auxiliary variables in the model have been omitted as well as the spatial-, trip-level-, technology-based subscripts. See Struben (2007) for a fully documented model description.

Figure 6: Key Feedbacks Represented by the AVMT Model [Adapted from (Struben 2007)]



Reinforcing Feedbacks. The most important positive reinforcing feedback processes in AFV market formation represented by this model are labeled **R** in Figure 6 and include:

<u>R1 – Social Exposure and Familiarity</u>

- Word of Mouth (R1a) - As more vehicles penetrate the market and more trips are taken with those vehicles, more non-adopters are exposed to the new AFV by talking with vehicle owners or other non-adopters who know about the AFVs and by seeing the vehicles in action. Eventually they become willing to at least consider such vehicles in their decision set.
- Endogenous Marketing (R1b) - As a firm's sales of the AFV increase, they have more revenue and can devote more resources to marketing the AFV, which grows consumer familiarity.
- Internalization (R1c) - Once aware of the AFV, further social exposure prevents forgetting, which in turn maintains higher adoption levels and more social exposure.

<u>R2 – Complementary Infrastructure Co-evolution</u>

- Chicken-Egg Co-evolution (R2a-R2f) - The co-evolution of fueling infrastructure and vehicle fleet is actually represented by six distinct reinforcing feedback paths in this model. Growth in fuel station coverage increases "utility to drive the AFV" via three important mechanisms:
    - o reduction of station search and trip travel times;

- o reduction of the perceived risk of running out of fuel; and
- o reduction of crowding and waiting times at fuel stations.

Each of these feedbacks acts through utility to increase *both* the number of AFVs purchased as well as the number of trips AFV owners choose to make with their AFV as opposed to another vehicle platform or mode of transportation. If utility of driving the AFV for a particular trip is high, the owner will choose not to use it. Thus, even if many AFVs have been purchased, a certain market demand for fuel is not assured; fuel sales per vehicle depends on station density, fuel cost, and other factors affecting the utility to drive the AFV.

- Reduced Topping Off (R2i) - Normally one decides to refuel when the fuel tank drops below a buffer level of about a quarter of the tank. However, when fuel station coverage is sparse and uncertain, this effective buffer is increased substantially and one's effective vehicle range is quite low. As station coverage increases, effective vehicle range increases, vehicle utility increases further supporting more fuel stations via the chicken-egg feedbacks. The modeling of this behavioral process reveals yet another hill to climb to compete with the incumbent via reinforcing feedback and also turns out to have important spatial implications.
- Fueling Station Scale Economies (R2j) – Initially alternative fuels typically cannot begin with as many fueling positions per station as typical for gasoline. As market demand for the fuel expands, stations expand or enter at greater sizes. As a result, fixed capital and operating costs can be spread over the greater number of fueling positions. Station expansion drives down the annualized fixed cost per fueling position, improves profitability, and reinforces further growth in the number and size of stations.

<u>R3 – Learning and Vehicle Porfolio Broadening</u>

- Develop Portfolio (R3a) - As vehicle sales grow, manufacturers gain the confidence in the market needed to introduce more new vehicle designs. The scope of the portfolio of AFV vehicle offerings begins quite small and broadens with annual vehicle sales. Increased vehicle choice then makes the AFV "nest" in the logit formulation more attractive to buyers.
- Vehicle Scale Economies (R3b) - As the rate of vehicle sales increases, they are manufactured on a larger scale and unit production costs per vehicle drop as fixed costs are spread over a greater number of units. The result is either a lower sales price or greater profits for the automakers. Note that this loop, faster and less persistent than the learning loops, was switched off within the model for most of the analysis in this paper.
- Learning-By-Doing (R3a) - Vehicle manufacturers gain production experience with each cumulative sale which leads to process innovation and production cost reductions. Extensive work supports theories of learning curves in which unit costs fall by a fixed fraction with every doubling of cumulative production experience across a variety of products and service industries (Henderson 1974; Teplitz 1991; Zangwill and Kantor 1998).
- Learning-By-Searching (R3b) - AFV sales also bring revenue that can be reinvested into R&D activities to build knowledge in both product and process design. Such knowledge gains lead to improved relative attributes and attractiveness of the AFV and to even more vehicle sales.

Balancing Feedbacks. Several equilibrating balancing feedback processes have also been identified as important in governing the system's behavior. They are labeled **B** in Figure 6. The time delays in these loops may lead to oscillation or even ultimate collapse in the system if they bring the dominant reinforcing cycles to turn from virtuous to vicious spirals. The balancing (negative) feedback loops represented in the model include:

<u>B1 – Social Exposure and Familiarity</u>

- Forgetting (B1a) - Potential adopters have limited attention and memory. Familiarity with a new vehicle technology (and the likelihood of including such an alternative in one's decision set) tends to decay toward zero if it is not refreshed with social exposure to such alternatives.

<u>B2 – Complementary Infrastructure Co-evolution</u>

- Station Size Adjustment (B2a) - As the station utilization factor goes either above or below the most profitable desired utilization, station owners respond by adjusting the size of fueling stations to bring actual utilization in line with the desired level. This information signal also comes to station operators through the station's profitability.
- Queuing at Station (B2b) - If total fuel demand grows much faster than fueling station capacity (determined by the number and size of stations), station utilization increases. Increased utilization not only induces station entry and expansion, but may also have feedback effects on fuel demand. If stations become crowded, queuing and long service time at the station causes one's utility to drive the AFV to fall and puts downward pressure on fuel demand. This balancing feedback loop thus also tries to bring actual utilization in line with desired station utilization, yet this time via the demand side.
- Crowding Fueling Market (B2c) - If total fuel station capacity grows too high relative to fuel demand, station utilization and profitability decrease which in turn leads to exits and reduction in fuel station capacity. Overcrowding of the fuel market triggering this loop could occur because competing entrant retailers do not have perfect information as to each other's supply line of stations in planning and development. This fuel market crowding loop is a third balancing feedback driving toward an implicit desired utilization level.
- Spatial Crowding and Permit Queues (B2d) - As the rate of stations trying to enter increases and/or as the density of existing stations increases, the delay times to find and select station locations, to plan stations, and to receive permits also increase, constraining entrance rates.
- Cut Price to Fill Line (B2e) - When station utilization is low, there is a pressure on station owners to reduce the retail markup on fuel in order to increase demand and undercut local competitors. Resulting increases in demand bring station utilization back to its desired level.

<u>B3 – Learning</u>

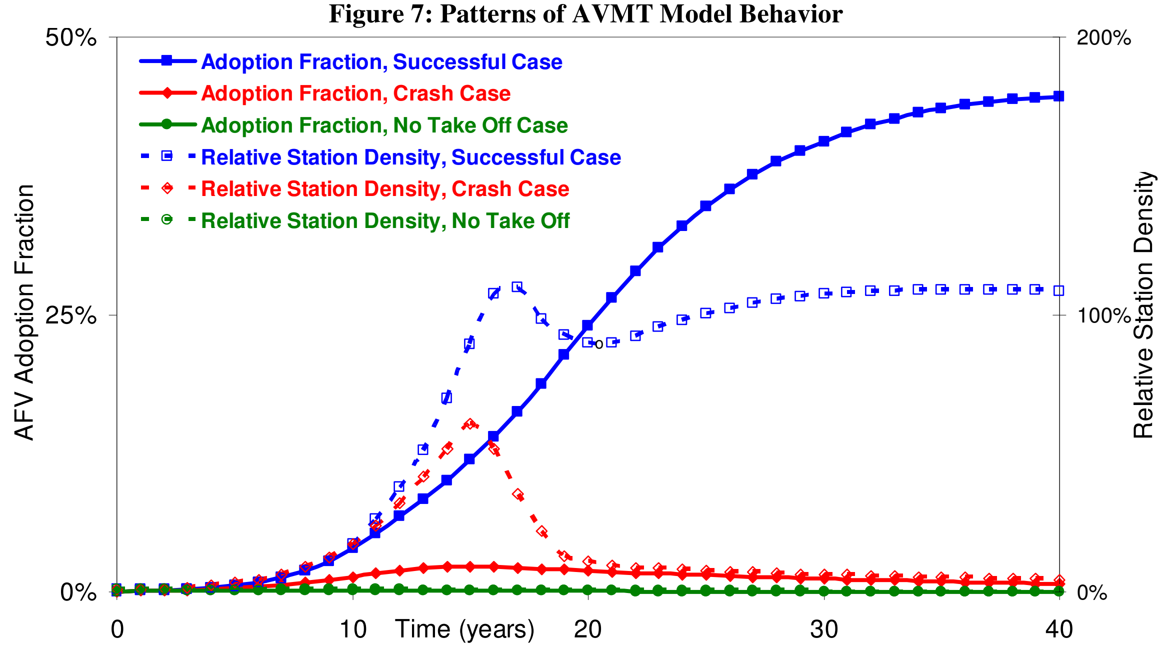
- Learning Spillover (B3a) - While knowledge accrues through learning to drive down the price and improve other attractiveness attributes of the AFV, some of this knowledge may also spillover to be applied to improve the conventional incumbent vehicle platform, reducing the AFV's relative attractiveness and limiting the strength of the reinforcing learning loops.

<u>Feedback Integration</u>

All of these reinforcing and balancing feedback loops and the time delays embedded within them together make the light duty vehicle market prone to tipping points and lock-in effects and make successful support of a transition towards alternative fuels a formidable challenge. The respective challenges presented by the various feedbacks must be well understood to inform both public policy and business strategy in this arena.

The fundamental behavior of the model can be summarized as very slow s-shaped (logistic) growth vulnerable to collapse or to stagnation at a low penetration equilibrium in which limited clustered adoption occurs only in urban areas where density can sustain a niche market.

Figure 7: Patterns of AVMT Model Behavior



As a generic and illustrative example of the modes of behavior the model generates, consider a hypothetical alternative fuel vehicle entrant technology called ENT that is equivalent in all aspects to the incumbent internal combustion vehicles (ICE) except that it cannot run on gasoline. Rather ENT vehicles run on another fuel called OTH that is equivalent in all costs and characteristics to gasoline. The three diffusion patterns are presented for the ENT platform in Figure 7, each conditioned by different policy settings.

Despite ENT's technological equivalence to the incumbent technology, the market for ENT vehicles does not take off without policy support. Infrastructure and consumer familiarity are not sufficiently developed to sustain growth without sufficient policy. An important implication is that alternative fuel vehicles (and policies to support them) may fail even if the technology is mature and its cost is competitive. Transition barriers created by feedbacks within the system must be overcome with policy for an AFV to achieve its true market potential.

As seen in the "crash case" plot, policy may temporarily excite the market, but if it is not strong enough for sufficient duration, the market may crash. The successful case is a scenario in which temporary policies are sufficient to bring the market to a self-sustaining level, reaching equilibrium near 45% adoption among households. Only 3% of households choose not to own a vehicle. The reason ICE finishes with a slightly larger market share than ENT even though the average density of OTH fuel stations reaches that of gasoline, the average OTH station size is still not yet as large as the average gasoline station in year 40.

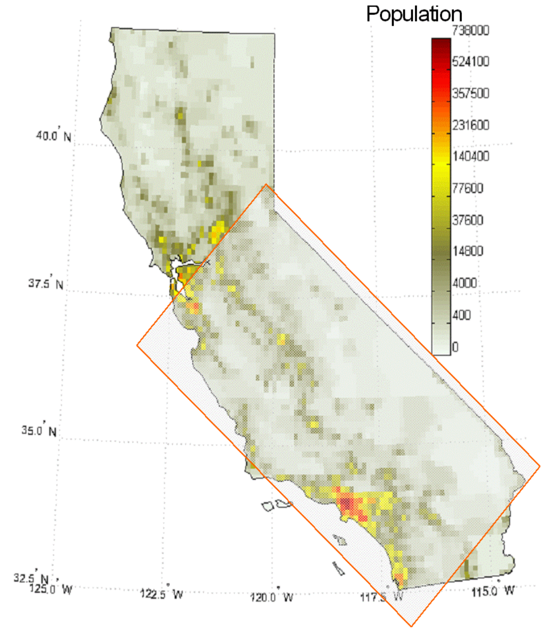
These dynamics will be discussed in greater detail in the following sections. This example is intended to give an introduction to the type of behavior the model generates.

Model Setup and Parameter Specification

Model settings, assumptions, and parameters were chosen for this analysis with three primary goals in mind: to build credibility in the AVMT model, to set parameters using the best available data from the literature and other detailed technical models, and to fix exogenous inputs for tractability of the model structure's endogenous behavior.

The nominal time horizon of the model is a 40 year period, such as 2010-2050. The continuous time model is simulated via numerical integration using a time step of one quarter of a year.

Illustrative Geographic Region



The model is applicable to any region of interest. As an illustrative laboratory for experimentation, simulations in this paper take place for a large Central/South subsection of California covering 89,000 square miles. To represent spatial asymmetries, this region is divided into 252 patches of equal size (~350 square miles). Perfect mixing is assumed in each patch so spatially relevant model variables (e.g. adoption fraction, station density, utility to drive) are calculated for each patch. The use of a specific region rather than a generic model not only makes the results more tangible but also provides a source of useful spatial data.

Driver trip generation in the model is based on a log-normal trip distribution frequency, with radially symmetric short trip frequency distributions and long trips weighted toward high population density region gravitational attractors (including those outside the region boundary). The average driver desires 12,000 vehicle miles per year.

The California region modeled has a fixed population of 28 million people and 13.5 million households. Simulations begin assuming a fully penetrated base of 13 million vehicles and 6,500 gasoline fueling stations distributed spatially according to US Census data.

Technical Parameter Estimates

A significant part of the research included the specification of several technical parameters the various fuels and vehicle drivetrains based on the best available data or estimations from the literature. For example, the parameter values for incumbent fuel, gasoline (GAS), are listed in Table 1 along with those for two entrant alternative fuels: hydrogen produced via steam methane reformation onsite at the station forecourt (H2FSMR) and compressed natural gas (CNG). Similarly Table 2 lists the drivetrain technology platform specific parameters for the incumbent spark-ignition internal combustion engines (ICE) along with hydrogen fuel cell vehicles (HFCV) and compressed natural gas engines (CNG).

For a more detailed explanation for the derivation of and the sources for specifying these parameters, see Appendix A: Technology Assessment.

Table 1: Fuel-Specific Model Parameters

Parameter	Units	GAS	H2FSMR	CNG
Planning & Site Selection Time	years	0.50	0.50	0.50
Permitting Time	years	0.50	0.75	0.50
Bidding and Construction Time	years	0.75	1.00	1.00
Fixed Area	acre/station	0.12	0.12	0.12
Variable Footprint Area per Fueling Position	acre/fueling position	0.0200	0.0253	0.0200
Ancillary Sales Revenue to Fuel Revenue Ratio	dmnl	20%	20%	20%
Typical Ancillary Sales Profit Margin (on Revenue)	dmnl	30%	30%	30%
Levelized Non-Land Fixed Cost per Fueling Position	$/year/fueling position	$30,000	$36,875	$33,000
Daily Storage or Production Capacity/Fueling Position	gge/fueling position/day	3,750	300	3,200
Fuel Dispensing Rate	gge/hour/fueli ng position	420	120	130
Total Fill-Up Time (Fixed & Variable)	hour/refill	0.0867	0.0875	0.1000
Unit Variable (Wholesale Fuel) Cost	$/gge	$1.30	$2.10	$0.92
Absolute Retail Fuel Markup	$/gge	$0.10	$2.00	$0.58
Federal, State, & Local Fuel Taxes and Underground Storage Tank Fees	$/gge	$0.50	$0.00	$0.00
Well-to-Wheel Emissions per GGE Fuel				
Greenhouse Gases (100yr GWP Adjusted)	kilogram CO2-equiv/gge	11.264	13.591	9.034
Volatile Organic Compounds (VOC)	gram/gge	7.564	1.381	3.882
Carbon Monoxide (CO)	gram/gge	94.662	3.337	77.235
Nitrogen Oxides (NOx)	gram/gge	9.151	8.286	6.748
Particular Matter <10 μm (PM10)	gram/gge	1.885	5.524	1.783
Particular Matter <2.5 μm (PM2.5)	gram/gge	0.794	2.647	0.677
Sulfur Oxides (SOx)	gram/gge	2.778	7.020	3.250

$ values in 2005 US$

gge = gallon gasoline equivalent (on energy basis)

The model uploads gasoline parameters as “normal” values and uploads ratios for the other parameters relative to the normal value. As fuel settings are decoupled from vehicle platform settings, one can test flex- or bi-fuel vehicle configurations as well as hypothetical configurations of fuels and vehicle platforms that are incompatible in reality.

As described in the next section, the base run begins with optimistic technical parameters for the alternative fuel vehicle entrant technologies because endogenous learning is switched off. When learning feedbacks are later included in the simulation, more realistic initial parameter values are selected. For a more detailed explanation for the derivation of and the sources for specifying these parameters, see Appendix A: Technology Assessment.

Table 2: Vehicle Drivetrain-Specific Model Parameters

Parameter	Units	ICE	HFCV	CNG
Average Vehicle Life	years	16	16	16
Learning Switched OFF				
Fuel Tank Capacity	gge	20.0	8.0	12
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	21.0	52.5	30.0
Max Range (Action Radius)	miles	420	420	360
Vehicle Performance	dmnl	1.00	0.75	1.00
Vehicle Production Cost	$/vehicle	20,000	25000	20,000
Vehicle Price (MSRP)	$/vehicle	25,000	32,500	25,000
Learning Switched ON				
Initial Fuel Tank Capacity	gge	20.0	5	12
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	21.0	40.0	30.0
Initial Max Range (Action Radius)	miles	420	200	200
Initial New Vehicle Performance	dmnl	1.00	1.00	1.00
Initial Vehicle Production Cost	$/vehicle	20,000	40,000	20,000
Initial New Vehicle Price (MSRP)	$/vehicle	25,000	50,000	25,000
Saturation Fuel Tank Capacity	gge	20	10	15
Saturation Vehicle Production Cost	$/vehicle	10,000	11,000	10,000
Reference Potential Fuel Economy	miles/gge	43.2	106.5	45
$ values in 2005 US\$ gge = gallon gasoline equivalent (on energy basis)				

Hydrogen Base Run

The base run used for this paper consists of a simplified scenario in which hydrogen fuel cell vehicles (HFCV) are introduced as the lone entrant competing against a spark ignition internal combustion engine (ICE) vehicles, which begin at an adoption fraction of 96% of households. In this scenario, hydrogen vehicles are incompatible with existing gasoline fueling infrastructure (GAS) and must develop an infrastructure of fueling positions at which hydrogen is generated at the station forecourt via steam reformation of natural gas (H2FSMR).

Before presenting the dynamics for the base run, now is a good time to re-emphasize that the AVMT model should not be misinterpreted as point predictive. The base run simulation plots are *not* to be interpreted as the most likely "business as usual" future, although the tendency to do so is strong. Rather, the purpose of the base run is to provide a starting point for comparison with addition simulations (Ford 1999).

It should also be noted that the Base Run is very optimistic in many assumptions and already includes some policy interventions. The reason such an optimistic case is chosen is to allow more variation in results by varying parameter settings and applying policies.

Optimistic assumptions must be made explicit. First, there is only one entrant fuel/vehicle pair (HFCV/H2FSMR) competing against only one incumbent pair (ICE/GAS). In reality, more fuels and platforms compete in the marketplace including diesel, compressed natural gas, and flex fuel vehicles capable of running on gasoline blends with up to 85% ethanol (E85), amongst others. In addition, population and motorization are constant over time to simplify behavior. To seed the market, simulations begin with 0.1% of household adoption (13,000 vehicles) and a hydrogen station density at 1% of the typical gasoline station density (65 stations).

Technical and economic parameters are also optimistic in this base run. The HFCV production cost and manufacturer suggested retail price (MSRP) is only 25% higher than conventional ICE vehicles. HFCVs are assumed to have 2.5 times the ICE vehicle's fuel efficiency (52.5 vs. 21 miles/gge). The HFCV tank capacity is 8 kg, or 40% on an energy basis of the typical 20 gallon ICE fuel tank. Eight kilograms is the U.S. Department of Energy's FreedomCar technology target for 2010 (US DOE 2003). Such aggressive fuel efficiency and tank capacity assumptions combine to give HFCV the same maximum range as ICE. Even assuming 75% vehicle performance (e.g. less cargo space) compared with ICE, this range is very optimistic.

Based on DOE's H2A model for forecourt steam methane reformation (H2FSMR) fuel stations, the annualized fixed cost per fueling position is 50% higher than gasoline stations. The variable cost at stations is assumed to cost $2.10 per gge of hydrogen delivered. Assuming a 70% energy efficiency in producing and compressing the hydrogen (4.635 cubic meters of natural gas per kilogram of hydrogen produced), this translates to a commercial natural gas price to the fuel stations of about $9 per thousand cubic feet of natural gas, which is conservatively high.

Hydrogen fuel stations have optimistically low initial permitting and entrance delays, albeit they are greater than those for gas stations due to unfamiliarity and safety concerns with the new fuel

technology. Again, these delays are dynamic in the model and increase as the market becomes crowded or as the rate of permit applications leads to long backlogs.
One of the only pessimistic settings for the initial base run is that learning feedback effects are switched off to first build understanding of other feedbacks and technical parameter sensitivities. Instead, initial attribute values are optimistic, as they are held constant for the forty year period.

Behavioral parameters for the value of service time, trip interdependency, and the sensitivity for topping off are also set conservatively so that these feedback concepts do not dominate dynamics. Because these feedbacks are not included in other models, they are set weak for now until more confidence is developed in their actual strength. Social exposure parameters are on the strong side compared to the marketing science literature estimates.

In terms of policy, the base run includes a strong fifteen year marketing promotion that reaches 4% of the non-adopter population per year, a ten year demonstration phase in which the retail markup on variable cost at the hydrogen fueling outlet is fixed at $3/kilogram, a two year station honeymoon in which none exit the market, and a full exemption for hydrogen on the $0.50/gallon gasoline tax (which includes federal excise taxes, state and local sales taxes, and the underground storage tank fee).

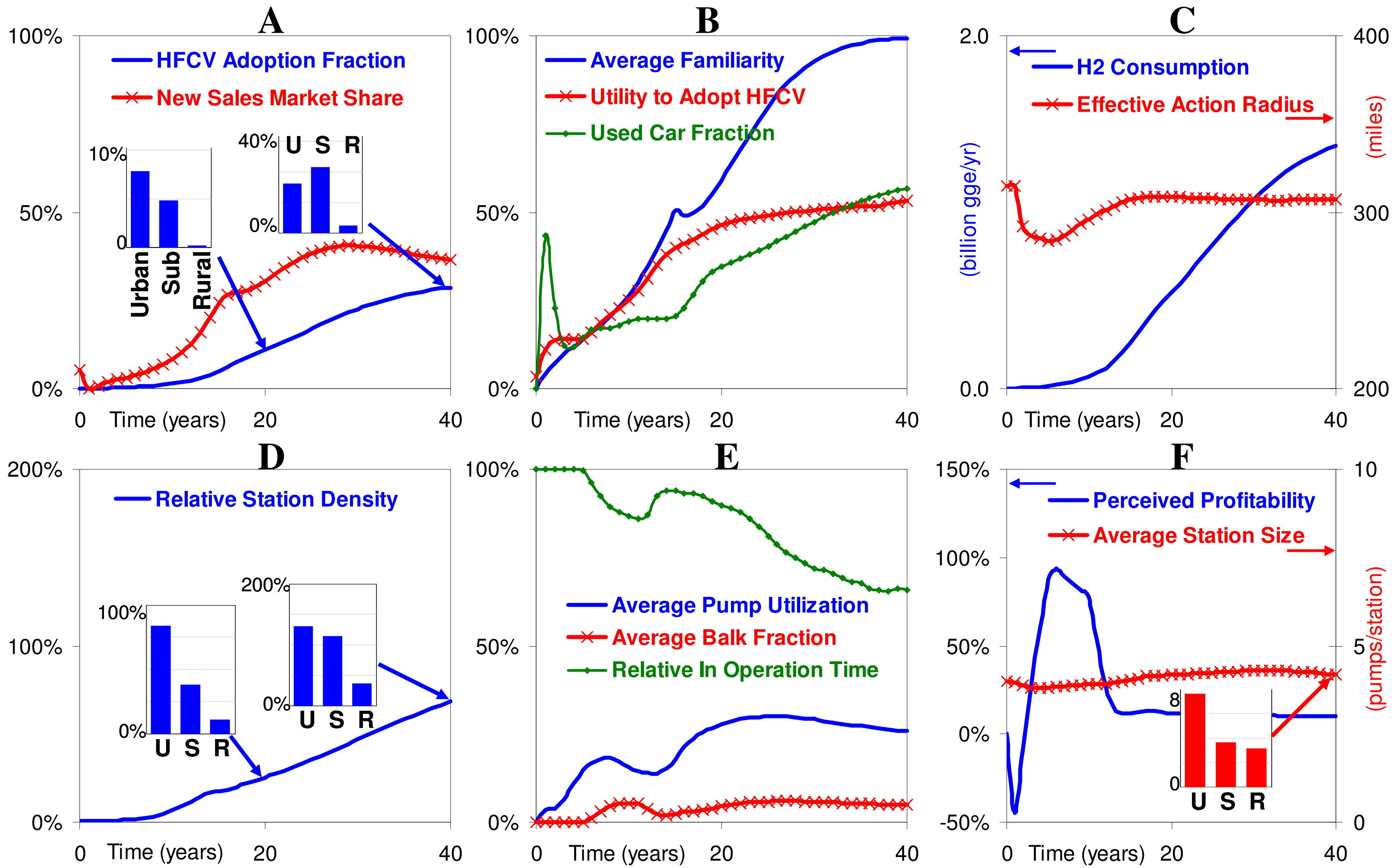
The key output variables are plotted for the forty year Base Run simulation in Figure 8. The Adoption Fraction, or fraction of households that own a hydrogen fuel cell vehicle, is plotted in frame A at the upper left. Despite all of the optimistic assumptions described, the adoption fraction grows quite slowly, reaching only 29% in year 40. Simulations of longer duration show this adoption fraction reaches equilibrium at 32% after about 70 years.

Plotted along with the adoption fraction is the HFCV market share amongst new vehicle sales. It is consistently higher, grows more quickly, and is markedly more volatile than the adoption fraction. The sales market share reflects the flow of new hydrogen vehicles entering the stock of vehicles on the road, which accumulates with news sales and decays with vehicle scrappage. Stock variables dampen volatility and give the system memory. The new sales market share has two small peaks over the first ten years. The fuel cell share of new vehicle sales is a function of both the familiarity amongst non-adopters with and relative utility of the HFCV. The first peak in new sales market share can be explained by examining the behavior of the “utility to adopt” variable, which is plotted in frame B.

As described in Figure 6, utility to adopt (or the attractiveness of purchasing) an AFV is a function of both vehicle attributes and the utility to drive that vehicle platform. It increases initially in the base run as fueling stations enter and coverage grows, yet it quickly saturates while station coverage continues to increase. This saturation is due to crowding at the stations as utilization increases (frame E). Drivers have to wait in lines for more than thirty minutes at some busy stations to refuel. As drivers see and hear about these queues, more choose to balk, that is to go elsewhere or not to make a trip at all due to inconvenient refueling in a patch. As a result of these pressures, the supply of refueling infrastructure works to catch up while growth is demand is suppressed until eventually utilization comes to balance at a reasonable level.

Hydrogen Base Run

Figure 8: HFCV/H2FSMR Base Run



The second local peak in the market share, occurring just after year 15, is the result of the consumer familiarity dynamics at play. Year 15 marks the end of the public marketing campaign, which had steadily increased familiarity over its duration as plotted in frame B of Figure 8. At the end of this aggressive marketing campaign familiarity dips slightly. Forgetting is slightly greater than new awareness generation because a limited fraction of households own and communicate about hydrogen vehicles. By this point however, fuel station coverage, utility to adopt, and the fleet of HFCVs have reached high enough levels to continue to grow familiarity via word of mouth and normal marketing funded by the manufacturers with a fraction of sales revenue. The tipping point threshold has been passed so that the installed base of vehicles and consumer familiarity continue to reinforce the growth of the other via positive feedback.

Upon first inspection, it is unclear why the HFCV share of new vehicle sales begins to drop over the final ten years even as familiarity, utility to adopt, and fuel station density continuing to increase. Yet this dip can be explained by the increasing share of hydrogen vehicles purchased from the used hydrogen vehicle market. By this point, the stock of used hydrogen vehicles for sale has increased substantially, which temporarily depresses the news sales growth rate.

The behavioral topping off phenomenon, described earlier, is reflected by the plot of "effective action radius" in frame C. The typical ICE driver chooses to refuel when at or below one quarter of the tank. The normal action radius is then 75% of the 420 mile maximum range, which is simply the tank capacity (8 gge) multiplied by the fuel economy (52.5 mi/gge). Yet, upon model initialization and endogenous calculation, the effective tank range drops for the HFCV because vehicle owners perceive very low station coverage and decided to refill sooner to maintain a larger safety buffer in the tank. As average station density increases beyond 15%-20% of the average gasoline station density due to perceived profitability of the industry (frame F), the effective action radius nearly fully recovers to its normal level by year 15.

Average station size, in red at the lower right, begins at four fueling positions per station and grows due to utilization and profitability. While the average size falls in the last five years, this is not because stations are contracting. Rather, large urban stations enter and saturate those markets first. Stations entering in later years are in rural areas and are typically smaller, bringing down the statewide average. Significant spatial heterogeneity is also large in the adoption fraction and fuel station densities as demonstrated by the snapshot bar graphs. Early adopters and stations are predominantly in urban areas where stations are most profitable. Rural areas lag.

Finally, the base run also reflects physical constraints in the volume of hydrogen that can be produced and stored at each fuel position, an important capacity constraint separate from a station's vehicle throughput capacity. Plotted in frame E, average operating hours fall because high utilization urban stations run out of fuel. Such station closures or interruptions for hydrogen tanker deliveries lead to even higher utilization and lines when stations are open, yet profits remain low (especially with the more competitive markups on fuel after year 20). Consequently, new station entrance to bring utilization in line with desired levels is constrained. This balancing effect is a strong barrier for alternative fuels with low volumetric energy density and hence expensive fuel station inventory holding costs.

Structural and Parametric Sensitivity Analysis

Prior to policy analysis, it is first necessary to build confidence in the model through partial model testing and to develop an understanding of what drives model behavior through sensitivity analysis. This exploration process provides a better sense of the landscape for the transition challenge to inform priorities for policy analysis and eventually policy design.

The purposes for sensitivity analysis are three-fold (Sterman 2000). First, if simulated behavior patterns are not fundamentally affected by varying input variables within potential error margins, confidence is built in the model's robustness and usefulness under uncertainty. Similarly, if behavior, even under extreme conditions, does not change with added model structure, such structure may be identified as superfluous. Second, identification of the most sensitive model structures and parameters provides direction in setting priorities for further data collection and efforts to improve the model. Time spent improving estimates for parameters that do not matter is time wasted. Finally, sensitivity analysis also identifies levers and effective entry points for policy instruments. This section highlights the most sensitive structures and parameters within the model. Additional results can be found in Appendix B.

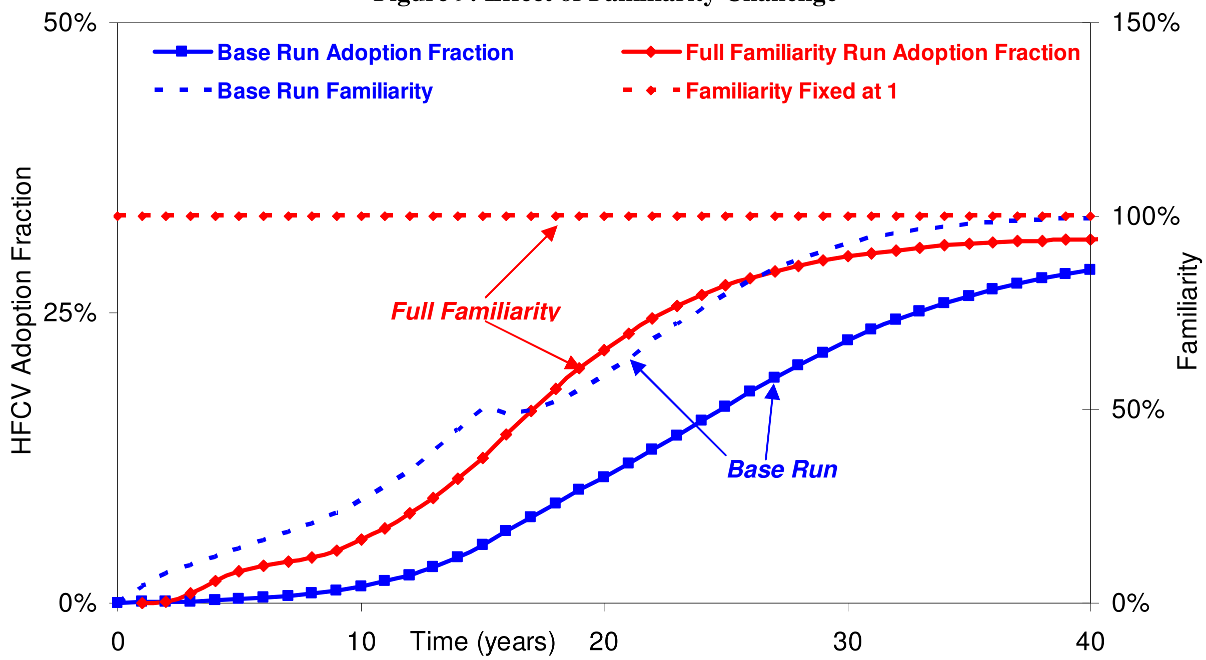
Structural Sensitivity

While conducting sensitivity analysis on uncertain input parameters is standard practice, it is probably most important, though more labor intensive, to consider the sensitivity of behavior to changes in model boundary, feedback structure and levels of aggregation (Sterman 2000). Some examples provide a better sense of what limits diffusion in the AVMT model.

<u>Development of Familiarity (R1)</u>

Figure 9 depicts a simple comparison between base run and a full familiarity case.

Figure 9: Effect of Familiarity Challenge

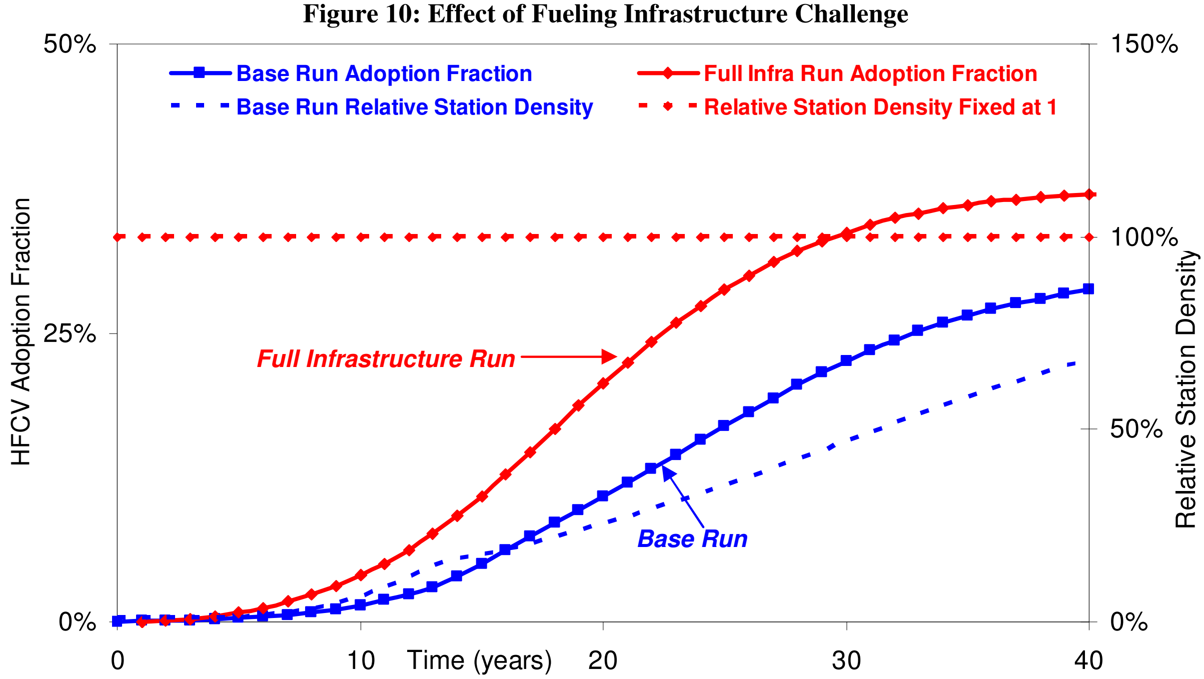


The "full familiarity" plot is a hypothetical scenario in which all California consumers are immediately familiar with the hydrogen fuel cell vehicle technology to the point that they include the platform in the set of vehicles under consideration, even though hydrogen vehicles are owned by only 0.1% of households (13,000 vehicles) when the simulation begins. In addition, there is no forgetting so familiarity is fixed at its maximum level.

The difference between the base run and the full familiarity case demonstrates that building familiarity through social exposure substantially limits the speed at which the AFV penetrates the fleet of vehicles. Inclusion of this endogenous feedback delays the time to 20% market penetration by more than ten years in comparison to the full familiarity run.

Development of Fueling Infrastructure (R2)
In the next case, rather than beginning with full familiarity, the simulation begins with a full infrastructure of hydrogen fueling stations equal in size and coverage to the current gasoline infrastructure. Thus the chicken-egg problem loop is clipped or "shorted" by fixing fueling stations as exogenous and independent of fuel demand or station profits.

Figure 10: Effect of Fueling Infrastructure Challenge



In this hypothetical scenario, what constrains the rate of market penetration includes: the relative aggregate vehicle value proposition, the vehicle lifetime and fleet turnover time, the development of familiarity, and the development of vehicle product breadth.

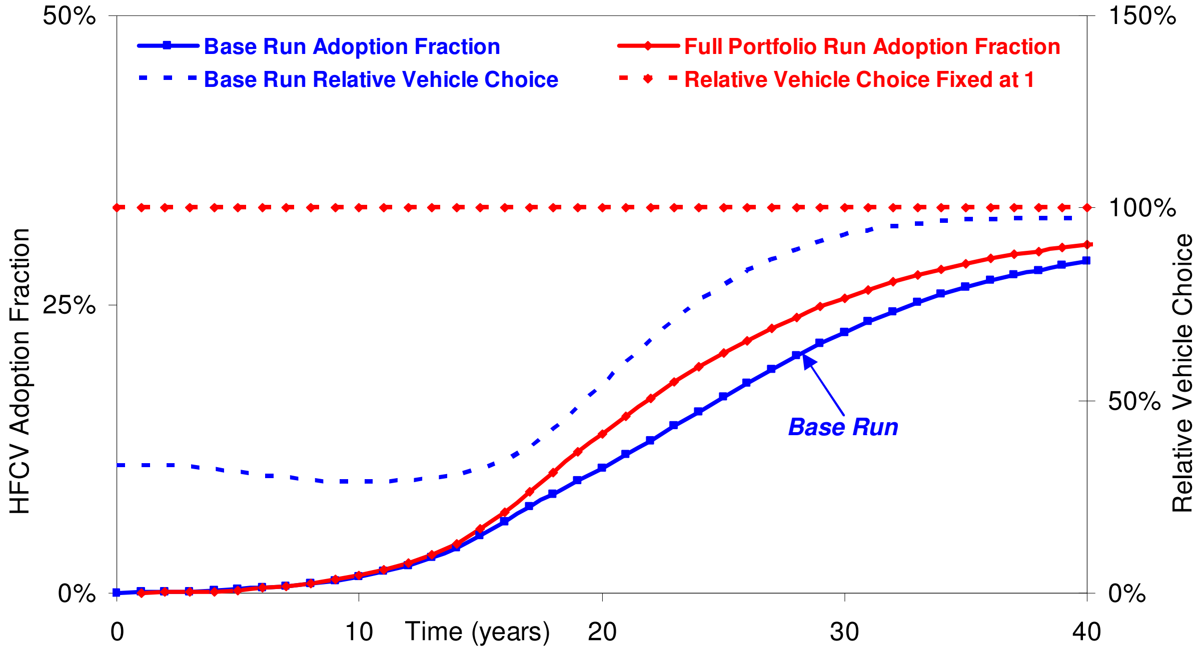
The equilibrium installed base penetration level for HFCVs, 37% in this case, is a function of only the relative values of technical attributes compared to ICE once full familiarity and scope are developed. Note that if the learning feedbacks were in effect, the HFCV would reach a much higher equilibrium adoption fraction as the four key vehicle attributes improve.

The takeaway from this test is that the infrastructure development challenge makes a big difference, not only in slowing adoption by decades but also in potentially causing the adoption rate to stagnate or crash if fueling stations are not profitable.

Development of Vehicle Choice Portfolio (R3c)

The last feedback that can be turned off for illustration is the development of breadth of choice in alternative fuel vehicle product portfolios of the vehicle manufacturers. As seen in the case of CNG vehicles or hybrid electric vehicles, new drivetrain options are initially offered for a small selection of vehicle models. Yet to effectively compete with the installed base, the AFV must be offered in a variety of sizes, styles, and colors, with all the available option packages.

Figure 11: Effect of Vehicle Portfolio Breadth Challenge

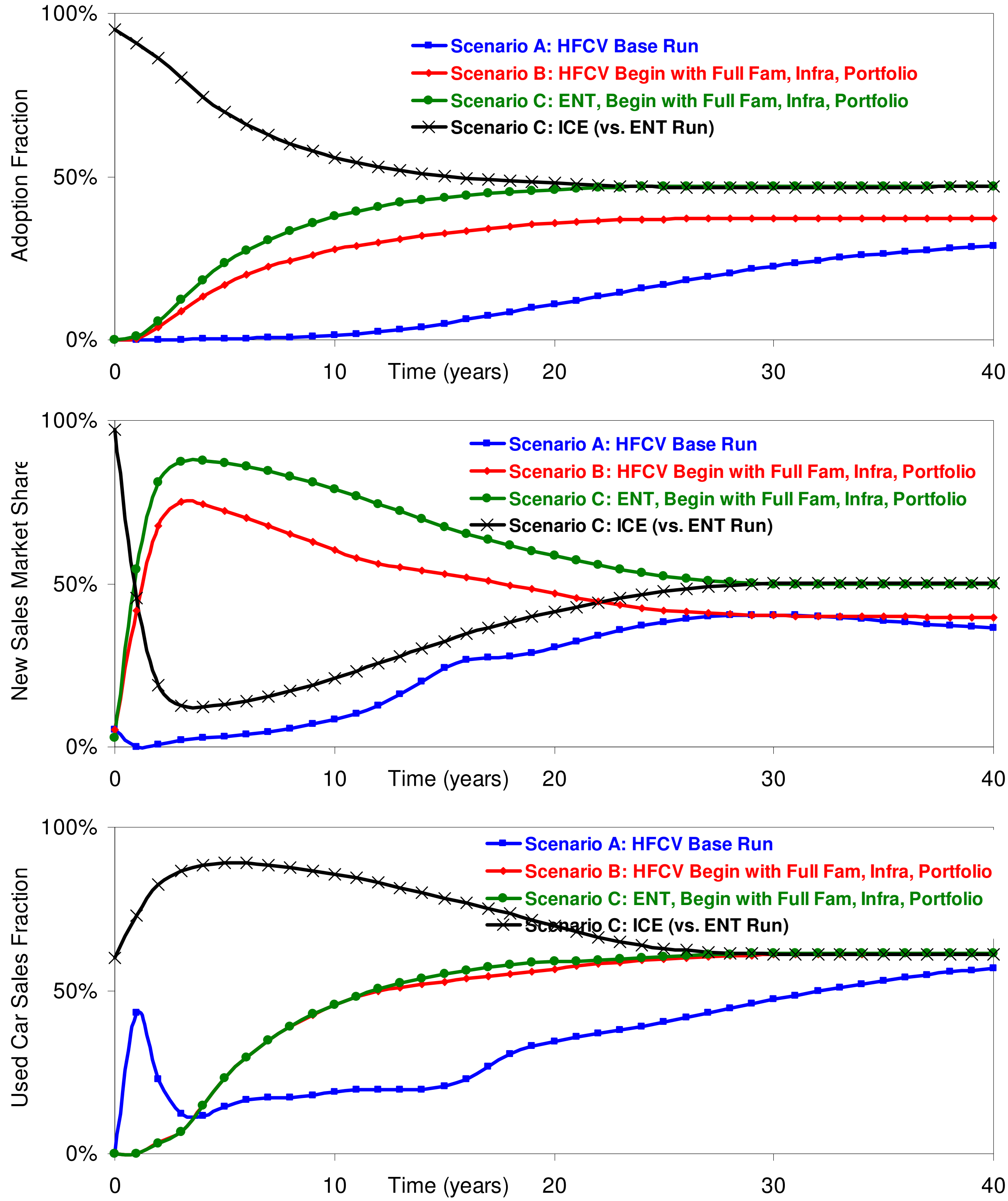


Although this loop does not slow adoption as much as the infrastructure or familiarity challenges, it is yet another metaphorical hill to climb and is only climbed once infrastructure and familiarity reach levels to sustain large levels of new vehicle sales.

What would be the effects if there were no hills to climb? That is, if a full infrastructure was in place, the entire population begins willing to consider the technology in their decision set, and automakers immediately made a full portfolio of vehicles available? Such a scenario is plotted in Figure 12. In this case diffusion is purely a function of the fleet turnover rate and the relative utility of the alternative fuel vehicle in comparison to the entrant. Simulations are plotted both for a static hydrogen technology and for the hypothetical ICE-equivalent entrant used earlier. As would be expected, the ICE equivalent entrant reaches equilibrium at 50% market share.

Yet, if the average vehicle life is 16 years, why does the entrant technology reach equilibrium so quickly? The answer lies in the disequilibrium dynamics of the used car market development for AFVs. As the AFVs enter the market, displacing ICE vehicles, the temporal oversupply of ICE used car vehicles, reduces the share of ICE vehicles purchased new rather than used. Yet it takes fifteen to twenty years for the used alternative fuel vehicle market to fully develop. A higher market share of new vehicle sales goes to the alternative, speeding its introduction relative to absence of any used car market in the model. Most of the other models used for AFV policy analysis do not explicitly represent the used car market and would miss this effect.

Figure 12: Structural Sensitivity, Begin with Full Complementary Assets

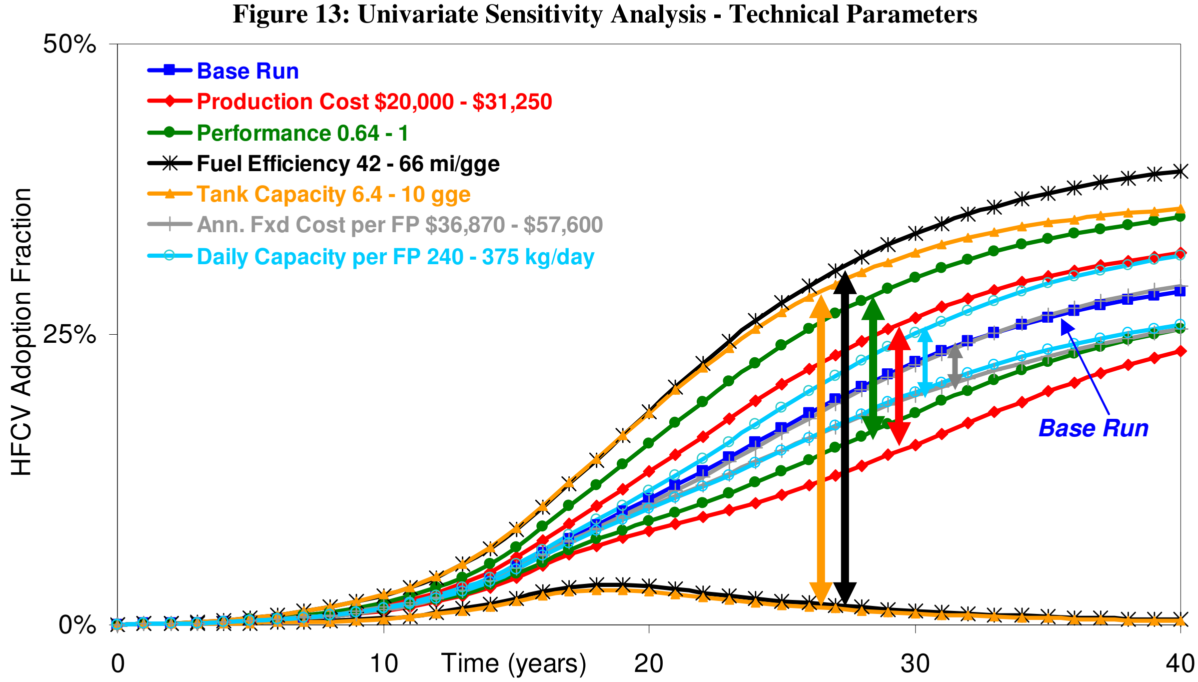


Technical Parameter Sensitivity

While the technological and economic parameters included in the model were informed by the best available data, they are rife with uncertainty, especially for the novel entrant technology parameters. Sensitivity analysis for these input parameters guides the understanding of what technological attributes are most important for enabling an AFV transition.

Figure 13 depicts a univariate sensitivity analysis in which the most important technical and economic parameters are varied by ±25% in comparison to the base case. This variation probably does not cover the entire range of uncertainty for these parameters, but gives some sense of relative sensitivity for fractional changes in each.

Figure 13: Univariate Sensitivity Analysis - Technical Parameters



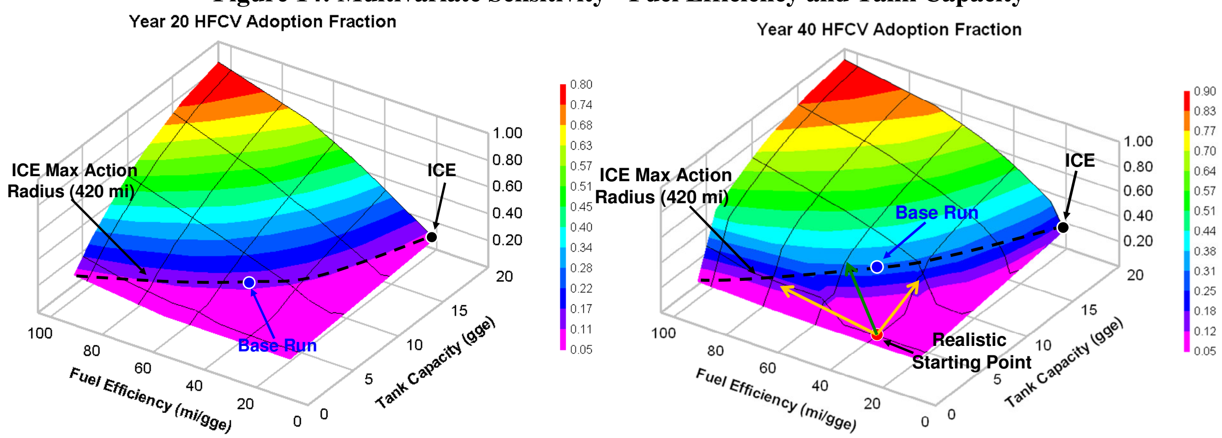
Fuel efficiency and tank capacity are the most sensitive vehicle attribute parameters because together they determine both the maximum range of the vehicle and the frequency of refueling, which affects several chicken-egg feedbacks. When vehicle range is low and refills must be made frequently, the costs of searching for a fueling outlet, running out of fuel away from one, or having to stay home become quite high, suppressing adoption.

Utility and hence adoption patterns are more sensitive to relative performance than relative vehicle purchase price, based on the specification of discrete choice sensitivity parameters taken from relevant studies of stated and revealed preference (Bunch, Bradley et al. 1993; Brownstone, Bunch et al. 2000). Because in the base run HFCV vehicle performance is lower and vehicle price is higher than the ICE value (which used for normalization), their impacts in this ±25% sensitivity test are asymmetric around the base run.

The annualized fixed cost of fueling stations is the least sensitive of the parameters. This insensitivity was initially surprising because the additional equipment and land necessary for hydrogen fuel stations is one of the most visible differences for that technology. So while the construction costs for hydrogen fueling stations can be quite high and uncertain, policy analysis should be robust under various capital cost assumptions, allowing extrapolation of this analysis to other types of hydrogen production and distribution infrastructure.

While a useful first step, univariate sensitivity analysis covers only limited vectors within the n-dimensional parameter space. *Complex nonlinear systems also require the exploration of multiple parameter changes at the same time to see the full range of system behavior* (Sterman 2000). Univariate sensitivity analysis neglects potentially critical interactions among variables. Figure 14 plots the adoption fraction at years 20 and 40 under variations in the two most sensitive parameters identified the univariate sensitivity tests: both fuel efficiency and vehicle tank capacity.

Figure 14: Multivariate Sensitivity - Fuel Efficiency and Tank Capacity



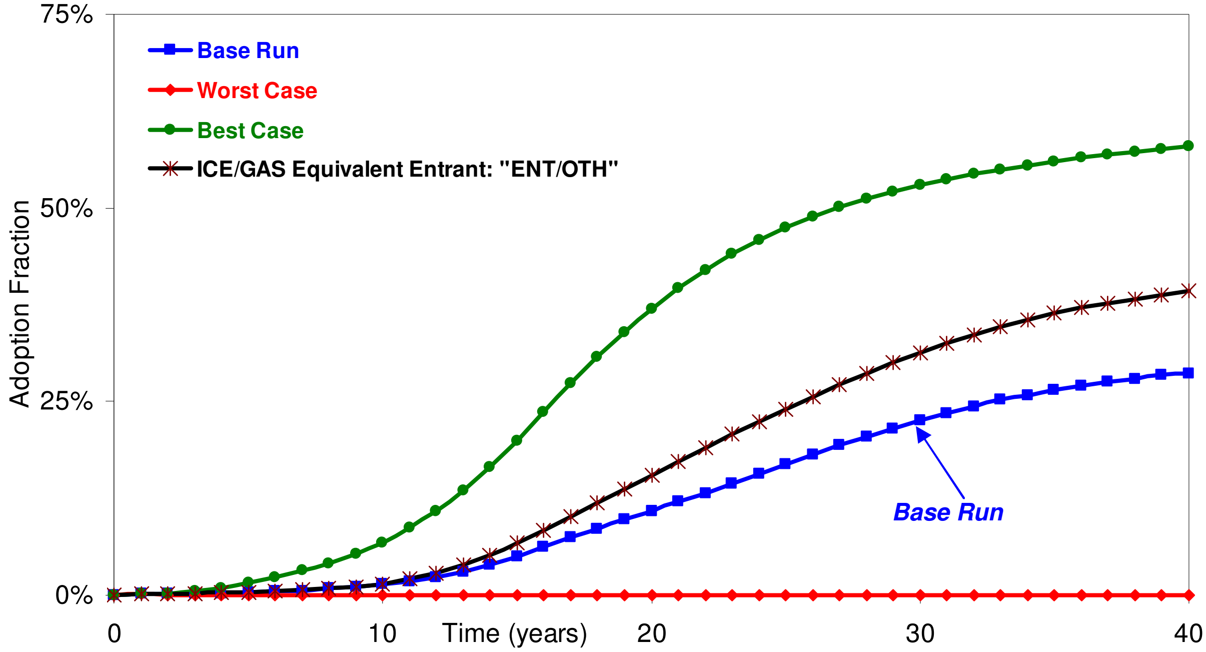
The three-dimensional bivariate sensitivity slopes show how important vehicle range or "action radius" is for adoption. However, it is very important to note that the contours of these adoption fraction snapshots do not rise exactly with range. For example, in moving along the dashed 420 mile action radius line from the base case to a higher fuel economy, lower tank range position of the same range, adoption fraction decreases. Higher fuel economy, while improving the vehicle's range and operating cost, also reduces total annual fuel demand and the profitability of stations. If vehicles are too fuel efficient (assuming margins do not change), stations will be unprofitable and the necessary chicken-egg growth will not occur (see Struben 2006).

If we move from the base case to much lower fuel economy and higher tank size, such as to ICE-equivalent settings for these two parameters, the twenty and forty years adoption fractions also decrease. Here we see the effects of increased fuel cost to the driver. Thus there is a sweet spot ratio with fuel economy mileage about five times the tank capacity. It appears that, from low levels of each, the year 40 adoption fraction rates rises slightly more rapidly with tank size than with fuel efficiency.

These multivariate plots, when combined with potential paths for learning-by-doing and learning-by-search, also give a sense of how the reinforcing learning feedbacks may impact the rate of penetration. Because fuel economy and tank capacity have a multiplicative effect in determining utility, R&D efforts should focus on both. If 40 miles/gge and a 5 gge tank capacity are realistic starting points for the HFCVs of today, it is more effective to increase each by 50% than to increase either one or the other by 100%.

Another common way to perform multivariate sensitivity analysis is to run best case and worst case technical parameter scenarios. Using the range of parameter values tested individually in the univariate case, Figure 15 plots simulations using the combinations of the best and worst values for the six parameters tested in Figure 13 along with the base run and a hypothetical, ICE-equivalent "ENT/OTH" introduction scenario. The disparity between the best and worse cases is significant. The ENT technology takes off more quickly as the infrastructure parameters allow for more rapid growth, yet ENT's relatively lower fuel economy and range ends up limiting its equilibrium adoption rate in comparison the "best case" hydrogen run.

Figure 15: Technical Parameter Sensitivity – Base Run, Worst Case, Best Case, ENT/OTH



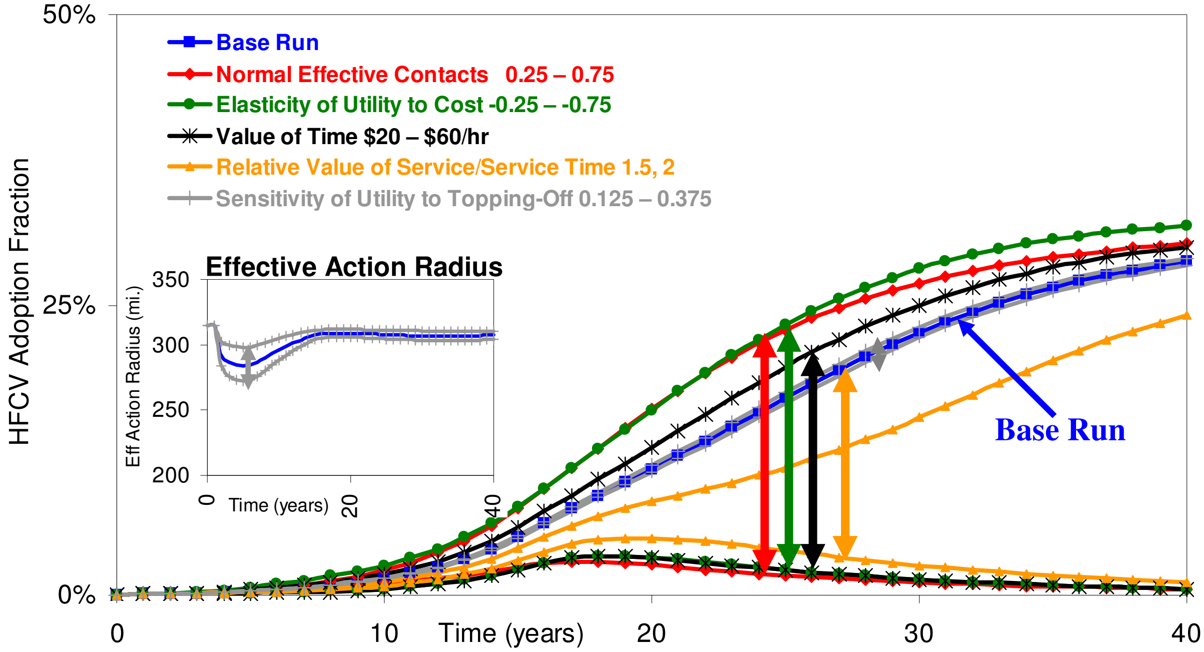
This example illustrates the need for policy testing to include a multivariate technical parameter sensitivity analysis with base case assumptions transparently stated. Only in doing so can one identify that policies are robust and effective in the face of uncertain technological futures. In addition, such multi-dimensional search is needed to explore for nonlinear interactions between parameters such as fuel economy and tank size.

Behavioral Parameter Sensitivity

The behavioral parameters in the model are even more uncertain due to the lack of empirical data available to estimate them. Thorough parametric sensitivity analysis was also performed for these parameters to scan for the most important for further research and estimation. Figure 16 depicts univariate analysis (±50%) for five critical behavioral parameters.

The social exposure contact rate, a variable related to Bass's "coefficient of imitation" or the "co-efficient of internal influence" is clearly very sensitive as indicated by the diamond plots. This sensitivity demands further empirical research of social exposure channels to better estimate the parameter for the new light duty vehicle technology industry.

Figure 16: Univariate Sensitivity Analysis - Behavioral Parameters



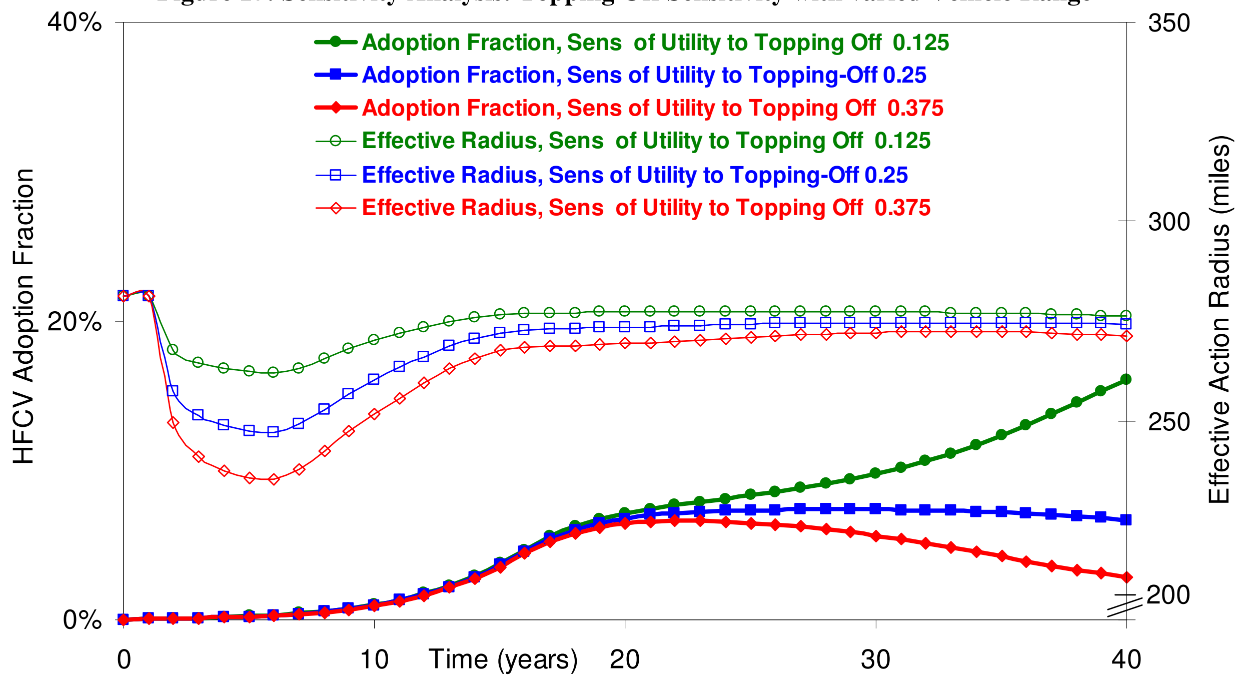
The elasticity of utility to cost is the fractional change in utility per fraction change in the total cost of a trip (e.g. fuel purchased, time spent, etc). The reference value of this parameter for the base run is -0.5 as based on Ben-Akiva and Lerman (1985). Marked by circles in Figure 16, as the absolute value of this negative parameter increases, market penetration is more heavily constrained because the relative utility of driving the AFV is lower with sparse station coverage.

A wide variety of work has been done to estimate the value of time. The reference value is set at $40/hour based on Brownstone and Small (2005). Yet other estimates from the literature fall into the range tested here. Simulation results are sensitive to this parameter. Counterintuitively, as the value of time increases, the rate of market penetration actually increases. The upper starred adoption fraction plot corresponds with $60/hour and the lower starred plot corresponds with $20/hour. As modeled, drivers compare the AFV driving experience to their normal trip efforts. By increasing the value of time parameter one also increases the reference trip cost used for normalization. However, a component of the reference trip cost, the cost of running out of fuel, is independent of the value of time in the model (Struben 2007). Hence as the value of time parameter increases, the cost of searching for a hydrogen fuel station increases by a greater fraction than does the reference trip cost used for normalization and the "relative cost of searching" decreases. The ultimate result is that the HFCV's relative utility improves when the value of time parameter is increased. Normalization could alternatively be formulated using a different cue, but wouldn't greatly impact dynamics.

In addition, the perceived value of time may vary by activity. For example, it may increase when one is doing something irksome such as waiting in line at a fuel pump. Therefore the AVMT model allows use of the variables "relative value of service time" and "relative value of search time" to reflect a greater value of time relative to the normal value while the car is being refueled or while a driver is searching for a fuel outlet. In the base run, this parameter is set to 1 and value of time is always $40/hour. As seen in the triangle marked plots, if the driver's value of time during these activities is 50-100% greater than usual, the transition is more difficult. Furthermore, this parameter's suppression effects are amplified in scenarios with more queuing.

The sensitivity to station coverage and utility to drive in making decisions to increase one's effective fuel tank buffer (and thus to "top-off" more frequently) is shown by the hash marked plots. As seen in the inset within Figure 16, as this sensitivity parameter increases, the driver's effective action radius drops more significantly for the same level of station coverage. The topping-off effect constrains diffusion not only by decreasing the AFV's utility but also by lowering fuel demand and station profits in rural areas. If this parameter is zero and there is no change in the perceived buffer, adoption improves only slightly. While not very sensitive under the base run conditions, results are more sensitive to this parameter when the vehicle's maximum radius is decreased to 375 miles for example (Figure 17), reiterating the importance of a multivariate sensitivity search in multiple dimensions of the parameter space at the same time.

Figure 17: Sensitivity Analysis: Topping Off Sensitivity with varied Vehicle Range

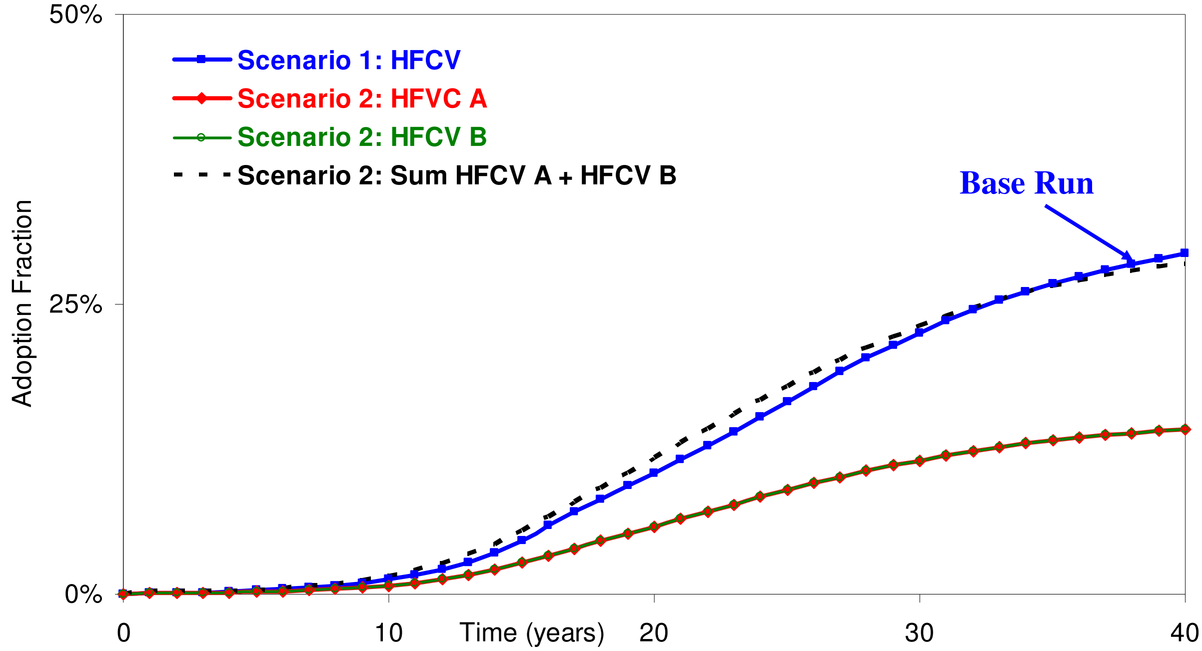


Multiple Competing Entrants

Another major model assumption that might be varied is the number of competing entrant platforms. For example, Scenario 2 in Figure 18 plots two competing entrant hydrogen vehicle platforms which have fueling infrastructure incompatible with one another. Each entrant technology must co-evolve with its own familiarity and infrastructure. The base run, with only one HFCV vehicle entrant vying to displace ICE is also plotted as Scenario 1 for reference.

In Scenario 2, the two hydrogen entrants (A and B) have the same parameter values for all technology attributes and thus, in this deterministic model without random noise, they achieve exactly the same penetration over time. This simulation also assumes some social exposure spillovers between the two similar but incompatible hydrogen platforms. Here it is also assumed that the consumer perceives the platforms to be similar and nearly correlated within the nested multinomial formulation discrete choice formulation.

Figure 18: Multiple Competing HFCV Entrants



Interestingly, the total sum of hydrogen vehicle adoption in Scenario 2 takes off faster and is initially higher than the base run for the first thirty years. The increased platform choice improves initial market share compared to the base run. However competing hydrogen platforms lead to infrastructure crowding and stagnation rather than growth and eventually the sum of hydrogen vehicles in Scenario 2 falls below that of Scenario 1 with a single entrant. With learning feedbacks at play there is even more suppression. Even with knowledge spillover, the sum of improvements made for two entrants is less than that in the one entrant case.

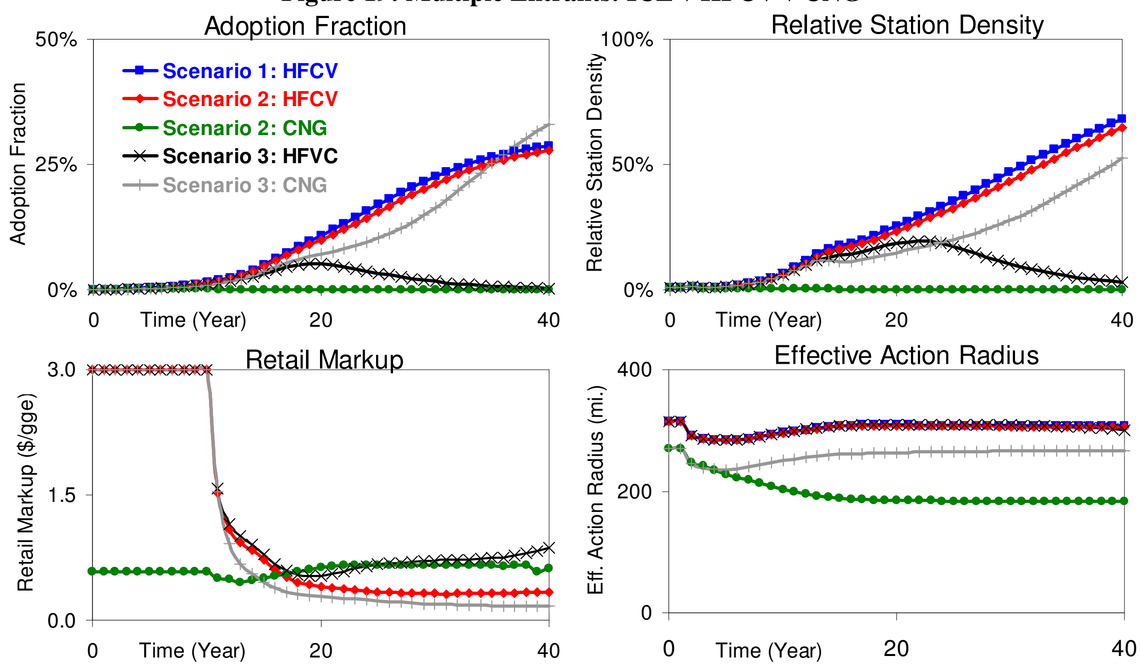
This example exhibits the clear benefits of standardization. There is a clear conflict between diversity of choice amongst competing platforms and the ability to grow necessary fueling and vehicle production infrastructure to provide a competitive total value proposition for the alternative fuel vehicle. While this difficulty may support the idea of "picking technology winners" to standardize earlier using policy, the potential lock-in effects make such a policy choice very hard to undo and the track record for governments to do so well is abysmal. As a middle ground, coordination and partnerships amongst those working to introduce the same fundamental alternative fuel molecule is very effective.

What happens when the two competing entrants are no longer equal? Figure 19 pits the HFCV against compressed natural gas (CNG) vehicles under fairly optimistic assumptions for that platform too (See Table 1and Table 2). The CNG vehicle's production cost is set equal to ICE (20% lower than HFCV). Its fuel economy, at 30 miles/gge, is less than that of fuel cell vehicles and it has a maximum radius of 360 miles versus 420 miles for the other two competing technologies. The CNG refueling stations have higher land requirements and fixed costs than gasoline outlets though not as great as the H2FSMR stations. Scenario 1 is again the base run used all along with only HFCVs as an entrant. In Scenario 2, CNG vehicles also compete and are given an identical initial shock as that for hydrogen. Yet the CNG retail markup begins at a competitive level in this scenario. The HFCV soon wins the competition between entrants, as

CNG infrastructure is slow to develop. Note the presence of the CNG competition slows the rate of HFCV adoption in comparison the base run.

In Scenario 3, the CNG retailers are also given a 10 year demonstration phase with a $3/gge markup. While such a markup brings CNG's retail price to about twice that of gasoline on an energy basis, the fuel is still attractive as we make a strong assumption that average CNG fuel economy is 50% higher than ICE vehicles. Despite the CNG vehicle's lower range, it actually overtakes hydrogen under this scenario causing HFCV adoption to crash.

Figure 19: Multiple Entrants: ICE v HFCV v CNG



Thus entrants must not only overcome several difficult hurdles, they must also compete amongst other alternative fuels, which can lead all entrants to stagnate. This inter-entrant competition is likely even more of a barrier when endogenous learning is in effect because, even with some spill-over effects, technological improvement is slowed by the lower sales volume of each competing entrant platform. As mentioned earlier, the presence of only one competing entrant in the base run should be regarded as a very unrealistic assumption, but one the eases the understanding of system behavior.

Limitations of this Sensitivity Analysis

It should be noted that the proceeding analysis is limited in that it makes little use of information about the relative uncertainty of the various parameters; it merely identifies parameters which, if they were uncertain, might have a substantial impact. Improved techniques such as multivariate Monte-Carlo analysis have not yet been employed due to both the substantial computing time requirements to implement hundreds of AVMT model runs and the lack of existing published estimates for the probability distributions for the inputs of interest. For the purposes of understanding what drives model behavior, rather than probabilistic prediction, simple sensitivity analysis over a broad multivariate parameter space is most appropriate.

Policy Testing

As demonstrated by the preceding section, the results of the AVMT model are sensitive to several parameters of uncertainty that are difficult to calibrate due to lack of empirical data. However, policy testing in complement with sensitivity analysis and extreme condition testing can provide some very useful qualitative insights. It should be emphasized that the purpose of the model is to understand how policy affects patterns of behavior, not for quantitative policy cost modeling or cost-benefit analysis. Such uses are premature due to uncertainty in technology attributes and in parameters conditioning consumer choice among AFVs. Nor is the model's purpose to provide forecasts of the most probable market penetration futures.

Rather, we focus on characterizing global dynamics and strategies for overcoming transition barriers. The model is a useful tool for understanding the relative directional impacts of public and private policies. The goal is to explore and identify which types of policies have significant leverage and under what context. Assessing the robustness of policies under varying model parameters also guides subsequent efforts to elaborate the model and gather needed data.

For the purposes of this analysis, policy is defined broadly as "a plan or course of action, as of a government, a political party, or a business, intended to influence and determine decision, actions, and other matters" (American Heritage 2004). Thus, policy testing includes regulatory requirements, government incentives, private firm strategies, or a combination thereof.

Individual Policy Testing

Policy testing begins by comparing the sensitivity of various public policies and industry strategies applied individually. An extensive list of policies have been tested and a plethora more have not yet been explored. To generally categorize the purposes of policies in support of low greenhouse gas emitting fuels, they either require or provide economic incentives for one or more of the following:

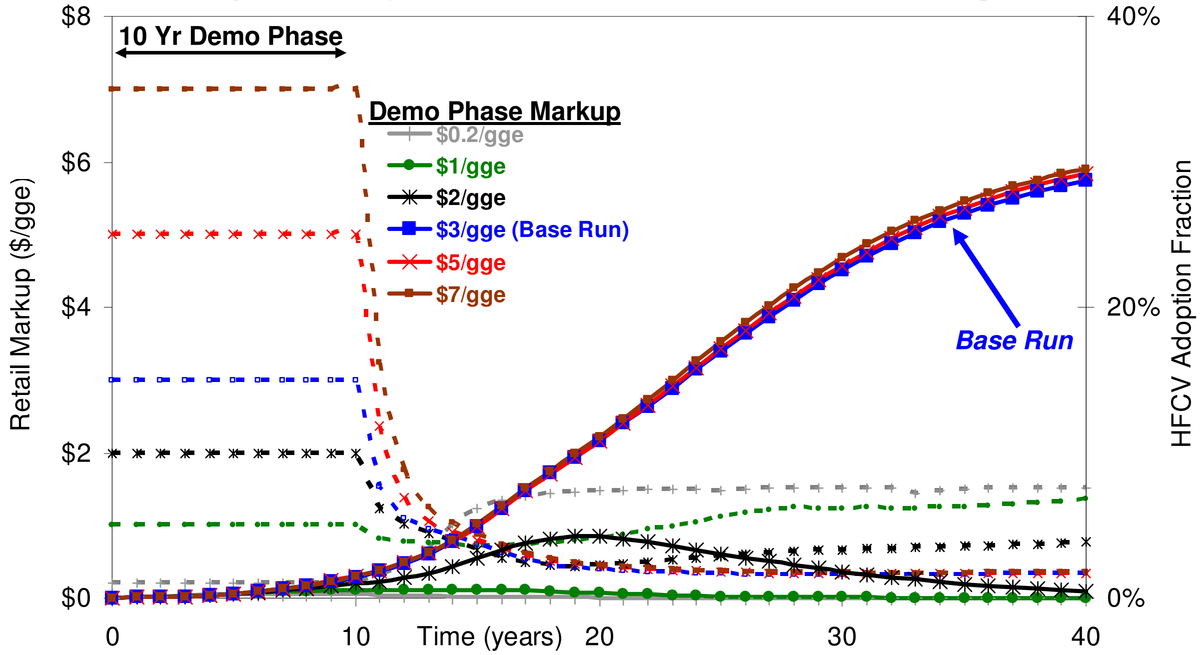
- alternative fuel vehicle purchase,
- alternative fuel use,
- alternative fuel vehicle production to the market,
- production and distribution of alternative fuel,
- more frequent vehicle replacement, and/or
- improved awareness and acceptance of the AFV as a viable option.

The most interesting findings from extensive scanning of individual policy tests are highlighted here. Other policy test results can be found in Appendix C: Additional Policy Tests.

Managing Retail Fuel Outlet Markup

The model draws most fuel station cost parameters from the Department of Energy's H2A forecourt station model (James, Lasher et al. 2006), which assumes a retail markup of \$5/kg hydrogen or \$5/gasoline gallon equivalent (gge) for stations to maximize profits. Yet this markup is an important policy choice for fuel providers.

Figure 20: Policy Test - 10 Year Demonstration Phase Retail Markup



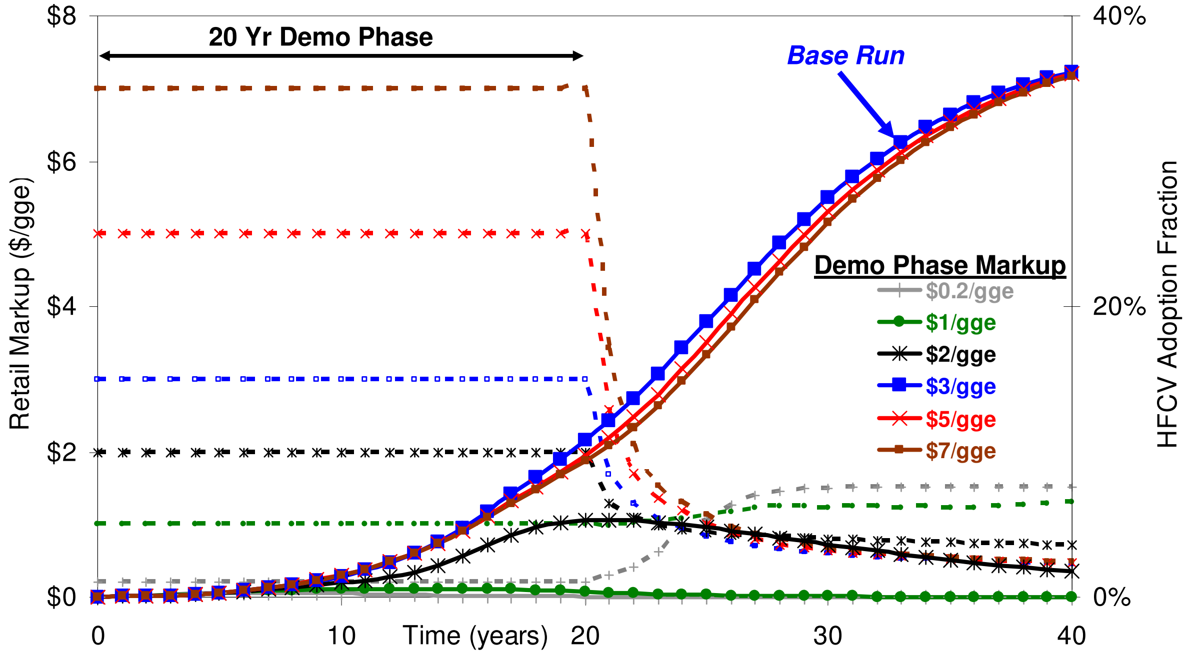
One policy, which could represent either industry coordination or govern minimum markup regulations, sets the retail markup at a fixed level for the first ten years during what might be called a "demonstration phase." After the demonstration phase, a transition to a deregulated commercial phase brings local markups to levels set based on competitive pressures.

In the test depicted in Figure 20 retail markups are plotted by the dashed lines and the starting level ranges from 20¢ to $7 per gge. If the mark-up starts too low, such as at current gasoline retailing levels, the system crashes; not enough stations enter to sustain AFV fleet growth. As this initial markup increases to $1-2, take off occurs faster and faster. However the market does not pass the self-sustaining tipping point until the initial markup goes above $3/gge (the base run setting). Because fueling infrastructure is such a dominant bottleneck, the markup for this short demonstration phase should be quite high to induce station entrance.

Yet when the duration of the demonstration phase is lengthened to twenty years (Figure 21), the potential downside to increasing the markup level becomes clearer. In moving above $3/gge, penetration is suppressed because of reductions in new vehicle purchase and fuel demand due to the high cost of hydrogen fuel. Thus, there is a sweet spot markup that is best for long term growth. In the twenty-year example, the best results are achieved with a $3/gge retail markup.

The implication of this policy test is certainly not a quantitative markup prescription of $3/kg over a twenty-year demonstration period. Rather, the key point is that retailing must be well managed by early entrants. Fuel retailing is a very competitive and low-margin business. If the hydrogen market becomes too competitive too early, sustained market growth will be impeded. The emergence of intellectual property rights for fuel production and dispensing technology is not modeled here, but it, along with permitting and construction delays, may constrain competitor entry enough to provide some early price-setting power by retailers. The qualitative insight is that there is leverage in ensuring high station profits early in the transition.

Figure 21: Policy Test - 20 Year Demonstration Phase Retail Markup



An ideal policy would be dynamic and adaptive, gradually ramping down the retail markup as the government observes large infrastructure development and growing profitability. For more testing of markup regime paths, see Appendix C: Additional Policy Tests.

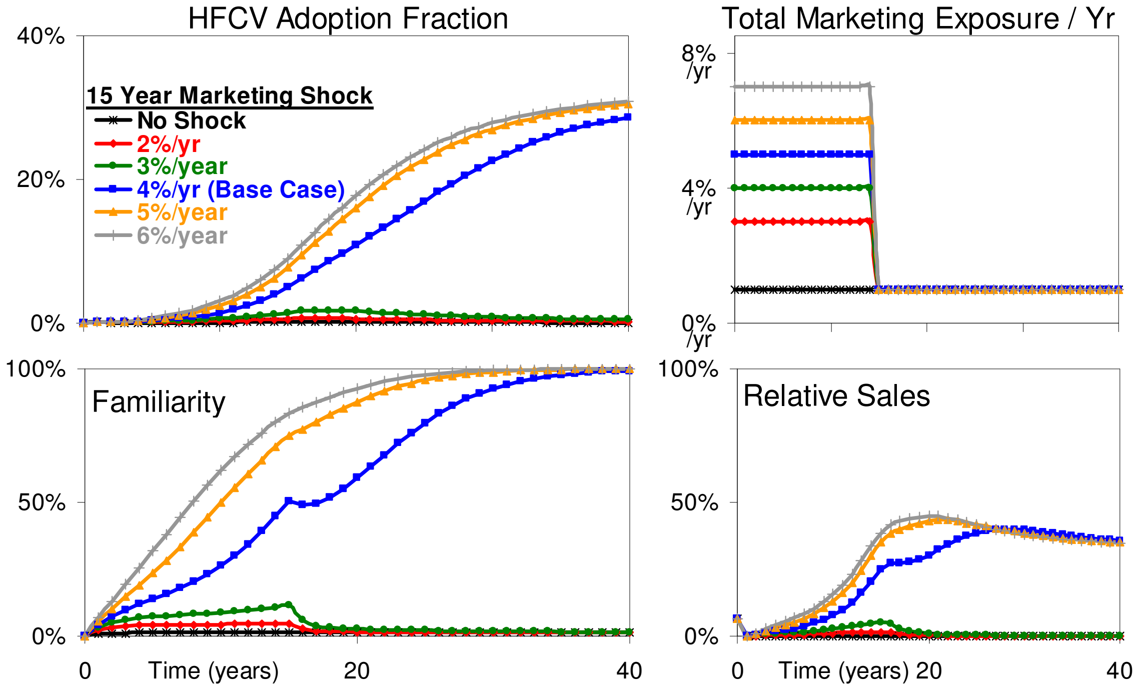
Marketing and Public Education

Policy can be and often is used to create awareness and acceptance of new technologies, behaviors, or business strategies. The structural sensitivity analysis demonstrated that reaching a threshold of self-sustaining consumer familiarity may be a more significant barrier than is commonly understood by policymakers. As discussed earlier, a driver's willingness to consider HFCV as a serious option is primarily increased through growth in the installed base of hydrogen vehicles on the road, but marketing is also an important early driver or trigger.

By explicitly representing these social exposure dynamics in the model, one can also more formally test marketing and public education policies. Such "soft policies" are only briefly mentioned in most policy analysis because their cost effectiveness is to hard quantify on a case by case basis. While the representation of familiarity development is subject to uncertain parameters, the model provides a framework for testing the impact of proximate indicators achieved by marketing policies. For example, the base run includes a fifteen year marketing shock of 4%/year effectiveness on top of the vehicle manufacturer's normal marketing efforts (with assumed 1%/year effectiveness). The direct effect of this shock is an additional 4% of the non-adopter population considering HFCVs when car shopping each year. The shock's larger effect is indirect and nonlinear, seeding word of mouth between non-drivers about hydrogen.

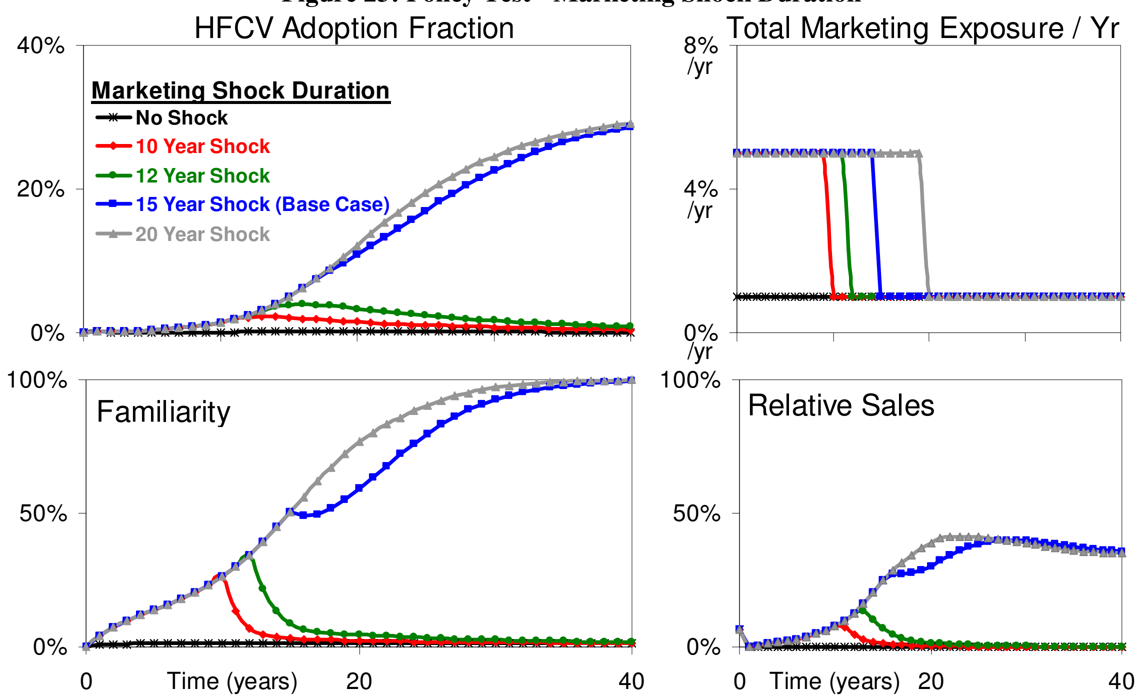
The effectiveness of the fifteen year marketing shock is varied from 0-6% per year in Figure 22. Shocks of these strengths are ambitious and very expensive but within the realm of possibility. Total marketing exposure is dominated by the shocks as normal marketing exposure is only 1%/year. Notably, a 1% increase in the effectiveness reduces the time to 15% fleet penetration by almost 10 years. Broad marketing and education are thus valuable policies.

Figure 22: Policy Test - Marketing Shock Effectiveness



In addition, such marketing policies must be of long enough duration to grow the HFCV fleet beyond the threshold at which it is large enough to sustain familiarity. Even at an effectiveness of 4%/year, ten and twelve year policies fail to push the system over the tipping point (Figure 23). *The takeaway is that familiarity is quickly lost if campaigns are ended after early success.*

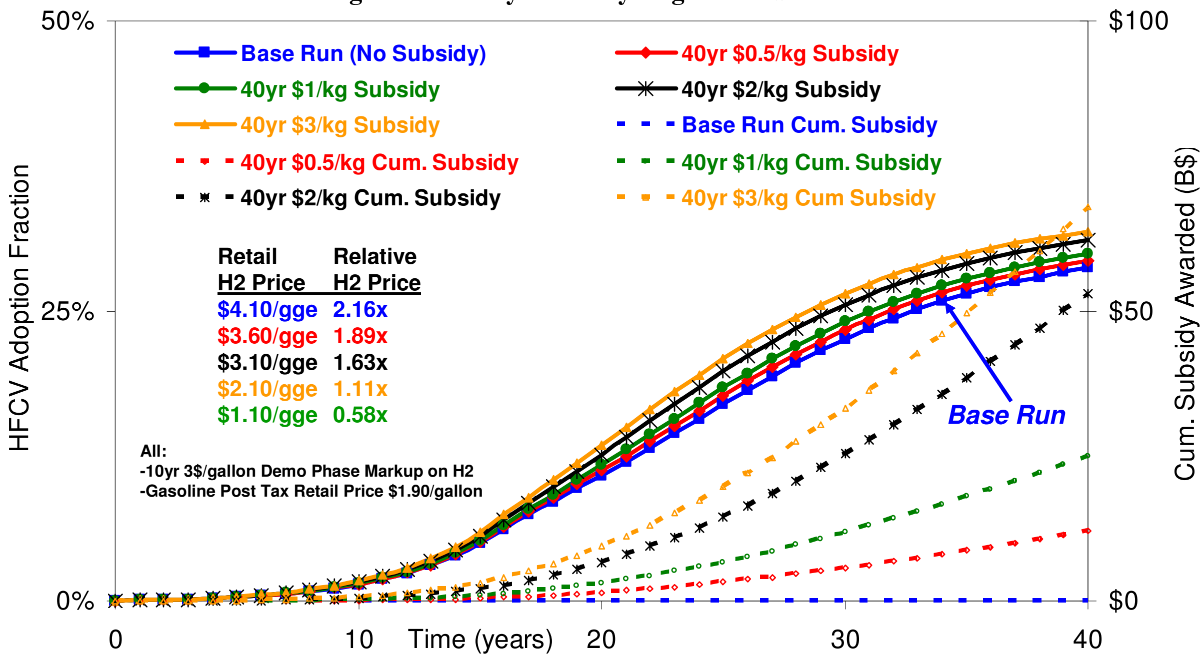
Figure 23: Policy Test - Marketing Shock Duration



Hydrogen Fuel Subsidies and Gasoline Taxes

Moving on to the more commonly suggested Pigouvian policy instruments intended to internalize externality costs (Pigou 1952) and align private economic incentives with the social interest, the comparison of fuel subsidies and gasoline taxes is a useful starting point. For one thing, these are probably the two most popular policies suggested to support alternative fuels. Habit rules and fuel subsidies (tax exemptions or tax credits) have been used to support ethanol as a fuel additive and substitute in the United States since the Energy Tax Act of 1978.

Figure 24: Policy Test - Hydrogen Fuel Subsidies

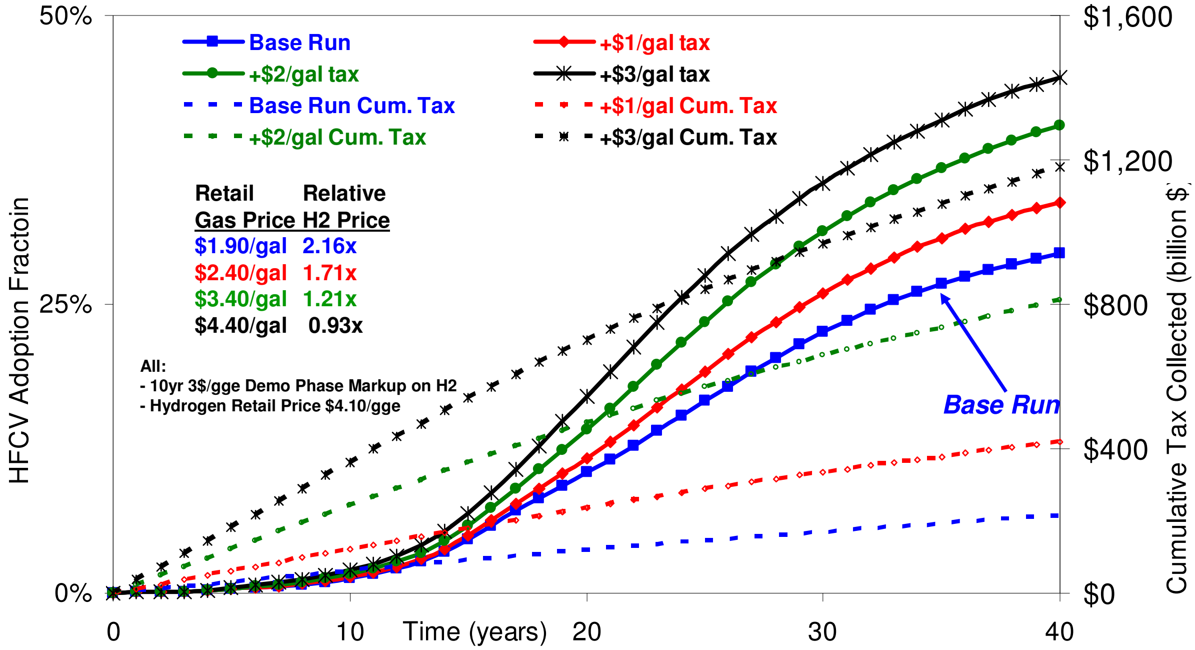


In the hydrogen scenarios depicted in Figure 24, fuel subsidies amounting to billions of dollars over the forty year time period do not appear to have a significant impact on top of the policies already included in the base case. An understanding as to why is developed by comparing hydrogen fuel subsidies with increased gasoline taxes depicted in Figure 25.

The results are consistent with intuition. In moving from the base case to scenarios improving the relative price of hydrogen to similar ratios, the gasoline tax has more leverage. The reason for this lies in the widely variant fuel efficiencies assumed for the two competing vehicle technologies. Recall that the average hydrogen fuel vehicle is assumed to be 2.5 times more fuel efficient than the average ICE vehicle. The HFCV's high fuel efficiency effectively dilutes the fuel subsidy whereas the added gasoline tax severely increases the cost of travel.

In short, it is the fuel cost per vehicle mile, not per unit of energy delivered at the pump, that determines the relative utility of driving an AFV in the model. Giving a fuel subsidy to a more fuel efficient entrant is a weaker incentive than imposing a tax on the fuel for the less efficient vehicle to establish the same relative price differential. This rationale may be fairly obvious but reinforces the idea the policy must be cognizant of what drives system behavior. It also raises an interesting behavioral question of consumer psychology.

Figure 25: Policy Test - Gasoline Taxes



Will drivers indeed make fuel price comparisons on the rational basis of cost per vehicle mile rather than the cost per gallon? This question is up for debate and may be very important for AFV platforms like hydrogen fuel cell vehicles that are lauded more for their radically increased fuel efficiency than for their ability to make use of rapidly renewable primary energy sources.

Because fuel economy will always vary by vehicle type and size, fuel retailers will not be able to advertise alternative fuel prices on a per vehicle mile basis for the typical value. Rather the cues accessible to consumer choice will be the price per unit weight, volume, or energy content. The implication is that it may then be a shrewd marketing strategy to sell hydrogen on a per weight basis in order to avoid the perceived cost per gallon equivalent comparison with gasoline.

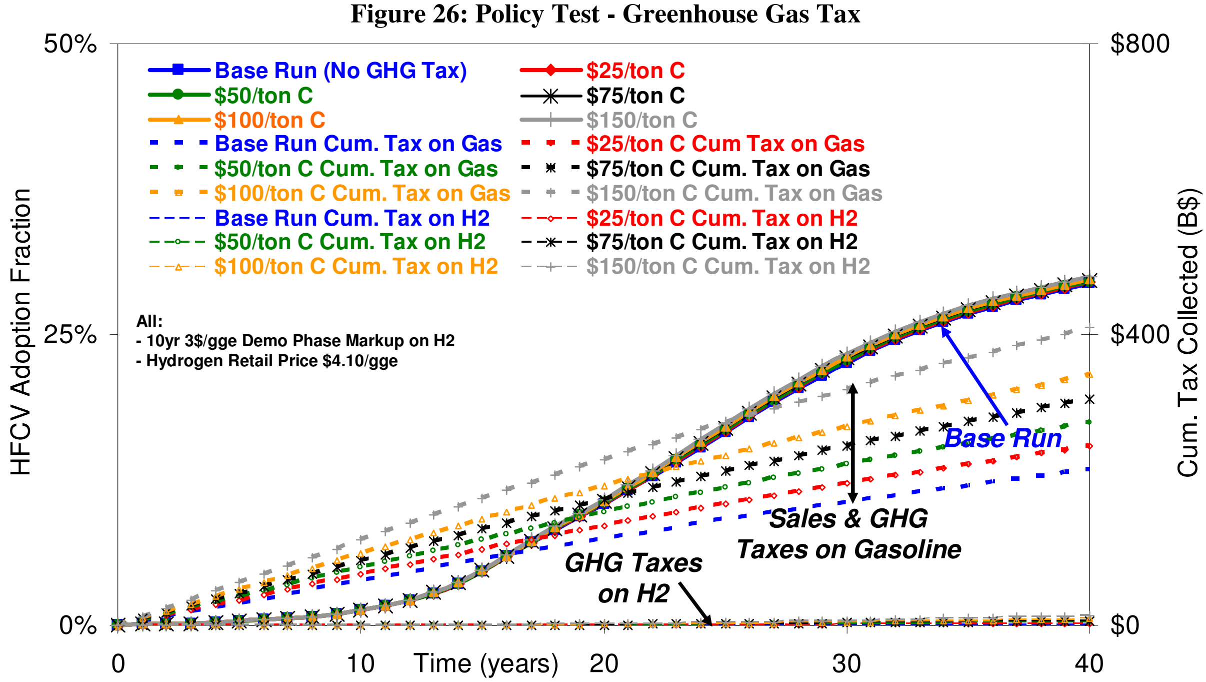
Regarding the attractiveness of using gasoline taxes to speed diffusion, political challenges are just as important a consideration as their relatively strong effectiveness in accelerating diffusion. Despite the power of market prices to signal reductions in fuel consumption as evidenced by demand response following the oil price shocks of the 1970s, more significant gasoline taxes comparable to those in other developed countries has been unpopular and overwhelmingly cast as “politically infeasible” in the United States.

Arguments of economic cost and regressivity of this type of tax stem largely from the observed small *short-term price inelasticity of demand* for motor fuels. On the order of days and months, the imposition of such taxes is likely to have very little effect on demand, and therefore is perceived as quite a burden on the economy. From a dynamic viewpoint, this apparent inelasticity may partially conflate actual price elasticity of fuel demand with the long physical time delays within the system to adjust to one’s new desired level of demand. There are long delays in replacing one’s vehicle with a more efficient model, finding new transport modes, changing travel patterns, or moving to more location efficient communities. In any case, any added fuel tax would require strong complementary fiscal policies to be politically feasible.

GHG Taxes (or Tradable Allowance Premiums)
The effects of policies to reduce greenhouse gas emissions by taxing them or by imposing a cap under which emission allowances can be traded are tested in the same way in this model. The model draws wells-to-wheels (WTW) emission factors for various fuel pathways from the GREET model (Wang 2007) to calculate the total effect of such taxes or allowance premiums on fuel price along the fuel production and distribution chain. As endogenous dynamic determination of the allowance prices resulting from a cap-and-trade system is well beyond the scope of this model, an exogenous allowance price based on estimates from the climate-economics literature is simply treated as a tax in the model.

In Figure 26, the greenhouse gas tax is varied from zero to the current voluntary trading market price ($25/ton carbon-equivalent) to higher levels across the range suggested by economists to be necessary to stabilize greenhouse gas concentrations at twice pre-industrial levels.

Figure 26: Policy Test - Greenhouse Gas Tax

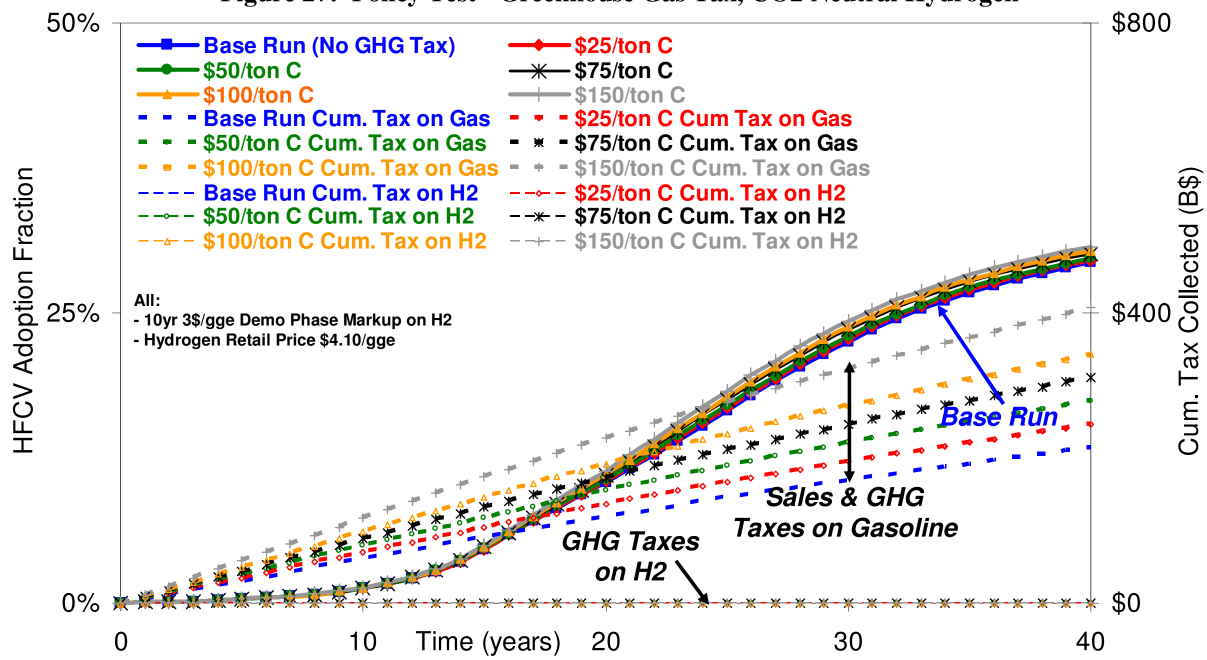


Greenhouse gas taxes have even less numeric sensitivity than hydrogen fuel subsidies under base run assumptions. The most important reason for this is that the well-to-wheel greenhouse gas emission factor for hydrogen reformed from natural gas is actually higher per gasoline gallon equivalent delivered at the fuel pump than the emission factor for gasoline. Of course, because of the fuel cell vehicle's higher fuel economy, the well-to-wheel emission factor per mile is lower for hydrogen, but not enough for the greenhouse gas tax to significantly speed penetration. One should note that the emission factors, drawn from 2010 from the GREET model, are used as static inputs for the purposes of this analysis, yet the dynamic modeling of endogenous learning in fuel production technology and the feedstock markets would add value for future analysis.

What if the hydrogen could be produced without greenhouse gas emissions, such as through carbon capture and sequestration or via electrolysis powered by renewable energy? Under an incredibly optimistic assumption that the hydrogen is carbon neutral along its entire production chain yet can be produced *at the same cost* that we've assumed thus far, the impact of a greenhouse gas tax on diffusion is presented in Figure 27.

Somewhat surprisingly, the policy impacts remain weak, though there is certainly a stronger effect than that observed in Figure 26. To explain the relatively small impact, it is useful to put the carbon tax policy in context. The carbon prices tested, from $25-150 per metric ton of carbon emitted (or ~$7-41 per metric ton of carbon dioxide equivalent), cover a range of estimates suggested to be necessary for stabilization of atmospheric greenhouse gas concentrations at a level that would prevent dangerous interference with the climate system (Sekar, Parsons et al. 2005). Yet such a carbon price only translates to an additional tax of 8-50 cents per gallon of gasoline, even when including the full well-to-wheel emissions for each gallon of fuel delivered to the vehicle. Thus, carbon taxes would have to be very high to play a significant role in speeding hydrogen fuel cell vehicle diffusion.

Figure 27: Policy Test - Greenhouse Gas Tax, CO2 Neutral Hydrogen

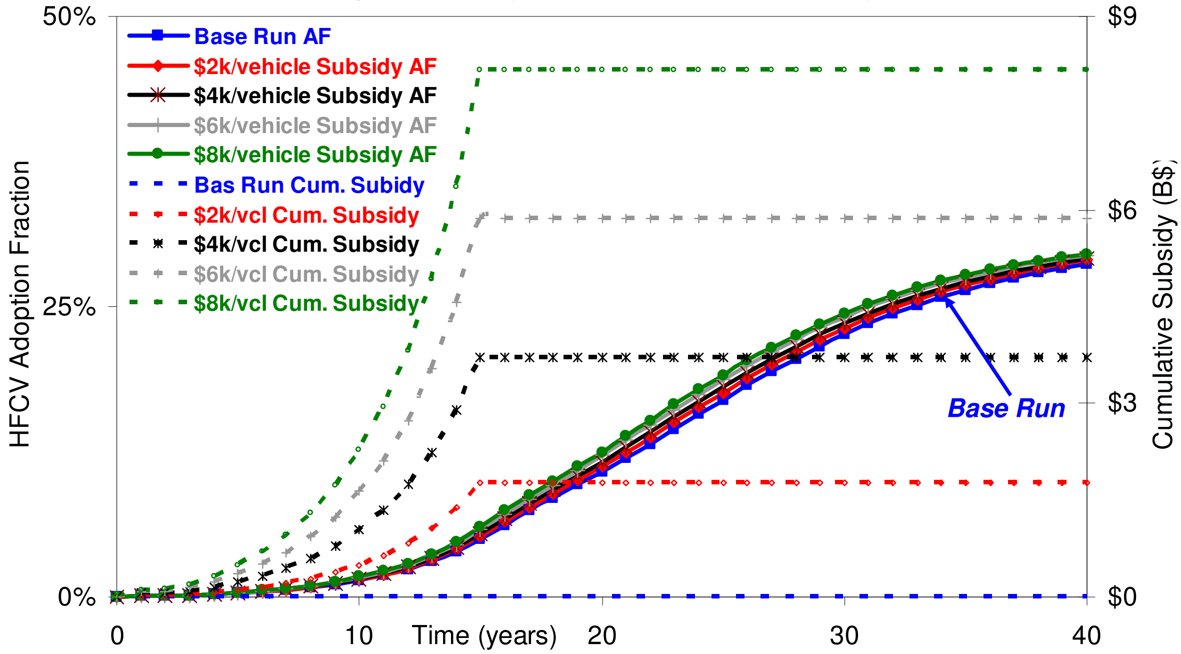


Vehicle Subsidies

Another popular policy instrument requested to bolster AFV sales are vehicle purchase tax credits or rebates. In Figure 28, one-time subsidies between zero and eight-thousand dollars are tested over a fifteen year period. Total cumulative subsidies are even greater than those over the first fifteen years in the fuel subsidies test, yet the policy's impact is quite small.

At least early in the transition, vehicle subsidies do not appear to have much leverage. As a useful point of reference, hybrid electric vehicles are currently eligible for a federal income tax credit of up to $3,400 depending on the manufacturer's cumulative sales volume. Yet even a subsidy at double that value, which more than makes up for the assumed incremental price of hydrogen vehicles, does not have a strong impact on the pattern and speed of vehicle diffusion.

Figure 28: Policy Test - 15 Year Vehicle Subsidy



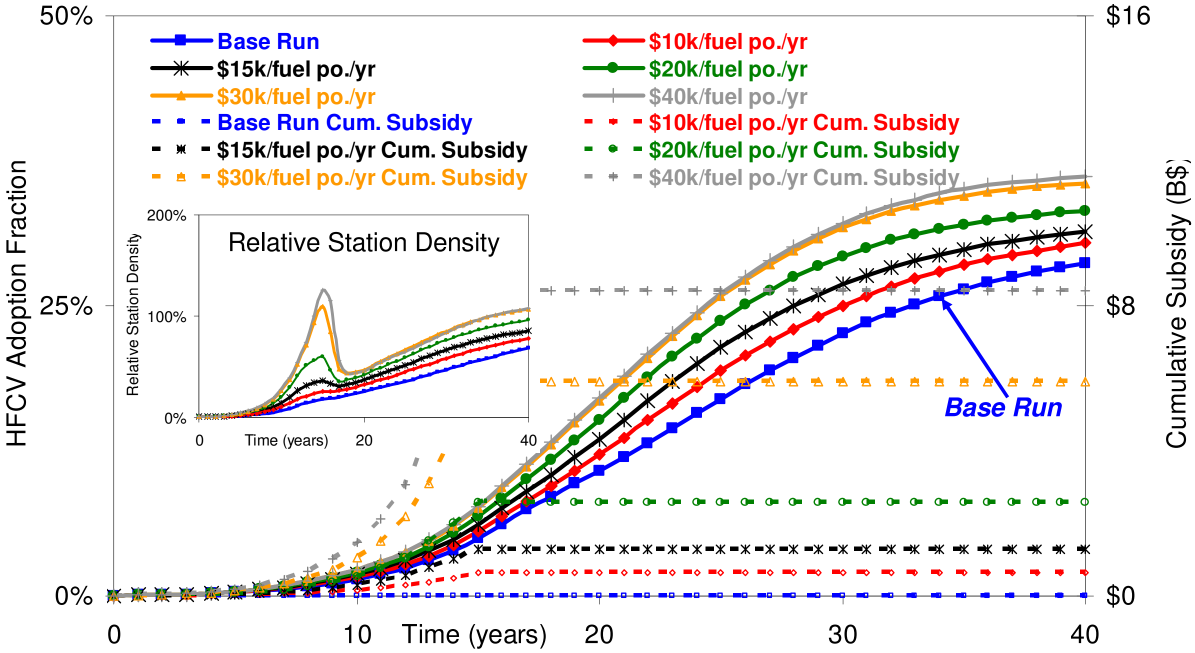
The small qualitative effect of this policy is initially surprising to most audiences. The explanation lies in the highly non-linear relationship of one's utility to drive the HFVC with increases in fuel station coverage. Without co-aligned incentives to directly support hydrogen infrastructure, subsidies for vehicles are ineffective. The problem with vehicle subsidies alone is that they directly bolster vehicle adoption but only indirectly provide incentives for alternative fuel use. Because utility to drive in the model remains unchanged, the vehicle purchase subsidies do help to bolster the depressed number of trips made with HFCV. *Simply put, subsidizing vehicle purchase does not ensure vehicle use.*

As a side note, this insight is particularly telling for the case of bi-fuel (or flex-fuel) vehicles. For example, while the Corporate Average Fuel Economy (CAFE) standard dual-fuel credit is intended as a fuel substitution incentive, very few flex fuel vehicles actually use high concentration ethanol fuel blends at all. The effective E85 use is certainly not enough to give credit for 50% gasoline displacement (Leiby and Rubin 2001). For this reason, the National Research Council recommended eliminating the dual fuel credits (NRC 2002).

Fuel Station Operating Subsidies

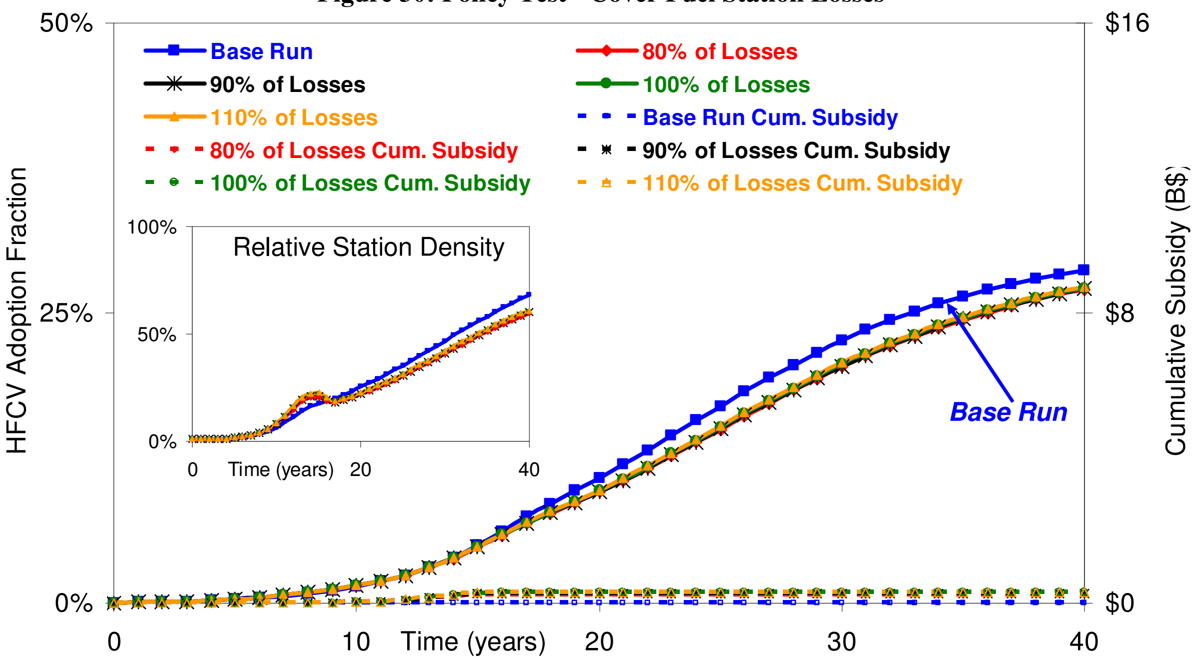
Compared to vehicle subsidies, operating subsidies to retail fueling outlets during the first fifteen years make more of a difference (Figure 29), reinforcing the importance of propelling infrastructure growth as quickly as possible in early stages of the transition. To reiterate the explanation, station subsidies have more leverage because the fueling station coverage is a bottleneck affecting so many strong feedbacks governing one's utility to drive hydrogen vehicles. Policy must support infrastructure growth before fuel purchases will provide enough revenue. These fuel station incentives are even more important when the new vehicle platform is highly fuel efficient and thus the total fuel demand is less than that for gasoline.

Figure 29: Policy Testing - Fuel Station Operating Subsidies



Another type of operating subsidy is to cover all station losses until a profitable fuel market develops. Such a mechanism would not be possible as public policy but would be a viable strategy for energy companies with other revenue streams. One might guess that this policy would have similar effectiveness to the previous test. Similarly, it would theoretically be more efficient in that profitable stations would not be "unnecessarily" subsidized beyond what they need to stay in business. However, this policy may distort the spatial distribution of stations and lead to perverse outcomes like that shown in Figure 30 where the policy actually slows adoption.

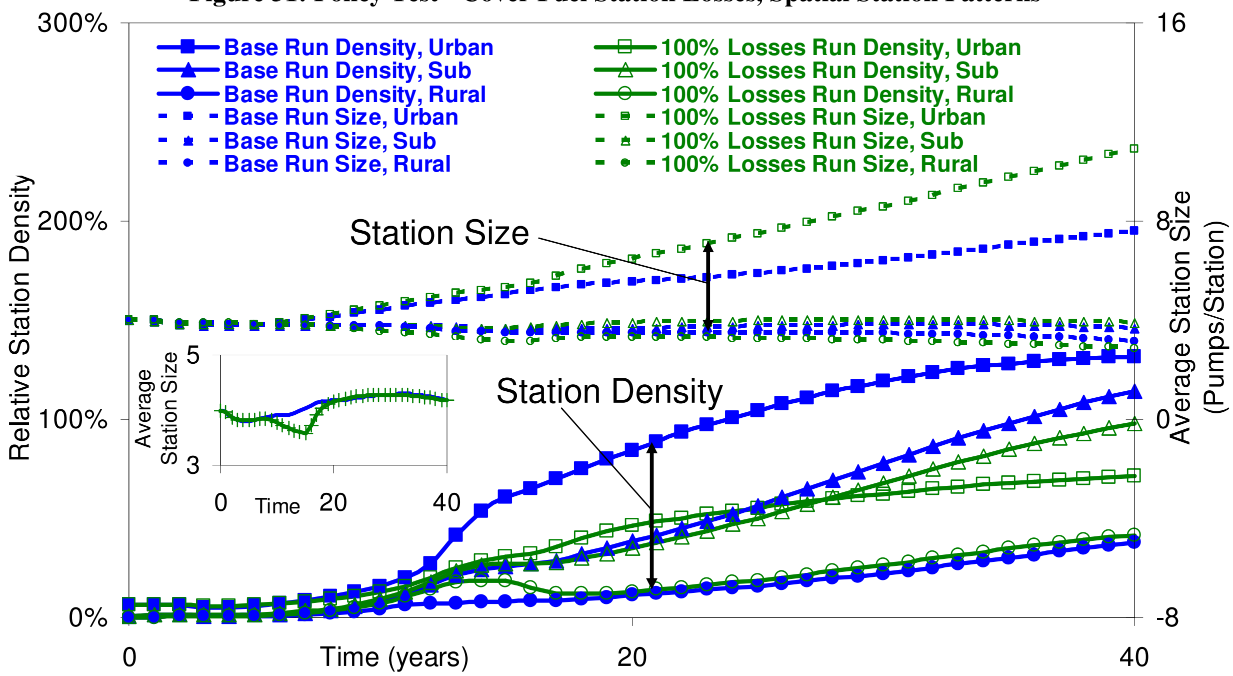
Figure 30: Policy Test - Cover Fuel Station Losses



The rationale for the policy's ultimate suppression of station density and vehicle adoption, in comparison to the base run, is that this subsidy mechanism shifts marginal investment from the most profitable patches to stations that would not otherwise be profitable. Plots of relative station density and size are spatially disaggregated in Figure 31 for the base run and the case above in which stations receive subsidies equal to one hundred percent of their losses.

As seen below, the effect of making station financial performance more uniform is increased rural station density, slightly lower suburban station density, and greatly reduced urban station density. By not subsidizing the already profitable urban market stations, the rate of early urban station entrance is less than optimal. The ultimate effect of the policy is busier pumps, longer waiting times, and eventually bigger stations in urban areas. To avoid such intended suppression effects, policy must be quite nuanced in overcoming the spatial non-uniformity challenge. Even though station subsidies are necessary for take-off, the use of markets and profit signals to guide infrastructure investments should not be thrown out with the bathwater.

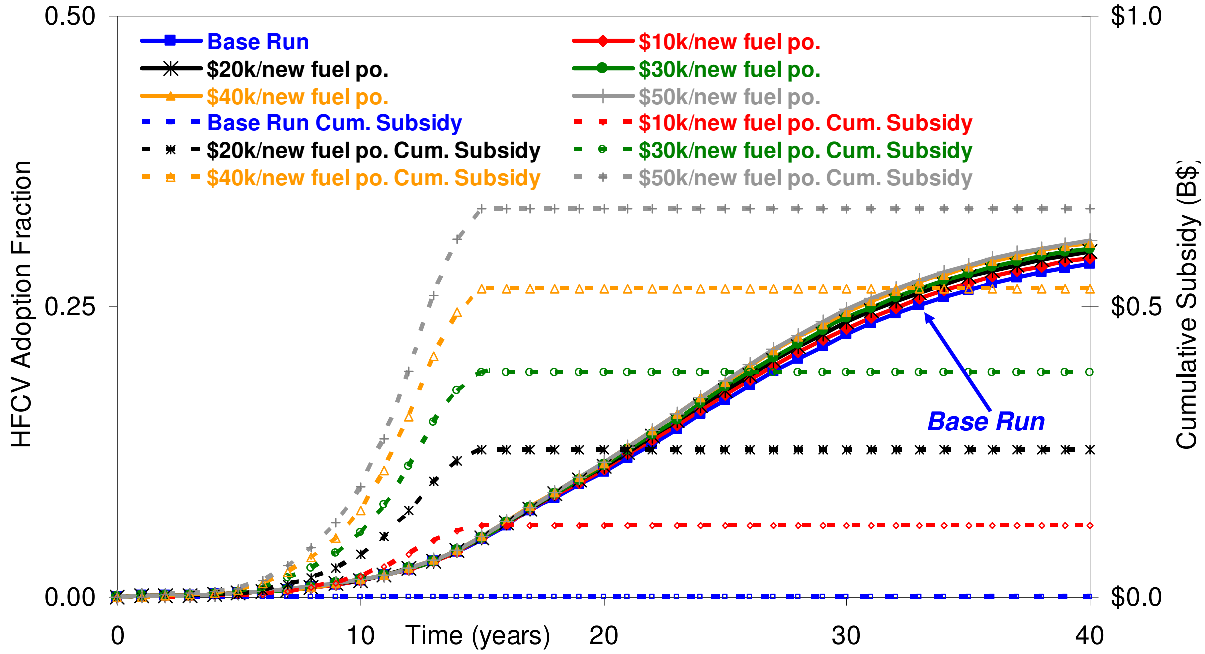
Figure 31: Policy Test - Cover Fuel Station Losses, Spatial Station Patterns



<u>Fuel Station Capital "Buy-Down" Grants</u>
Another incentive mechanism to grow station infrastructure is to use subsidies to buy down the high capital cost of hydrogen production, compression, and dispensing systems. Under the policy presented in Figure 32, new or recently expanded stations during the first fifteen years receive a grant upon completion of construction varying between \$25,000 and \$100,000 to defray the initial capital cost of about \$250,000 per fueling position. There are benefits to front loading the subsidy in this way, even on a net present value basis. Not only does the grant reduce capital depreciation charges for the fuel stations, it also uses the public dollars to leverage additional savings in reducing debt service costs to further decrease annualized fixed costs.

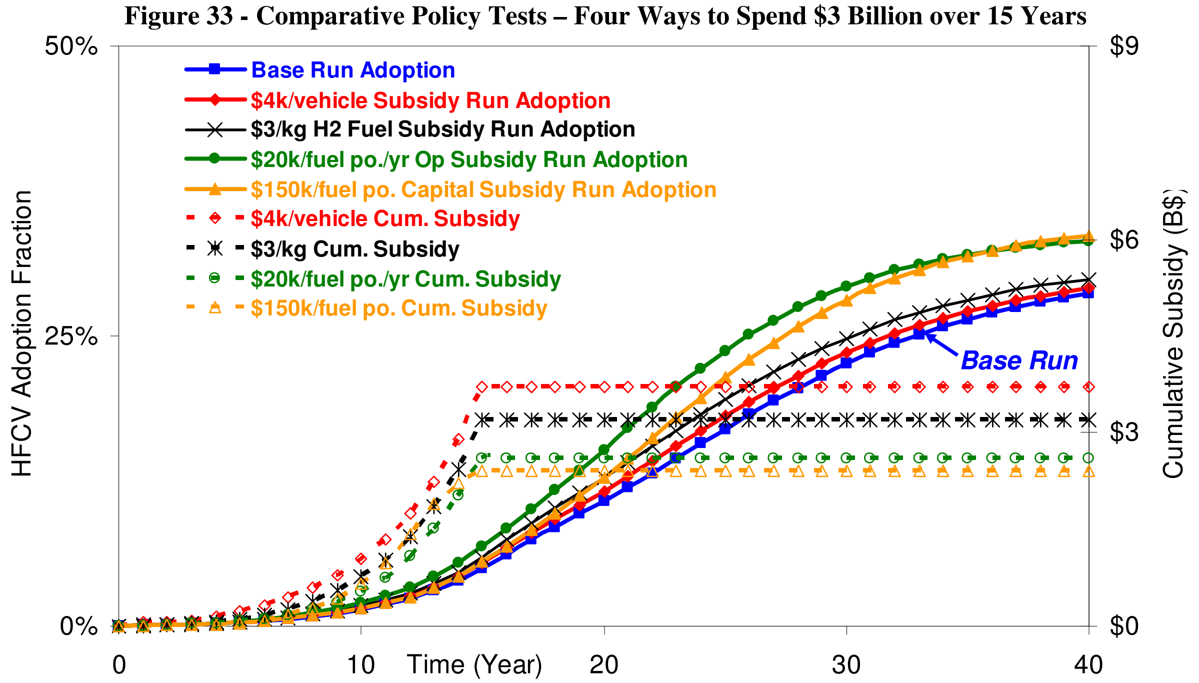
Additional types of station capital subsidies and cumulative net present value accounting for this type of policy is presented in Appendix C: Additional Policy Tests.

Figure 32: Policy Test - Fuel Station Capital Subsidies



As these later policy tests illustrate, it appears to be more effective to offer stations direct incentives than to subsidize vehicle buyers to compensate for lack of infrastructure. This comparison is made directly in Figure 33, with station operating subsidies having the greatest leverage under the base run conditions. Using the chosen policy parameters listed in the plot legend, these policies require similar levels of cumulative public investment over a fifteen year period (~$3 billion), yet they have quite different impacts in improving upon base run diffusion.

Figure 33 - Comparative Policy Tests – Four Ways to Spend $3 Billion over 15 Years



This order of effectiveness amongst individual policies is also observed when applied to a failure reference case in which a lower demonstration phase markup is set (see Appendix C). Early in the transition, it is most important to build familiarity with the marketing shock and to grow infrastructure with station incentives. Yet once sufficient station coverage is reasonable, the vehicle subsidies may gain slightly more leverage in overcoming attribute shortfalls such as a greater vehicle production cost and retail price to buyers.

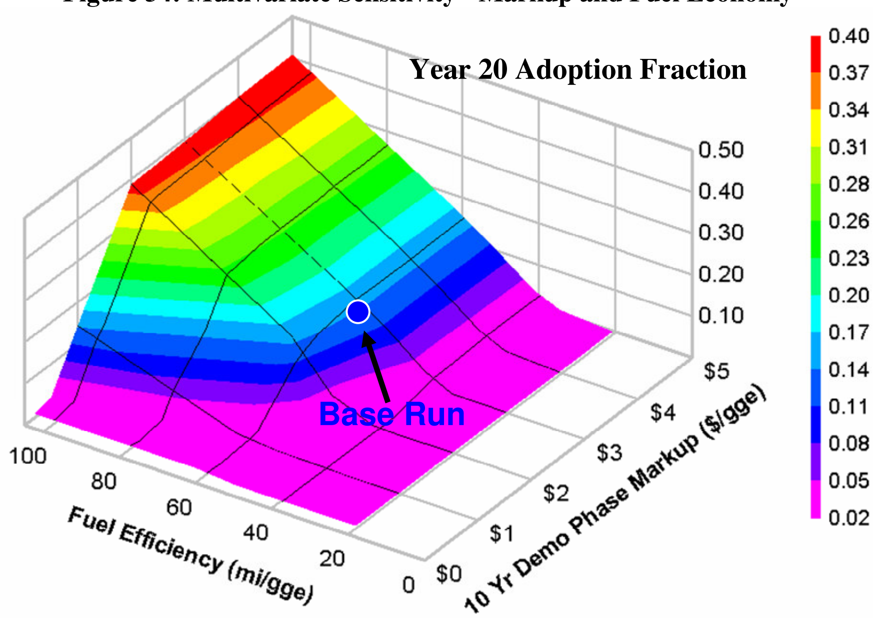
The key to designing effective portfolios of policies lies in designing them to adapt to which bottleneck is dominant at a particular moment in time. In other words, to the extent policy can be dynamic, it should respond to observed conditions by accelerating whichever reinforcing feedback is not keeping pace with the rest. In most cases, the lagging complementary asset is likely to be fueling infrastructure, particularly in rural areas.

Multivariate Policy and Parameter Sensitivity

Policy testing becomes more interesting and robust as sensitivity analysis across the space of technical, cost, and behavioral parameters is implemented at the same time. In the face of inherent uncertainties, policy analysis must seek to find policies that have robust leverage under a variety of scenarios.

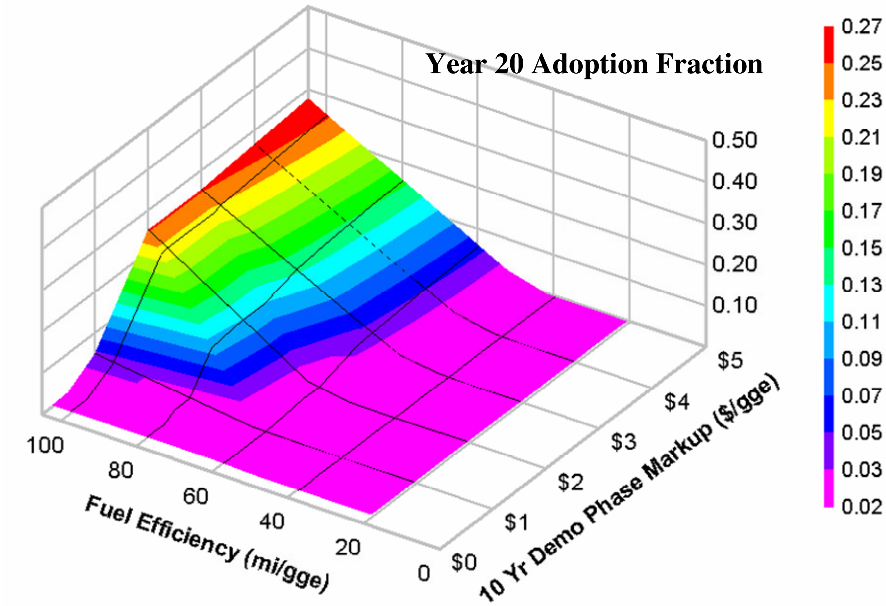
In Figure 34, the HFCV adoption fraction in year 20 is plotted for fifty model runs with varying demonstration phase markup policies and with varying average fuel efficiency assumptions for the fuel cell vehicle. As you would expect, high fuel economy cases generally achieve greater diffusion but only if markup is sufficient to build station coverage.

Figure 34: Multivariate Sensitivity - Markup and Fuel Economy



When the markup is low, market penetration remains low no matter what the fuel efficiency, further reinforcing the importance of retailer decision-making. In the univariate markup sensitivity plot back in Figure 21, it was observed that when markups are too high ($5-$7/gge) penetration occurs more slowly than at the sweet spot. Another insight from this plot is that high fuel efficiencies allow even the very high markup cases to succeed. In fact as average HFCV fuel efficiency is as high as 80 miles/gge, it is best to raise markups to more than $4/kg in order to sustain revenues as drivers need less fuel. The position of this slope across this parameter space depends greatly on other assumptions. As tank capacity is decreased, this slope shifts to the left as shown for the 6kg tank HFCV in Figure 35.

Figure 35: Multivariate Sensitivity – Markup and Fuel Economy (Tank Size = 6kg)



Multi-Policy Portfolio Exploration

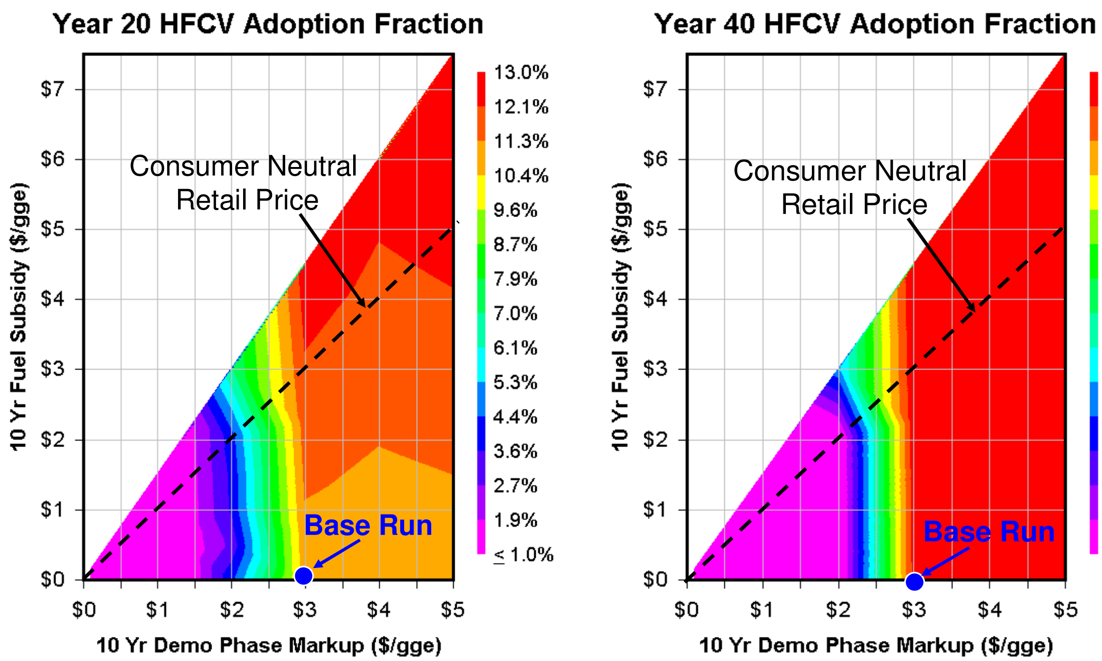
After sufficient individual policy testing, the next challenge is to explore coordinated multi-policy approaches to find high leverage portfolios of complementary strategies that harness synergies and balance cost amongst political stakeholders. The interplay of policies may result in impacts more powerful than the summation of individual policy impacts.

<u>Retail Markup and Fuel Subsidies</u>

As one example of such multivariate policy testing, Figure 36 plots the year 20 and year 40 adoption fraction as the demonstration phase retail markup and ten year fuel subsidy are varied.

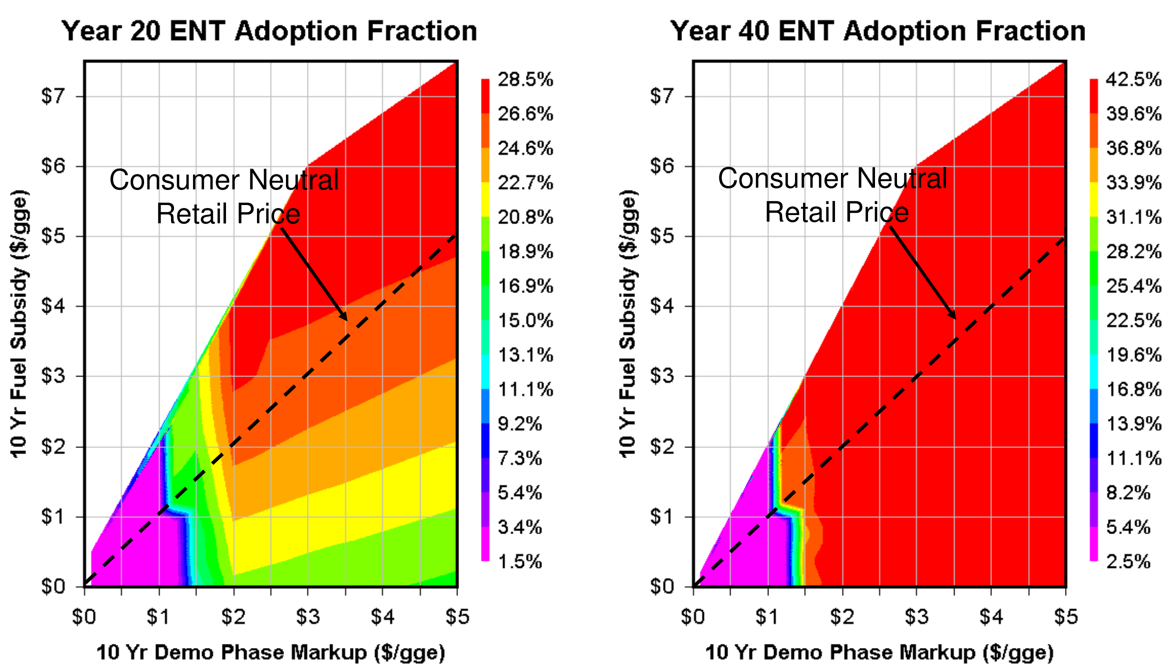
When the retail markup is less than $1.50/gge, subsidies make very little impact, suggesting that there is a station bottleneck problem. Again, a non-linear relationship in the equilibrium level of adoption with the demonstration markup level is clear. In addition, as the markup increases and stations are profitable, the fuel subsidy policy has more of an impact; a gradient exists in moving upward on the year 20 adoption plot at the higher markup levels. Thus, these two policies combine nicely to allow station profits while at the same time keeping hydrogen fuel costs per vehicle mile competitive with gasoline for consumers.

Figure 36: Multivariate Policy Testing – 10 Year Markup and Fuel Subsidy - HFCV/H2FSMR



It is worth re-emphasizing that the landscape is quite dependent on technical and behavioral parameter assumptions. The pattern changes significantly in Figure 37 where the same test is performed for the hypothetical ICE-equivalent entrant vehicle technology ENT.

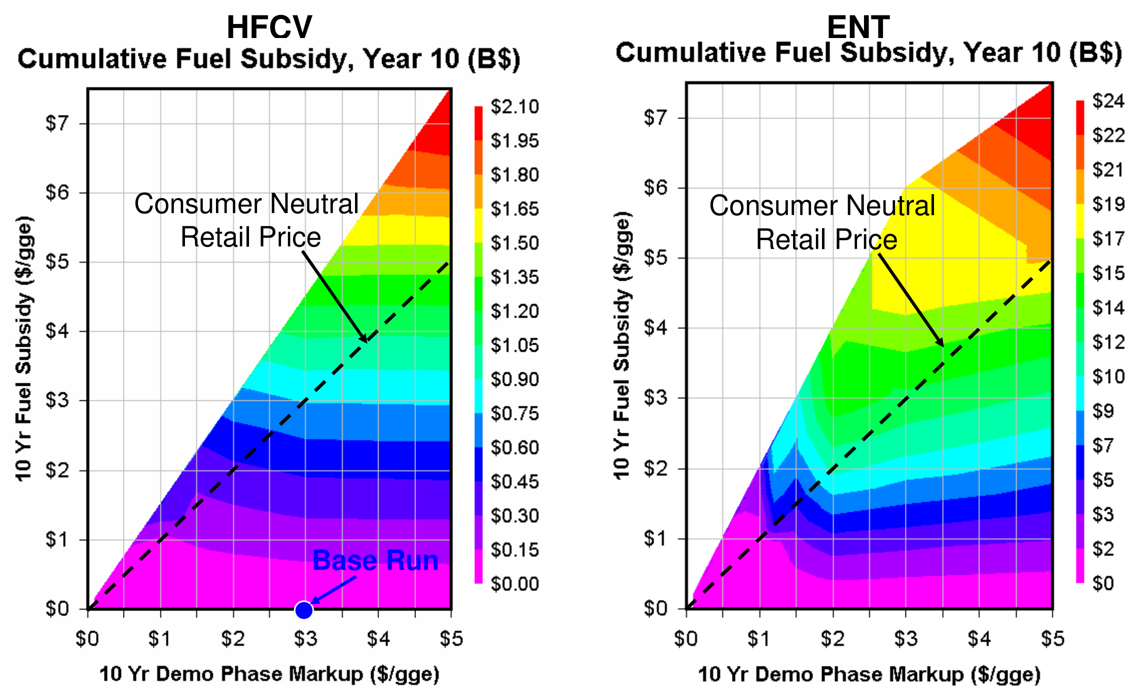
Figure 37: Multivariate Policy Testing - Markup and Fuel Subsidy – ENT/OTH



For the ENT vehicle with a range and fuel economy equal to ICE, subsidies begin to make a difference at a much smaller markup and almost always help. The non-linear relationship between adoption and markup is also not as steep as that observed for hydrogen. In addition, the plateau of more successful cases along the consumer neutral line is much broader across the space of retail fuel markups for this technology.

Another difference from the hydrogen case resulting from the lower fuel economy is that when there is no fuel subsidy and high retail markups, the year 20 ENT penetration is much lower compared to its market potential. This attribute also results in the distribution of the best ENT penetration cases falling above the consumer neutral price line. The take-away from this comparison is that multi-policy approaches to support an alternative fuel may differ by context, such as the key attributes of the entrant vehicle technology.

Figure 38: Multivariate Policy Testing – HFCV and ENT, Cumulative Subsidy



The cumulative subsidy plots indicate a wide variance in cost effectiveness of the fuel subsidies. This variance should be enough to make every policymaker to exercise caution in approving a fuel subsidy. It is clearly easy to make substantial public investments with the intention of overcoming transition barriers without knowing that subsidies are ineffective and/or superfluous. In some cases, such subsidies are unhelpful and essentially a simply a wealth transfer to AFV users. Significant caution on the part of policy designers must be taken to ensure policies target and adapt to the dominant transition barriers at a particular moment in time, rather than simply throwing money at the problem.

Policy Testing with Integrated Learning Feedbacks

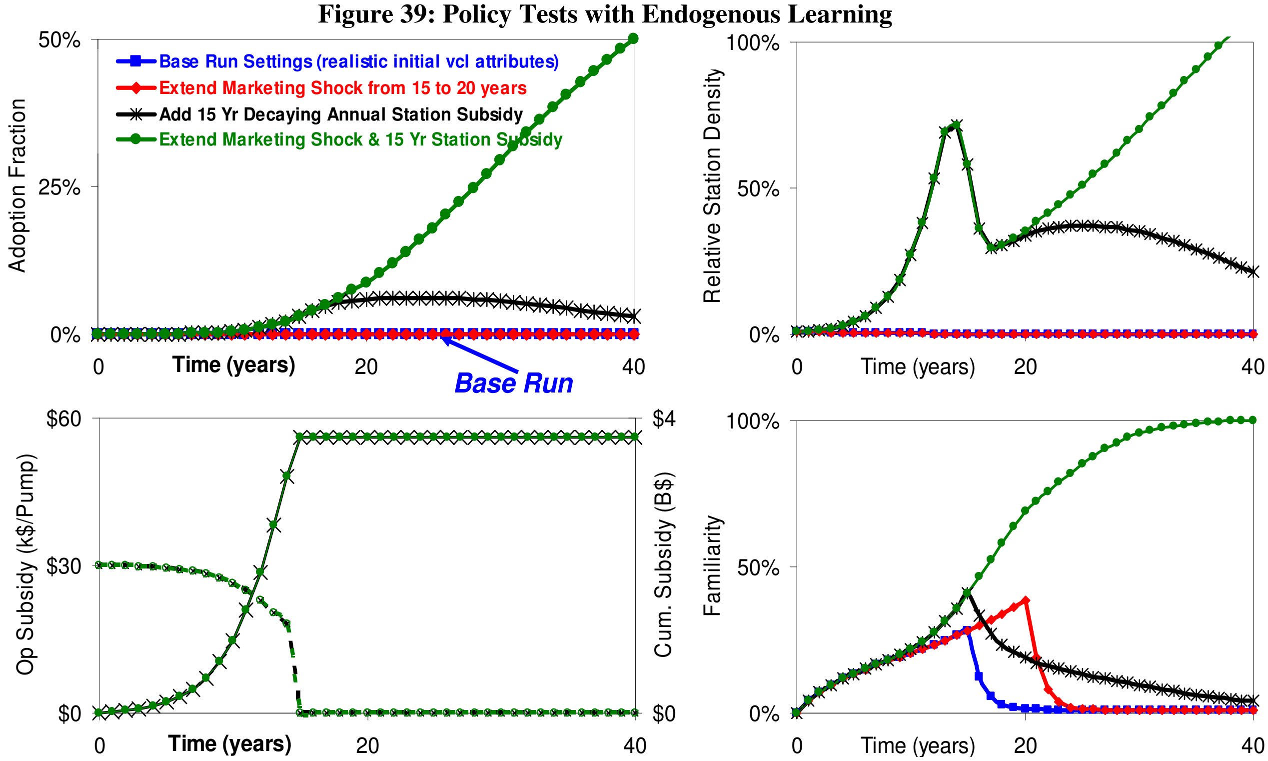
Unfortunately, when the endogenous learning feedbacks are switched on and more realistic initial parameter values are selected for the hydrogen fuel cell vehicle (Table 2), the transition challenge appears even more daunting and tipping dynamics become more pronounced.

While learning feedbacks, once strong, help the hydrogen fuel cell vehicle to reach a higher ultimate adoption fraction, the development of original equipment manufacturer (OEM) knowledge represents another threshold or metaphorical hill that must be climbed to achieve self-sustaining markets. Learning curve and scale economy effects only become strong once familiarity, infrastructure and adoption surpass limited levels.

In Figure 39, the base run settings remain the same except that initial parameter values are less optimistic but learning feedbacks are in effect. In this case, even with the ten year $3/gge fixed markup and the fifteen year marketing shock, there is no takeoff.

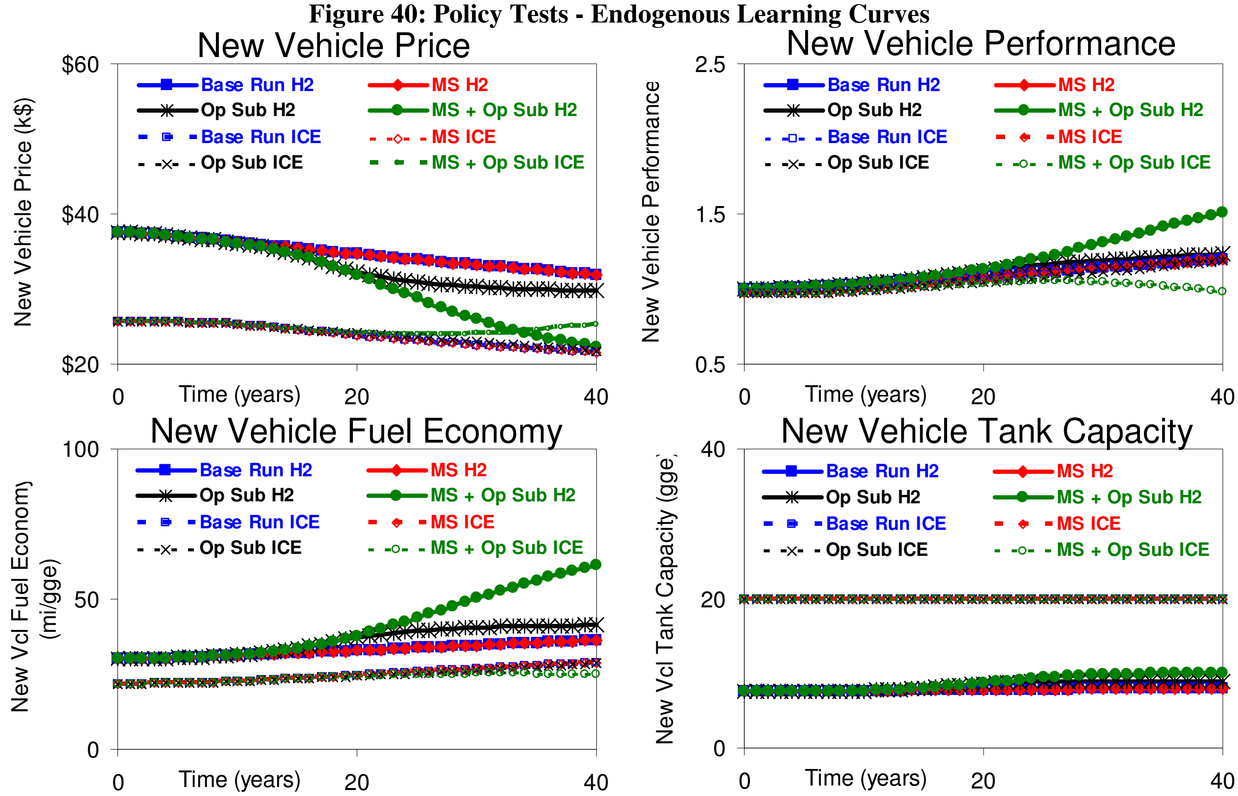
Multiple policies were tested to further bolster early growth from the base run failure case. Consistent with earlier results, vehicle adoption subsidies alone had no strong effect. Two additional policies changes were necessary to achieve successful take-off. First the marketing shock was extended by five years to twenty total years in duration. Second, all hydrogen fuel stations are given an annual operating subsidy per fueling position that begins at $30,000 and decays over the fifteen year subsidy period as the cumulative subsidy approaches eight billion dollars. Notably, applying either of these policy changes alone is insufficient to surpass the requisite thresholds. Yet application of both policy changes results in markedly successful diffusion compared to the other cases plotted below.

Figure 39: Policy Tests with Endogenous Learning



As expected, once the market surpasses the tipping points, further diffusion occurs more and more quickly due to endogenous learning effects. In fact the adoption fraction is still continuing to climb rapidly at year 40. The improvement curves for the respective HFCV and ICE vehicle parameters for these four policy test runs are plotted in Figure 40.

Figure 40: Policy Tests - Endogenous Learning Curves

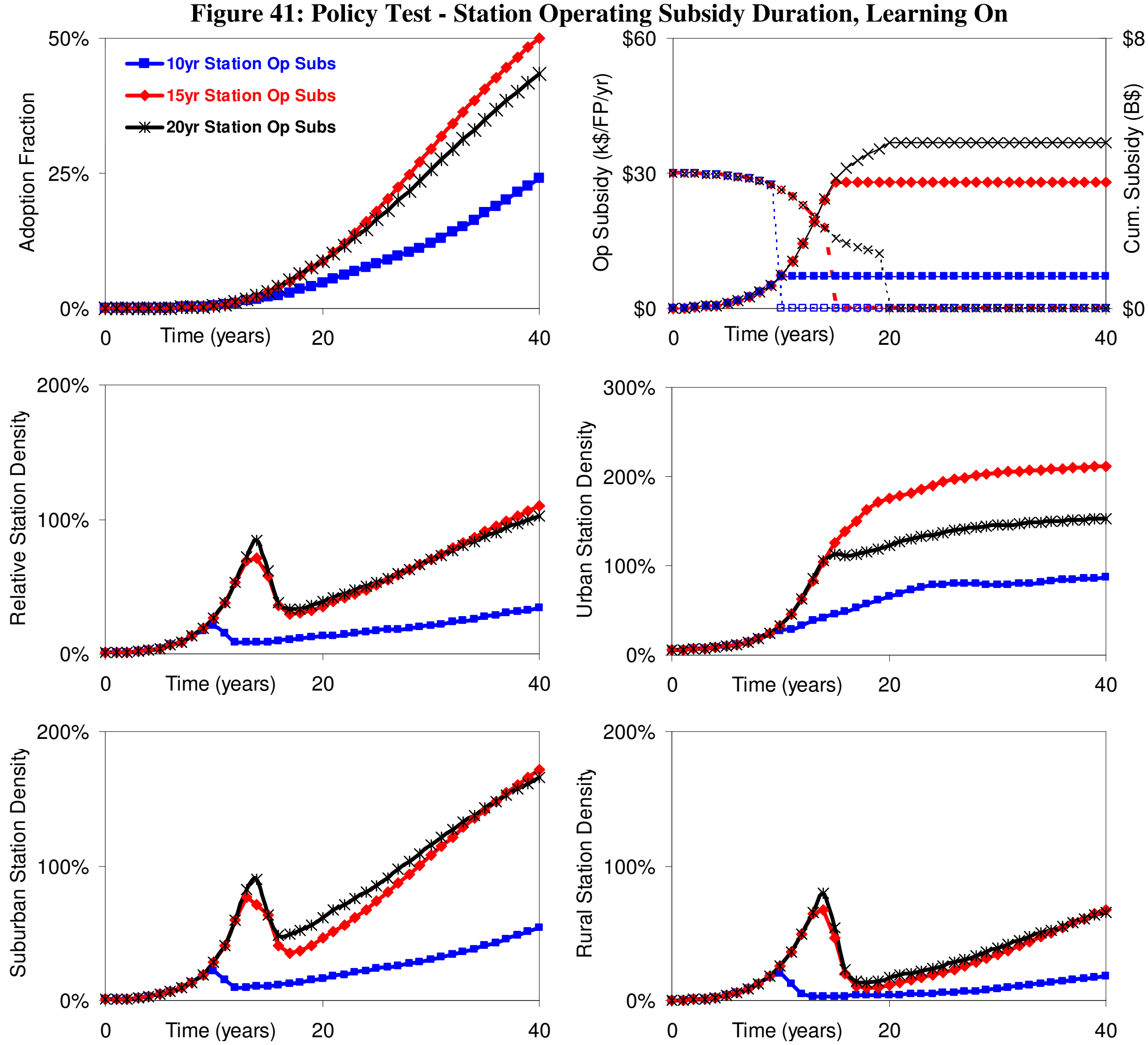


One reason the transition challenge becomes harder with endogenous learning feedbacks is because the ICE incumbent vehicle improves too. As observed in Figure 40, ICE's performance and fuel economy continue to climb while vehicle production costs fall. Of course, because cumulative fuel cell vehicle production is growing at a greater exponential rate from a small base, its rate of learning and attribute improvement is greater. Hence, as long as the market is sustained by policy for long enough duration, the learning feedbacks will eventually become stronger and improve the ultimate level of adoption of the hydrogen vehicle.

Although the station operating subsidy is the most effective policy found to complement the demonstration phase markup and marketing shock to achieve successful take-off, further policy testing again demonstrates the need for great care in applying this type of instrument. As illustrated in Figure 41, diffusion is actually limited by increasing the duration of the annual subsidy per fueling position from fifteen to twenty years. There is a strong sweet spot in policy duration. The system requires more than ten years to properly accelerate station development, yet if the subsidy is left in place too long, it distorts the spatial distribution of fueling stations from the optimum that emerges under competition without such supports.

As one would expect the longer subsidy policy results in more total stations. However, it also results in significantly less urban stations and slightly more rural and suburban stations. This difference in geographic distribution reduces utility to drive and ultimately HFCV adoption. This example mirrors the negative impacts seen earlier when testing the strategy of subsidizing station losses over the first fifteen years.

Figure 41: Policy Test - Station Operating Subsidy Duration, Learning On

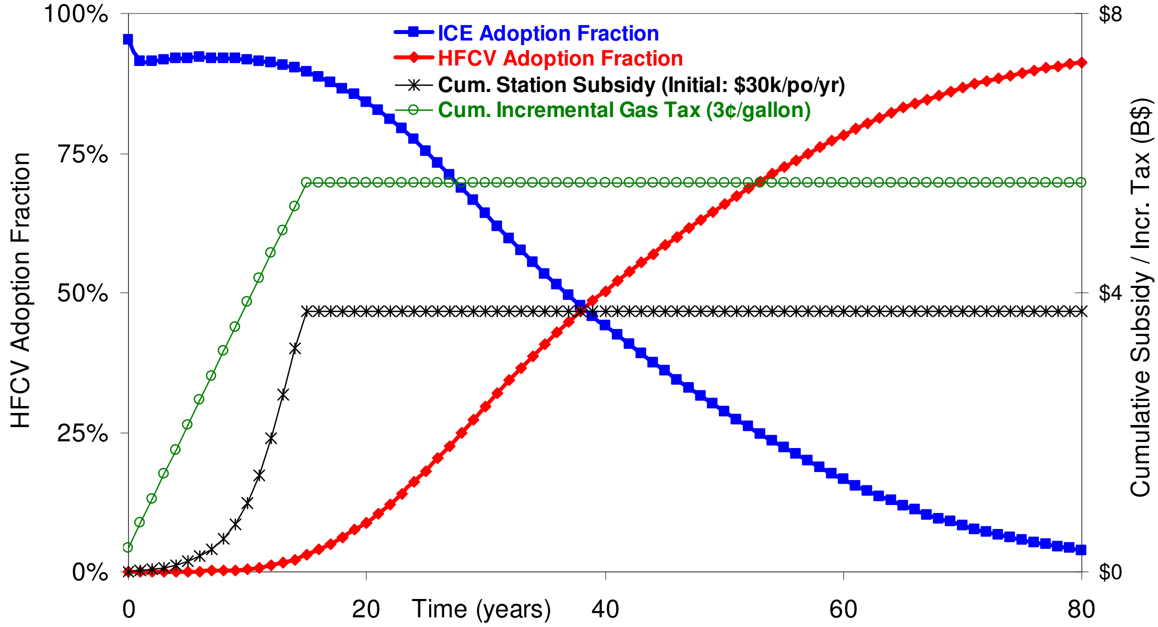


So, while the chicken-egg dilemma in achieving rural station density is an important challenge to overcome, it appears that policies intended to do so may overcompensate and actually constrain market penetration rates. The need to overcome market and behavioral failures does not preclude the goal of harnessing competitive markets for the optimal emergence of infrastructure.

With so many uncertainties, how are policy designers to choose the appropriate duration to avoid such unintended consequences? Unfortunately the AVMT model does not provide perfect forecasts to do so. However, it does provide an understanding of system structure that would enable an adaptive policy approach in which, for example, policymakers knew such subsidies could be phased out after reaching average rural relative station densities greater than 50%.

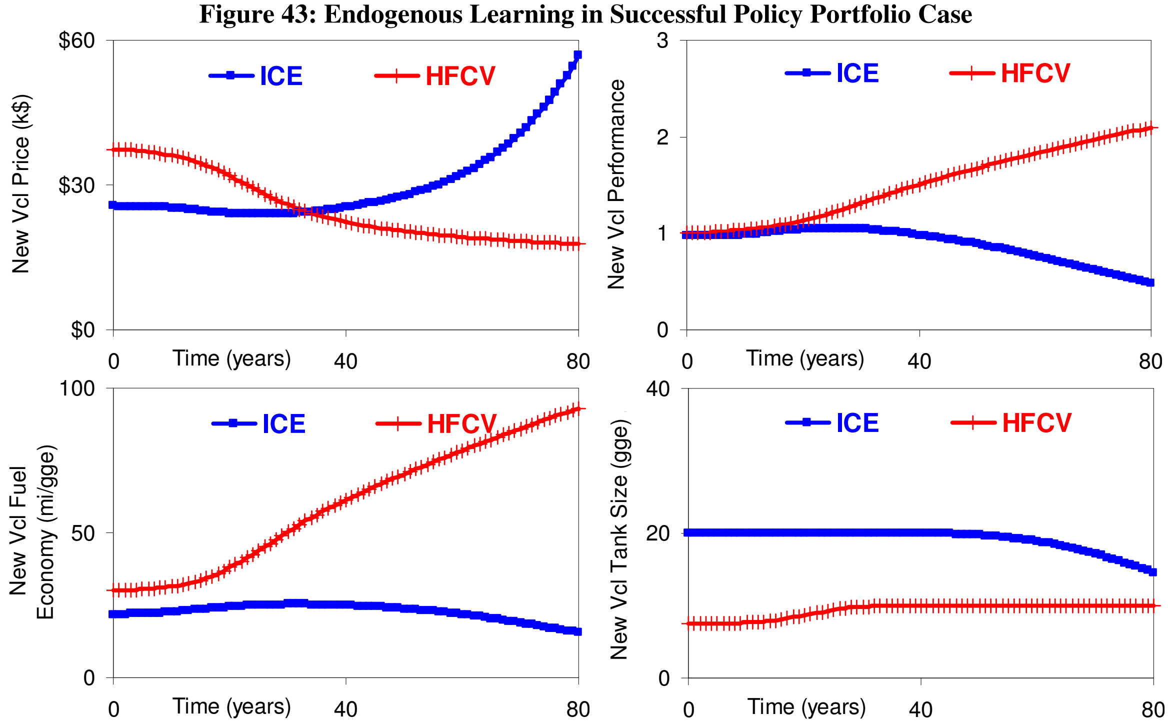
The effects of endogenous learning are particularly powerful in influencing dynamics after some threshold of successful take-off has been reached. Once these reinforcing feedbacks are enabled, they strongly improve the ultimate equilibrium level of AFV penetration.

Figure 42: 80 Year Simulation, Successful Policy Portfolio with Learning



In fact, if the successful policy portfolio from the previous example is simulated for eighty years, HFCVs grow to fully penetrate the market (Figure 42) rather than equilibrating at around 45% of market share as seen in the prior success cases without the learning feedback effects. Once tipping points are surpassed, learning feedbacks bring HFCVs great advantage (Figure 43).

Figure 43: Endogenous Learning in Successful Policy Portfolio Case

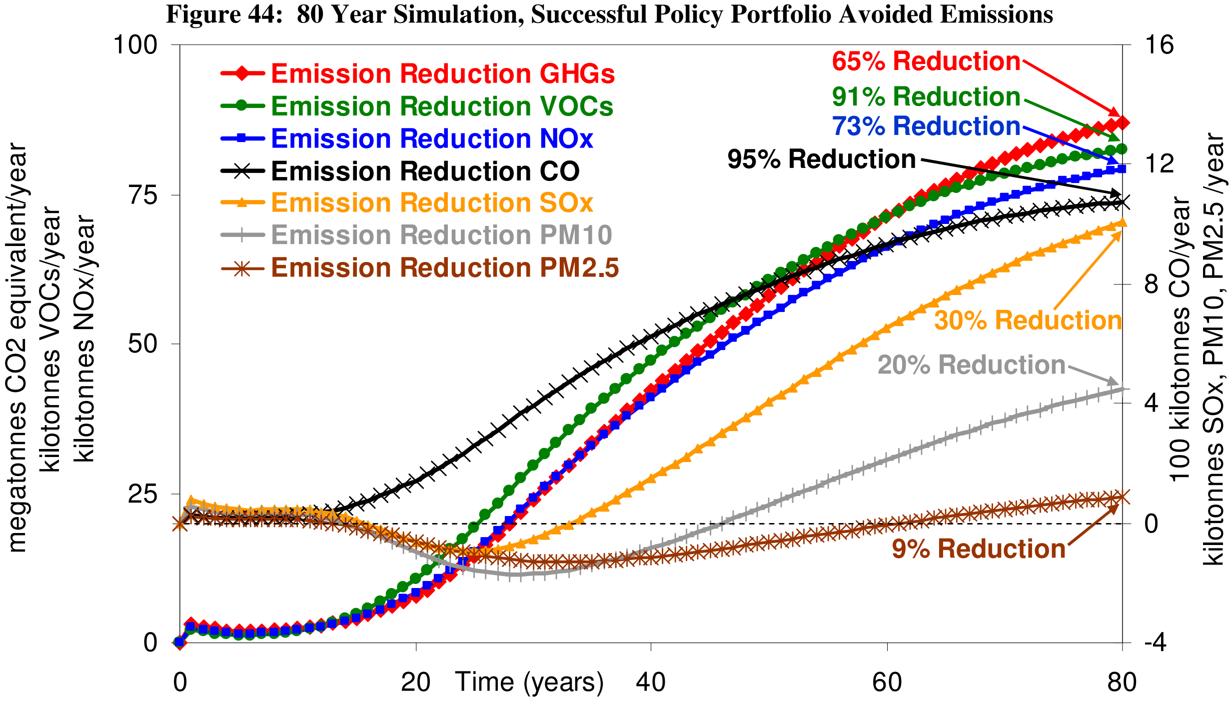


In addition, Figure 42 illustrates that endogenous OEM knowledge can also be lost with drastic decreases in vehicle sales. As the ICE is edged out of the new sales market, its technical attributes actually worsen. Thus, one can see how reinforcing learning feedbacks give great advantage to the market leader or to a new technology growing quickly from a small base of cumulative production.

Furthermore, this policy portfolio example illustrates that an additional gasoline tax of only 3¢/gallon over the first fifteen years is more than enough to fund the necessary fuel station operating subsidies that are necessary on top of the base run policies to achieve take-off when learning effects are modeled endogenously. The strong marketing shock to building awareness and comfort with the new technology will also be very expensive. Yet, after subtracting funds for station subsidies, the multi-billion dollar surplus from this incremental tax revenue could also fund the marketing shock to make the entire policy portfolio revenue neutral.

This sort of revenue neutral program of moderate taxation and government subsidy would be well justified to create the simulated emission flow reductions plotted in Figure 44. Particularly dramatic are the savings achieved in carbon monoxide and nitrogen oxides emissions compared to reference levels. Thanks to the HFCV's radically increased fuel efficiency, the reduction in greenhouse gas emissions is also significant. Interestingly, although the policy actually results in worse sulfur oxide and particulate matter emissions initially due to the emissions during hydrogen production, eventually the fuel efficiency improvements achieved via learning lead to substantial reductions in the emission rates for these pollutants too. On the whole, even if hydrogen continued to be produced from natural gas as assumed in this run, the emissions from a fixed-level stock of light duty vehicles would be much improved.

Figure 44: 80 Year Simulation, Successful Policy Portfolio Avoided Emissions



Conclusions & Recommendations

General Conclusions

The AVMT model represents several important feedback relationships that govern the effectiveness of policies to displace conventional motor fuels with substitutes. In a simplified, one-entrant scenario, the hydrogen fuel cell vehicle can diffuse to a self-sustaining level but *requires strong policy support over decades*, confirming earlier conclusions (Struben and Sterman 2006) now with a broader integrated model that has been carefully parameterized for that vehicle technology and hydrogen fuel reformed from natural gas at the station forecourt.

The rate of market penetration is sensitive to policy, behavioral, and technology assumptions, but remains longer than commonly conceived in all cases. In cases of successful diffusion, equilibrium market shares depend primarily on the relative technical attributes (price, performance, range) across the competing vehicle platforms. However, the *likelihood of a successful transition is strongly dependent on the rate of growth in three critical complementary resources*: spatially balanced refueling infrastructure, consumer familiarity with the technology, and OEM knowledge for vehicle design and production. Nonlinearities in utility as these assets increase necessitate that each be grown beyond thresholds to reach financially sustainable fuel and vehicle markets. In other words, there are *multiple important tipping points*.

Developing statewide average station densities at 15-20% of gasoline station infrastructure is not sufficient alone for the market to become self-sustaining. Infrastructure coverage in infrequently visited rural areas plays a disproportionate influence on both vehicle purchase and trip destination choice. Integrated model results confirm that locally rational behavior of drivers and fuel providers reinforces the spatial asymmetry problem. Because urban fuel markets are most profitable early on, they attract the most station entrance. Drivers then make a habit of topping-off in and/or traveling to urban areas where perceived station density is high rather than risk running out of fuel in remote areas, further reinforcing the low profitability in rural locations (Struben 2006). Unless this urban-rural asymmetry chicken-egg problem is overcome, the system will come to an equilibrium consisting of only niche market adoption in urban clusters.

On top of these hurdles, competition between various AFV entrants is to the detriment of all, making the transition challenge even more staggering. A balance must be achieved between coordination and competition needed to avoid lock-in to other inferior technologies.

The presence of the used car market is another important feature of the AVMT model. While it has both reinforcing and balancing effects, the net effect of this structure is to speed AFV penetration as there is a larger shift in the share of ICE vehicles that are purchased used.

Sensitivity analysis repeatedly reinforced the importance of a wide multivariate search of the parameter space when testing policies to influence systems with nonlinear relationships. The important role of some parameters, such as a driver's sensitivity to station coverage in adjusting their fuel tank buffer, would be overlooked by univariate sensitivity analysis, no matter how precise the probability distribution for inputs. Such multi-dimensional search is also needed to observe nonlinear interaction effects between parameters like fuel economy and tank capacity.

Policy Recommendations

The broad lesson from this analysis is that policies to support technology transitions should be designed cognizant of the system structure driving dynamic behavior. Most importantly, coordinated portfolios of policy instruments must be used over long enough duration to surpass thresholds in complementary assets before markets will become self-sustaining. Simply assembling a politically feasible package of policies used in the past without attention to the system's dynamic structure is likely to be insufficient to surmount the key transition barriers within reasonable costs.

More specifically, this analysis provides examples of how policy leverage varies with an alternative vehicle's technological attributes and infrastructure needs. It is understandably intuitive for policymakers to try to apply policy instruments that worked to speed diffusion for one technology (e.g. tax credits for efficient household appliances) to others such as hydrogen fuel cell vehicles. Yet in cases where requisite complementary assets are highly non-linear in shaping the attractiveness of driving a vehicle, such purchase incentives have little impact and will go wasted if not combined with higher leverage incentives and coordination strategies to grow familiarity and infrastructure. Simply put, *subsidizing vehicle purchase does not ensure vehicle use* and a level of fuel demand to sustain infrastructure. This lesson is just one example of the type of insight that system modeling efforts produce.

Several tests illustrated the additional policy challenges for AFV platforms with lower driving range or radically higher fuel economy. A key insight gained from the behavioral model is that management of retail margins by early hydrogen station entrants is critical. Even supplemented by ancillary sales revenues, the competitive retail margins seen in gasoline retailing would not be enough to drive growth in capital intensive hydrogen fuel stations. The importance of this decision rule would be missed by economic optimization models that do not include this agent's behavioral decision-making. What is the potential for high markups during a demonstration phase? In addition to intellectual property and technology leadership, the time delays for station entrance (permitting, etc.) may be important in constraining the entrance of competitors so that early entrants will be able to maintain relatively high margins. Clearly, early competitive price wars will thwart the transition. This challenge also suggests a strategy of looking for complementary hydrogen applications such as stationary backup electric power provision.

The demonstration markup and fuel subsidy policies also raise the important question of how consumers perceive the cost of driving. With entrant AFVs that are more fuel efficient compared to the incumbent, all else equal, it is important to help drivers perceive cost on a per vehicle mile basis. Retail markups on variable cost to cover more capital intensive fuel production processes at the fuel outlet can then be higher while consumers would still perceive prices to be competitive with gasoline. This challenge becomes easier if such the higher markups are combined with a gasoline tax, which could also be temporary.

Despite the relative effectiveness of policies such as fuel station operation subsidies or gasoline taxes observed in the analysis, these policies face major political hurdles. If large oil companies dominate alternative fuel production and retailing, imagine the difficulty of convincing legislators to subsidize their alternative fuel operations. Indeed, political stakeholder considerations are just as important a policy portfolio design constraint as any transition barrier, particularly because of the need for stable policies over durations longer than several election cycles for this type of technology transition. For this reason alone, the effective transition-oriented policies may need to be complemented by direct incentives to households, such as the provision of tax credits on the total volume of alternative fuel purchased over the course of a year. Other fiscal policy measures to reduce the net regressive impact of gasoline taxes would also be a vital complement to that policy.

Regarding infrastructure policy incentives, coordination to achieve comparable growth rates in the vehicle fleet and fueling infrastructure is paramount. Choice of incentive instruments for fueling stations provides another example of the need to derive polices from an understanding of the feedback and behavioral processes at work. Analysis of the urban/rural asymmetry problem suggests that an effective transition requires a disproportionate share of public support for fueling outlets outside urban areas. Yet, a strategy of covering all fuel station operating losses may overcompensate for the rural station development challenge. It was observed that some station incentives distorted spatial distribution from the appropriate geographic balance resulting in too small an urban concentration. This finding, along with the political difficulties of awarding asymmetric subsidies to various cities and counties, suggests uniform capital grants or operating subsidies per fueling position are the most appropriate policy incentive for stations.

In addition to infrastructure incentives, the analysis emphasizes the criticality of *aggressive consumer marketing campaigns* over long periods for emerging technologies competing with durable goods with long lifetimes such as automobiles. Technological superiority alone will not necessarily lead to widespread diffusion without efforts to build awareness and willingness to consider the new technology. Such marketing campaigns will be more expensive than manufacturers and fuel retailers can afford using early sales revenues alone. Stable government support for such education is critical and should not be terminated early even the AFV appears to be having early success, because *familiarity can collapse fairly quickly.*

In summary, the three dominant reinforcing loops operating in AFV market bring growth potential but also instability into the system. The aspiration of policy engineers should be carefully coordinated policies to simultaneously develop consumer familiarity, fueling infrastructure, and OEM knowledge at similar rates in order to avoid overshoot and collapse. Even better, policy should dynamically adapt to observed conditions to identify and lessen the dominant transition constraints in effect. It cannot be emphasized enough that policy incentives must be stable over long duration to surpass multiple tipping points in the system. Policy and strategy makers should be warned from the outset that successful diffusion will take a long time.

Supporting the transition to a self-sustaining AFV market is a staggering challenge. Yet smart policy and bold leadership can result in successful market transformations, creating long lasting private and social benefits.

More generally, although policy analysis guided by system dynamics modeling may require more time up front to build an understanding of the feedback structures underlying a problem, it will serve entrepreneurs, policymakers, and their public quite well.

Recommendations for Further Research

A model, by definition, is a simplified representation of reality. Thus "all models are wrong" in that they cannot and should not attempt to capture all relationships in a system. When analysts speak of model validation, they investigate whether the model is the most useful model for the problem at hand. In other words, can the model be extended or refined to improve its credibility, its tractability, or its resulting insights into the challenge(s) of interest?

There are several model extensions and several partial-model calibrations that would be useful for further building credence in the AVMT model or for enabling new types of policy testing. It is important that the sensitive model structures and parameters be further refined using partial model tests against patterns of empirical historical data that are available.

Used Car Market. Sensitivity analysis demonstrated that the used car market plays an important role in shaping the speed of diffusion. It has also been demonstrated that policies to accelerate vehicle retirement and scrappage would have significant leverage in speeding diffusion (Struben and Sterman 2006). In order to explore such policies further, a more comprehensive used car market structure should be developed such that used vehicle prices are determined endogenously and incorporated into vehicle platform choice by consumers.

Social Exposure Calibration. This analysis also revealed the importance of social exposure and aggressive marketing policies to accelerate the number of drivers willing to consider the alternative fuel vehicle. Awareness begins quite low and requires a significant share of AFVs on the road to sustain itself. Further research is needed to build confidence in social exposure parameters within the model. Additionally, there is little research in existence to estimate the costs of a government marketing policy to build awareness 2-4% of non-adopter pool per year.

Fuel Supply. Although the AVMT model already has a very broad boundary, additional expansions may be useful. As the alternative fuel surpasses the tipping point thresholds and grows to gain a major share of transport fuel consumption, the markets for feedstocks and other primary energy sources for conversion will be affected. Thus, energy supply to the retail outlets should be endogenous in order to capture unintended consequences or additional transition barriers. Endogenous technology improvement of fuel production systems and dispensers with their cumulative production would add another weak reinforcing loop, which may be important under some conditions. The capital cost and land requirements for these technologies are likely to fall from initial levels due to learning.

Behavioral Markup Setting Decision. The retail markup on variable cost at the fueling station was identified as a very important variable in determining the likelihood of successful diffusion. The model represents the markup setting decision by fuel retailers as an anchoring and adjustment process in response to several "pressures" including operating costs, recent and expected utilization, geographically local price competition, and expected profitability. Due to the importance of this structure, additional fieldwork and partial model calibration are in order to capture how markup decisions are actually made with high fidelity. If there are major differences in this process across station ownership and management structures (e.g. company-operated, lessee dealer-operated, branded independent franchise, and unbranded independent stations), is such disaggregation useful for business policy testing? As alternative fuel producers confront the problem of designing distribution system architecture, the ability to vary this decision-making process in the model could be useful.

Vehicle Production Capacity. The AVMT model settings were optimistic for this analysis in that alternative fuel vehicles were always available if consumers were interested in buying them. In reality, OEMs face the challenge of matching production capacity to vehicle demand, and there are substantial time delays in adjusting such capacity. Model extension would allow additional policy analysis focused on decision optimization for AFV production capacity planning by vehicle manufacturers.

Bi-fuel Vehicles. The AVMT model is also able to test the introduction of multi-fuel vehicles including those compatible with multiple types of endogenous fueling infrastructure. Platforms of interest to policy and strategy makers include E85 compatible flex-fuel vehicles (FFVs), hydrogen/gasoline internal combustion engine vehicles (HICE), or plug-in hybrid electric vehicles (PHEVs). Policy exploration in this thesis focused on "dedicated" alternative fuel vehicles that are incompatible with incumbent fuels (although technology learning spilled over across vehicle platforms).

The transition dynamics will differ for multi-fuel vehicles in comparison to "dedicated" alternative fuel vehicles examined in this paper. While bi-fuel vehicles demonstrably allow more rapid adoption early in the transition, they make long-term dominance over the incumbent fuel very difficult because fuel infrastructure is even more likely to end up only in urban clusters.

In addition, the introduction of bi-fuel vehicles leads to more market instability for the alternative fuel. Not only does that make fuel price more volatile, it also contributes a more rapid potential collapse in vehicles adoption rates. These differences have great relevance for policy designers trying to promote a shift away from petroleum or fossil fuels. While policies to support flex fuel vehicles will be measurably more effective in the short term than those focused on dedicated vehicles, the early victories may be more easily dissolved in the long run. These policy implications for multi-fuel vehicles should be explored further using the AVMT model.

Endogenous Policy Environment. Finally, while policies were tested in this analysis as exogenous interventions into the system in order to evaluate their effectiveness, the policy environment and type of regulations enacted are clearly endogenous to the behavior of the system itself. Success or lack thereof amongst alternative fuel and vehicle providers will shape political relationships and decision-making. Apparent early success may lead policymakers to shift fiscal priorities prior to the emergence of a self-sustaining market. Considering the importance of long duration policies demonstrated by this work, formal modeling of regulatory capture and dynamic policy response to the success or failure of AFV diffusion may be justified.

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Appendix A: Technology Assessment

A survey of available literature and detailed technology models informed the specification of technical parameters for the various competing fuels and vehicle drivetrains in the AVMT model. These parameter values and the sources for their derivation are included in the following tables for each type of fuel and each type of vehicle drivetrain.

Table 3: Gasoline Fuel and Infrastructure Technical Parameters & Source

Parameter	Model Units	Value	Other Units	Value	Source(s)
Planning & Site Selection Time	years	0.50	weeks	26	(Morris 2006)
Permitting Time	years	0.50	weeks	26	
Bidding and Construction Time	years	0.75	weeks	39	
Ancillary Sales Revenue to Fuel Revenue Ratio	dmnl	20%			(PFC 2001; NACS 2006)
Typical Anc. Sales Profit Margin (on Revenue)	dmnl	30%			(NACS 2006)
Fixed Area	acre/station	0.12	square meter	500	(EA Engineering 1999; NACS 2006)
Variable Footprint Area per Fueling Position	acre/fueling position	0.0200	square meter	80	
Land Rent	$/acre	200,000	% Land Value	5%	(PFC 2001; Wheaton 2004)
Overnight Station Capital Cost (non-land) per Fueling Position	$/fueling position	125,000			(PFC 2001; Spinetti 2005; NACS 2006; NPN 2006)
Fixed O&M per Fueling Position: Labor, Utilities, Maintenance, Debt Service, Commission, Ancillary Sales	$/year/fueling position	24,000			
Levelized Non-Land Fixed Cost per Fueling Position	$/year/fueling position	30,000			
Daily Storage or Production Capacity/Fueling Position	gge/fueling position/day	3,750			(Geyer 2006; Oil Express 2006)
Fuel Dispensing Rate	gge/hour/fueling position	420	gallons/minute	7	(US 40 CFR 80.22; (EPA 1997)

Parameter	Model Units	Value	Other Units	Value	Source(s)
Total Fill-Up Time (Fixed & Variable)	hour/refill	0.0867	Minutes/refill	5	(EA Engineering 1999)
Daily Operating Hours	hours/day	18			(NACS 2006)
Unit Variable (Wholesale Fuel) Cost	$/gge	1.30			(EIA 2004; CEC 2006; EIA 2006c; EIA 2006b)
Absolute Retail Fuel Markup	$/gge	0.10			
Federal, State, & Local Fuel Taxes and Underground Storage Tank (UST) Fees	$/gge	0.50			
Well-to-Wheel Emissions per GGE Fuel					
Greenhouse Gases (100yr GWP Adjusted)	kilogram CO2-equivalent/gge	11.264	lb CO2 equiv/gge	24.84	GREET Model (Wang 2007)
Volatile Organic Compounds (VOC)	gram/gge	7.564			
Carbon Monoxide (CO)	gram/gge	94.662			
Nitrogen Oxides (NOx)	gram/gge	9.151			
Particular Matter <10 µm (PM10)	gram/gge	1.885			
Particular Matter <2.5 µm (PM2.5)	gram/gge	0.794			
Sulfur Oxides (SOx)	gram/gge	2.778			
$ values in 2005 US$ gge = gallon gasoline equivalent (on energy basis)					

Table 4: Hydrogen Forecourt Steam Reformation (H2FSMR) Technical Parameters & Source

Parameter	Model Units	Value	Other Units	Value	Source(s)
Planning & Site Selection Time	years	0.50	weeks	26	not available
Permitting Time	years	0.75	weeks	39	Sparse (Honda Motor Company 2002)
Bidding and Construction Time	years	1	weeks	52	(James, Lasher et al. 2006)
Ancillary Sales Revenue to Fuel Revenue Ratio	dmnl	20%			(PFC 2001; NACS 2006)
Typical Anc. Sales Profit Margin (on Revenue)	dmnl	30%			(NACS 2006)
Fixed Area	acre/station	0.12	square meter	500	(James, Lasher et al. 2006; NACS 2006)
Variable Footprint Area per Fueling Position	acre/fueling position	0.0253	square meter	100	
Land Rent	$/acre	200,000	% Land Value	5%	(PFC 2001; Wheaton 2004)
Overnight Station Capital Cost (non-land) per Fueling Position	$/fueling position	237,000			(Mintz, Molburg et al. 2000; Weinert 2005; James, Lasher et al. 2006)
Fixed O&M per Fueling Position: Labor, Utilities, Maintenance, Debt Service, Commission, Ancillary Sales	$/year/fueling position	25,000			
Levelized Non-Land Fixed Cost per Fueling Position	$/year/fueling position	36,875			
Daily Storage or Production Capacity/Fueling Position	gge/fueling position/day	115-300			(Mintz, Molburg et al. 2000; Weinert 2005; James, Lasher et al. 2006)
Fuel Dispensing Rate	gge/hour/fueling position	120	kg/minute	2	(US DOE 2003)
Total Fill-Up Time (Fixed & Variable)	hour/refill	0.0875	Minutes/refill	5.25	calculated
Daily Operating Hours	hours/day	18			n/a

Parameter	Model Units	Value	Other Units	Value	Source(s)
Unit Variable (Wholesale Fuel) Cost	$/gge = $/kg	2.10	$/mcf natural gas	9	(EIA 2006a; James, Lasher et al. 2006)
Absolute Retail Fuel Markup	$/gge	3	$/kg	3	
Federal, State, & Local Fuel Taxes and Underground Storage Tank (UST) Fees	$/gge	0			
Well-to-Wheel Emissions per GGE Fuel					
Greenhouse Gases (100yr GWP Adjusted)	kilogram CO2-equivalent/gge	13.591	lb CO2 equiv/gge	29.97	GREET Model (Wang 2007)
Volatile Organic Compounds (VOC)	gram/gge	0.001			
Carbon Monoxide (CO)	gram/gge	0.003			
Nitrogen Oxides (NOx)	gram/gge	0.008			
Particular Matter <10 μm (PM10)	gram/gge	0.006			
Particular Matter <2.5 μm (PM2.5)	gram/gge	0.003			
Sulfur Oxides (SOx)	gram/gge	0.007			
$ values in 2005 US$ gge = gallon gasoline equivalent (on energy basis)					

Table 5: Compressed Natural Gas (CNG) Fuel and Infrastructure Technical Parameters & Source

Parameter	Model Units	Value	Other Units	Value	Source(s)
Planning & Site Selection Time	years	0.50	weeks	26	(CNERFSO 2000; Alizadeh 2006)
Permitting Time	years	0.50	weeks	26	
Bidding and Construction Time	years	1	weeks	52	
Ancillary Sales Revenue to Fuel Revenue Ratio	dmnl	20%			n/a
Typical Anc. Sales Profit Margin (on Revenue)	dmnl	30%			(NACS 2006)
Fixed Area	acre/station	0.12	square meter	500	(GRI and AGA 1995; Clean Energy Fuels Corp. 2002; Silicon Valley Clean Cities Coalition and City of San Jose 2003)
Variable Footprint Area per Fueling Position	acre/fueling position	0.0220	square meter	95	
Land Rent	$/acre	200,000	% Land Value	5%	(PFC 2001; Wheaton 2004)
Overnight Station Capital Cost (non-land) per Fueling Position	$/fueling position	260,000	$/scfm	1,000	(GRI and AGA 1995; Silicon Valley Clean Cities Coalition and City of San Jose 2003; Riding and Dahlquist 2006)
Fixed O&M per Fueling Position: Labor, Utilities, Maintenance, Debt Service, Commission, Ancillary Sales	$/year/fueling position	20,000			
Levelized Non-Land Fixed Cost per Fueling Position	$/year/fueling position	33,000			
Daily Storage or Production Capacity/Fueling Position	gge/fueling position/day	3,200	Cubic meters/day	1,700	(GRI and AGA 1995; Silicon Valley Clean Cities Coalition and City of San Jose 2003)
Fuel Dispensing Rate	gge/hour/fueling position	420	standard cubic foot/minute	0.25	(GRI and AGA 1995; IGU 2005)
Total Fill-Up Time (Fixed & Variable)	hour/refill	0.0867	Minutes/refill	5	calculation
Daily Operating Hours	hours/day	18			n/a

Parameter	Model Units	Value	Other Units	Value	Source(s)
Unit Variable (Wholesale Fuel) Cost	$/gge	1.30			(EIA 2006a; Riding and Dahlquist 2006)
Absolute Retail Fuel Markup	$/gge	0.10			
Federal, State, & Local Fuel Taxes and Underground Storage Tank (UST) Fees	$/gge	0.50			
Well-to-Wheel Emissions per GGE Fuel					
Greenhouse Gases (100yr GWP Adjusted)	kilogram CO2-equivalent/gge	9.034	lb CO2 equiv/gge	19.92	GREET Model (Wang 2007)
Volatile Organic Compounds (VOC)	gram/gge	0.004			
Carbon Monoxide (CO)	gram/gge	0.077			
Nitrogen Oxides (NOx)	gram/gge	0.007			
Particular Matter <10 μm (PM10)	gram/gge	0.002			
Particular Matter <2.5 μm (PM2.5)	gram/gge	0.001			
Sulfur Oxides (SOx)	gram/gge	0.003			
$ values in 2005 US$ gge = gallon gasoline equivalent (on energy basis)					

Table 6: Spark Ignition Internal Combustion Gasoline Engine (ICE) Vehicle Technical Parameters and Source

Parameter	Model Units	Value	Other Units	Value	Source
Average Vehicle Life	years	16			(Davis and Diegel 2006)
Learning Switched OFF					
Fuel Tank Capacity	gge	20.0	liters	75.8	(Weinert 2005)
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	21.0	liter/100 kilometers	11.2	(Heavenrich 2006; EIA 2007)
Max Range (Action Radius)	miles	420	kilometers	676	calculated
Vehicle Performance	dmnl	1.00			n/a
Vehicle Production Cost	$/vehicle	20,000			(NADA 2006; J.D. Power and Associates 2007)
Learning Switched ON					
Initial Fuel Tank Capacity	gge	20.0	liters	75.8	
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	21.0	liter/100 kilometers	11.2	(Heavenrich 2006)
Initial Max Range (Action Radius)	miles	420	kilometers	676	calculated
Initial New Vehicle Performance	dmnl	1.00			n/a
Initial Vehicle Production Cost	$/vehicle	20,000			(NADA 2006; J.D. Power and Associates 2007)
New Vehicle Price (MSRP)	$/vehicle	25,000			
Saturation Fuel Tank Capacity	gge	20	liters	75.8	(Weiss, Heywood et al. 2003)
Saturation Vehicle Production Cost	$/vehicle	10,000			n/a
Reference Potential Fuel Economy	miles/gge	43.2	liter/100 kilometers	5.44	(Weiss, Heywood et al. 2003)
$ values in 2005 US$ gge = gallon gasoline equivalent (on energy basis)					

Table 7: Hydrogen Fuel Cell Vehicle (HFCV) Technical Parameters and Source

Parameter	Model Units	Value	Other Units	Value	Source
Learning Switched OFF					
Fuel Tank Capacity	gge	8	kg	8	(Weiss, Heywood et al. 2003; US DOE 2004)
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	52.5	kg/100 kilometers	1.18	(Ogden 2004b; Wang 2007)
Max Range (Action Radius)	miles	420	kilometers	676	calculated
Vehicle Performance	dmnl	0.75			n/a
Vehicle Production Cost	$/vehicle	25,000			
Learning Switched ON					
Initial Fuel Tank Capacity	gge	5	kg	5	GM, Personal Communication, 2007
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	40	kg/100 kilometers	2.07	
Initial Max Range (Action Radius)	miles	225	kilometers	362	
Initial New Vehicle Performance	dmnl	1.00			
Initial Vehicle Production Cost	$/vehicle	40,000			
New Vehicle Price (MSRP)	$/vehicle	50,000			
Saturation Fuel Tank Capacity	gge	10	kg	10	(Weiss, Heywood et al. 2003)
Saturation Vehicle Production Cost	$/vehicle	10,000			n/a
Reference Potential Fuel Economy	miles/gge	106.5	kg/100 kilometers	0.58	(Weiss, Heywood et al. 2003)
$ values in 2005 US$ gge = gallon gasoline equivalent (on energy basis)					

Table 8: Compressed Natural Gas (CNG) Vehicle Technical Parameters and Source

Parameter	Model Units	Value	Other Units	Value	Source
Learning Switched OFF					
Fuel Tank Capacity	gge	12	kg	31	(IGU 2005), CNG Crown Victoria
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	30	kg/100 kilometers	5.32	(EIA 2006a) Supplement Tables--NEMS assumptions for 2010 fleet
Max Range (Action Radius)	miles	360	kilometers	580	calculated
Vehicle Performance	dmnl	1.00			n/a
Vehicle Production Cost	$/vehicle	20,000			n/a
Learning Switched ON					
Initial Fuel Tank Capacity	gge	8	kg	21	Honda Civic GX
Initial Fleet Average *and* New Vehicle Fuel Economy (EPA Adjusted 55%City/45% Highway)	miles/gge	30	kg/100 kilometers	5.32	(EIA 2006a)
Initial Max Range (Action Radius)	miles	240	kilometers	387	calculated
Initial New Vehicle Performance	dmnl	1.00			n/a
Initial Vehicle Production Cost	$/vehicle	20,000			na
New Vehicle Price (MSRP)	$/vehicle	25,000			
Saturation Fuel Tank Capacity	gge	15	kg		n/a
Saturation Vehicle Production Cost	$/vehicle	10,000			n/a
Reference Potential Fuel Economy	miles/gge	73.5	liter/100 kilometers	2.17	(Weiss, Heywood et al. 2003)

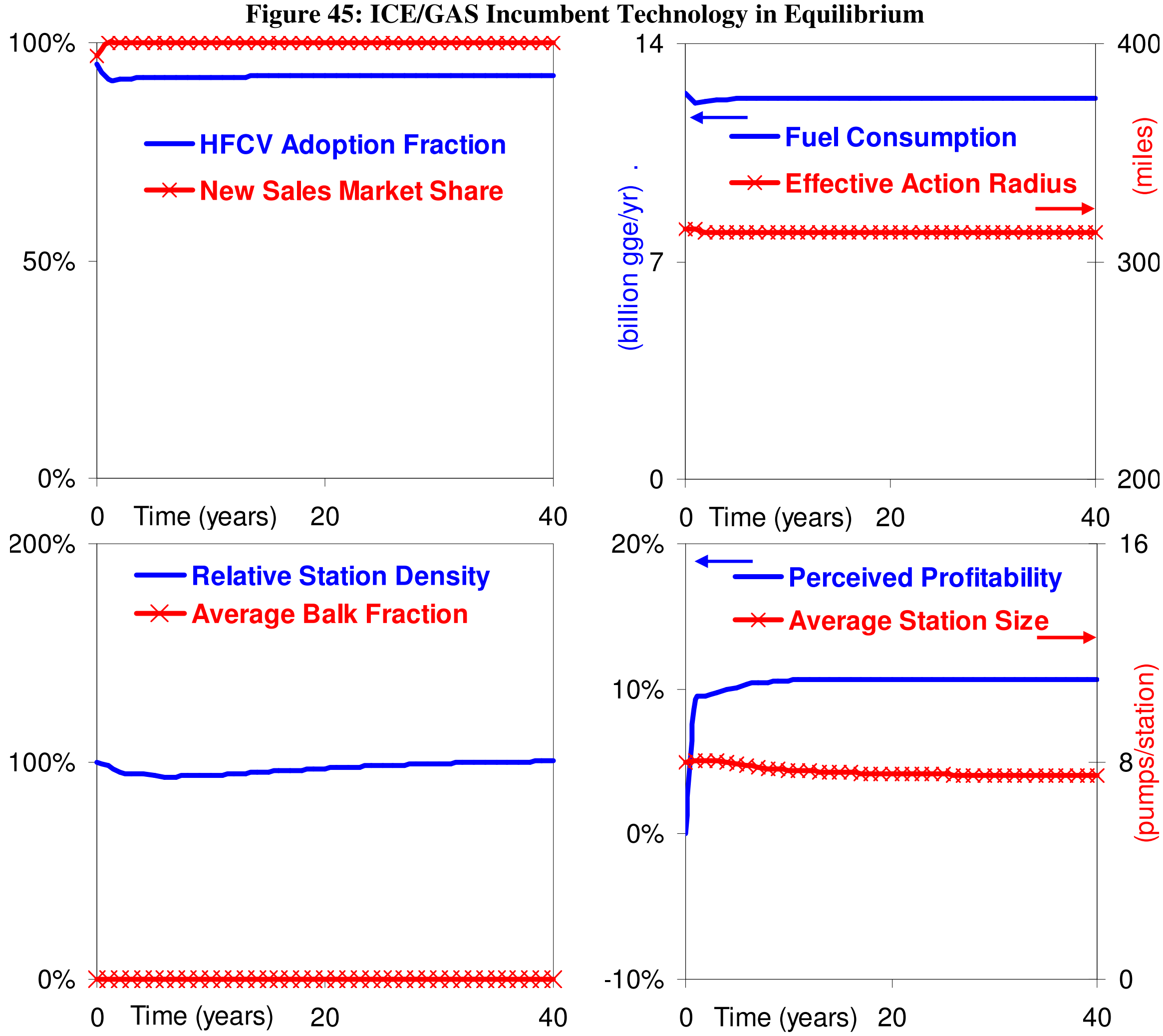
$ values in 2005 US$
gge = gallon gasoline equivalent (on energy basis)

Appendix B: Additional Sensitivity Analysis Results

ICE Explicit Equilibrium
As a confidence building test in the model, the incumbent vehicle and fuel (ICE/GAS) is modeled explicitly along with an entrant that fails to achieve any penetration. Familiarity, station entry and exit, and station capacity adjustment is endogenous for both platforms. Model behavior should be reasonable when ICE maintains full new sales market share.

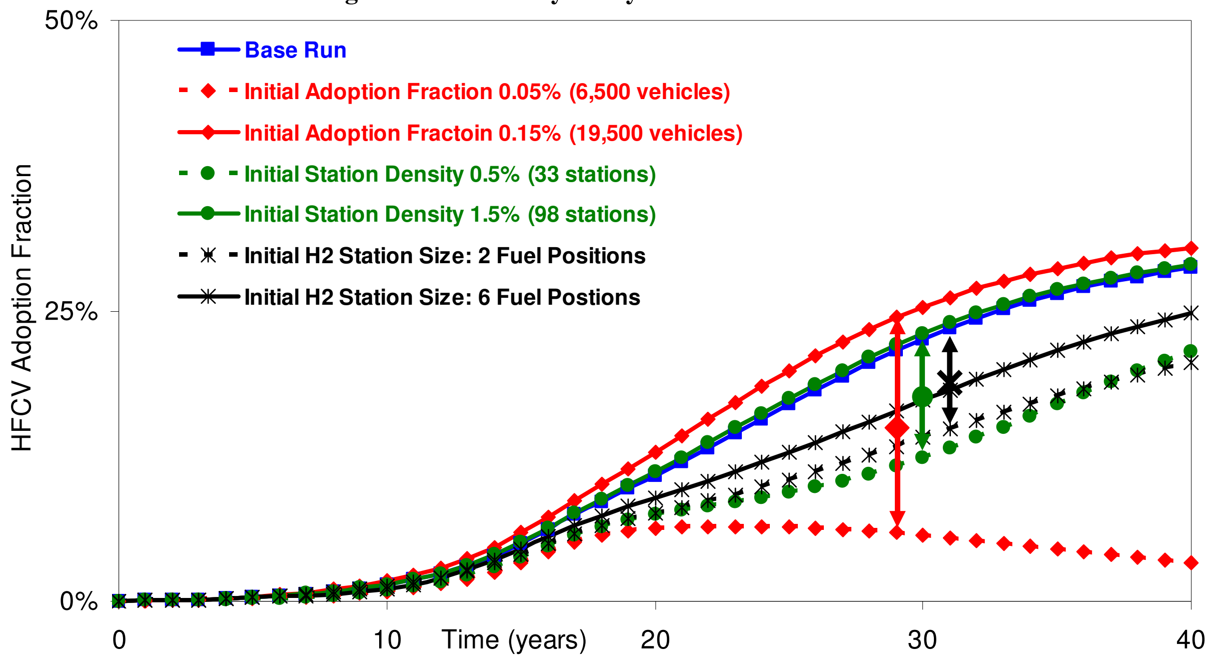
As a reminder, the population, motorization, and miles traveled are fixed for the runs in this analysis to ease our understanding of behavior created by the endogenous system structure. Here the ICE/GAS platform is simulated over forty years along with an entrant platform that quickly fails. As one would expect, the system quickly reaches an equilibrium that is similar to the initial conditions. The adoption fraction equilibrates at 97% of households; the rest choose not to own a vehicle at all. Station density and size also equilibrate to a constant level very close to initial conditions as profitability is also flat at the reference 10% annual pre-tax return on investment. With full familiarity and unchanging station density, driving behavior is unaffected from the normal frequencies and distributions. Hence the rate of fuel consumption is also flat.

Figure 45: ICE/GAS Incumbent Technology in Equilibrium



Initialization Settings
In the base run, simulations begin with 13,000 hydrogen vehicles (0.1% of households) and 65 fueling stations (1% of gasoline station coverage) to seed the market. In addition it is assumed that initial hydrogen fuel stations enter with four fueling positions per station. Due to the path dependency and tipping dynamics, simulation results are sensitive to these initial settings.

Figure 46: Sensitivity Analysis - Initial Conditions



The initial adoption fraction is the most sensitive initialization parameter under base run conditions. If initial adoption is less policy must be of even longer duration to support the transition. The speed of diffusion is also sensitive to the initial station density, which makes sense because of the importance of station coverage during the first ten years of the transition.

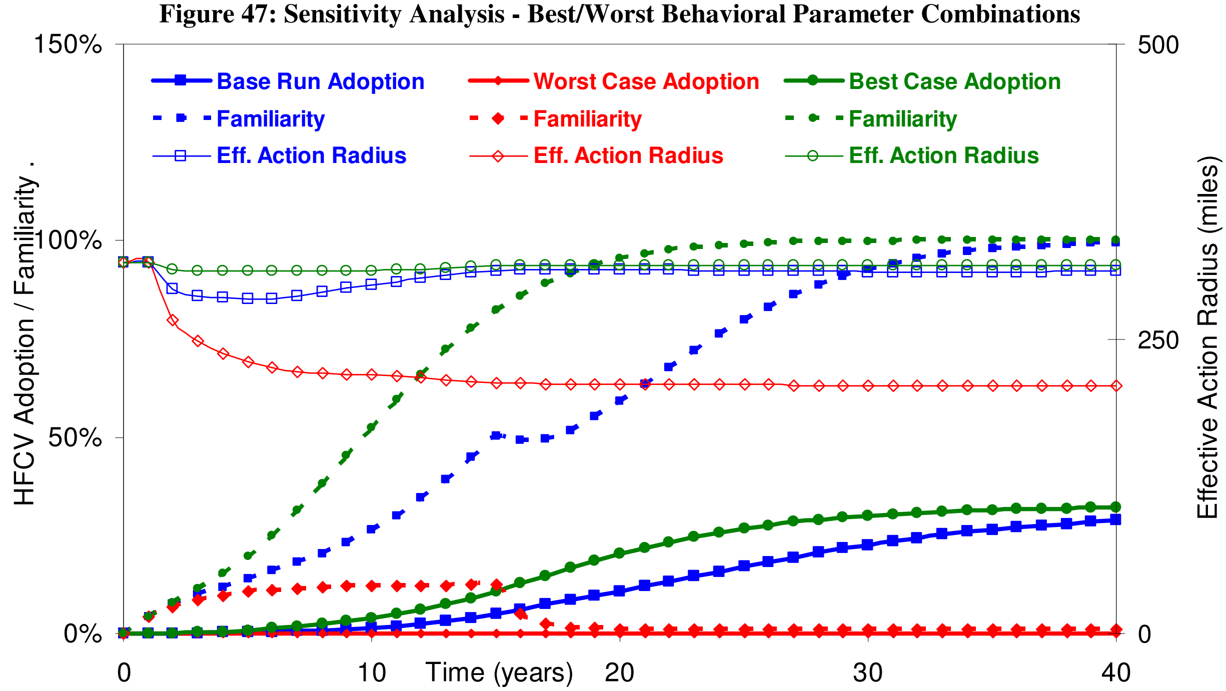
Interestingly, decreasing or increasing the initial size of hydrogen fuel stations both have suppressing effects on adoption. There is a need to for station managers to balance capital cost and waiting times. Four fueling positions per station results in a low probability of queues for early adopters while requiring only moderate capital expenditures and associates risks.

Behavioral Parameter Best/Worst Combination Sensitivity
By examining two extreme cases, the combination of the best and worst combinations of the five behavioral parameters tested in the univariate analysis presented in Figure 16, the widest window of potential diffusion pattern outcomes can be examined.

Under the worse case parameter assumptions, which are not unreasonable, it is very difficult to reach a self-sustaining market. Even in the presence of an aggressive and costly marketing shock policy, familiarity does not come anywhere near the threshold level necessary to sustain awareness. In addition, the effective action radius drops significantly and never recovers. If these worst case parameter settings properly represent reality, it would be tremendously difficult to introduce any new alternative fuel vehicle that isn't vastly superior to ICE.

Under the best case assumptions, familiarity builds rapidly and the HFCV driver's effective action radius is hardly affected. The rate of vehicle diffusion is faster in this case but does not improve by as much as one might guess. Part of the constraint is that the equilibrium adoption fraction remains limited by the HFCV's static value proposition relative to ICE vehicles in this test. Not only are there transition barriers, but HFCVs are also disadvantaged in ultimate market potential by their lower performance and higher price.

Figure 47: Sensitivity Analysis - Best/Worst Behavioral Parameter Combinations



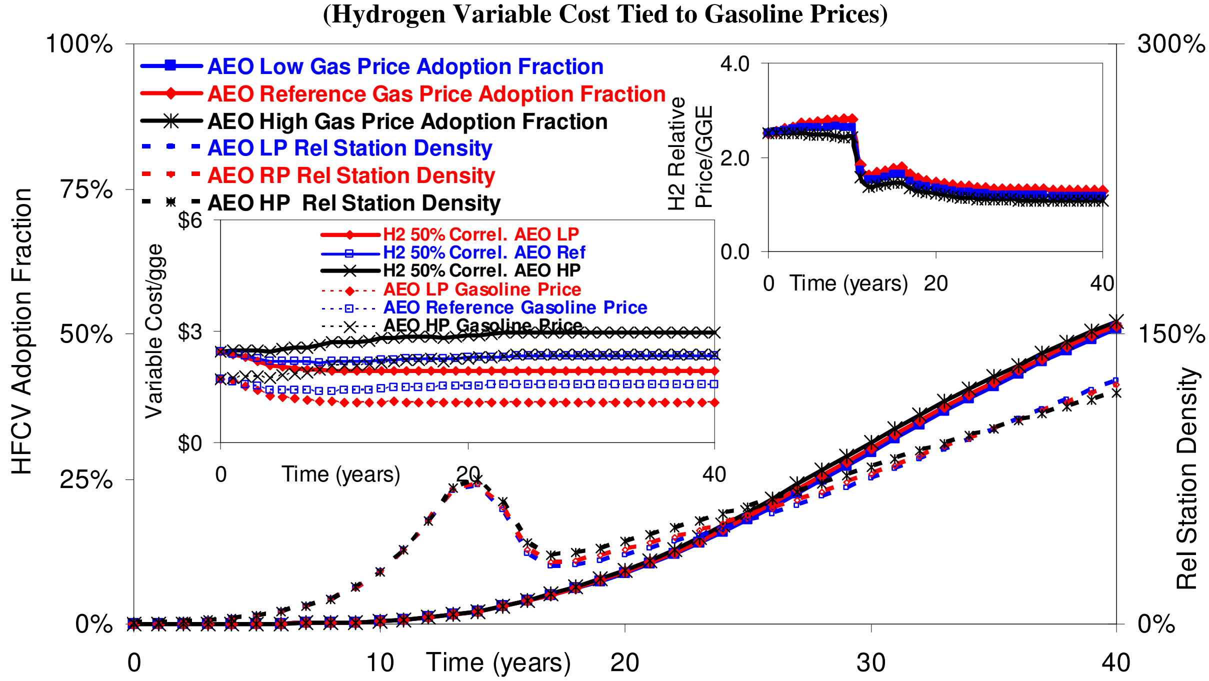
Fuel Price Scenarios
Primary energy and feedstock prices are an important exogenous input to the model. The base run assumption includes a fixed $1.30/gallon wholesale dealer tank wagon (DTW) gasoline price upon which retail markups and taxes (state sales and excise taxes, federal excise taxes, and the underground storage tank fee) are added to give a retail gasoline price of $1.90/gallon.

Similarly, the variable cost of hydrogen reformed from natural gas and compressed is exogenously fixed at $2.10 per kilogram of hydrogen produced. This cost is dominated by the commercial natural gas feedstock price of $9/thousand standard cubic feet. It also includes small costs for electricity, process water, and waste disposal (James, Lasher et al. 2006)

With a better understanding of model behavior and the sensitivity of various policies, one can explore policy scenarios under varying potential trends in underlying energy costs. Using the successful policy case from the section with learning switched on as a reference run, the simulation in Figure 48 draws exogenous time-series wholesale gasoline prices from three Annual Energy Outlook (AEO) forecasts by the Energy Information Administration using its National Energy Modeling System (NEMS). Despite all the uncertainties in geopolitical dynamics and the ability to produce cost effective substitutes for diminishing light, sweet crude oil reserves, the three AEO price scenarios are actually quite similar and stable compared to behavior one might expect to see in oil prices. Yet, as these forecasts are the most widely used, it is valuable to determine how the AFMT model responds when integrated with NEMS results.

NEMS does not include forecasts for retail hydrogen production prices. Of course, the price of natural gas is closely related to that of oil. For these scenarios, a simple and arbitrary assumption is made that for every fractional change in wholesale gasoline prices, there is a corresponding change of half that magnitude in variable costs for hydrogen from the $2.10/gge initial value.

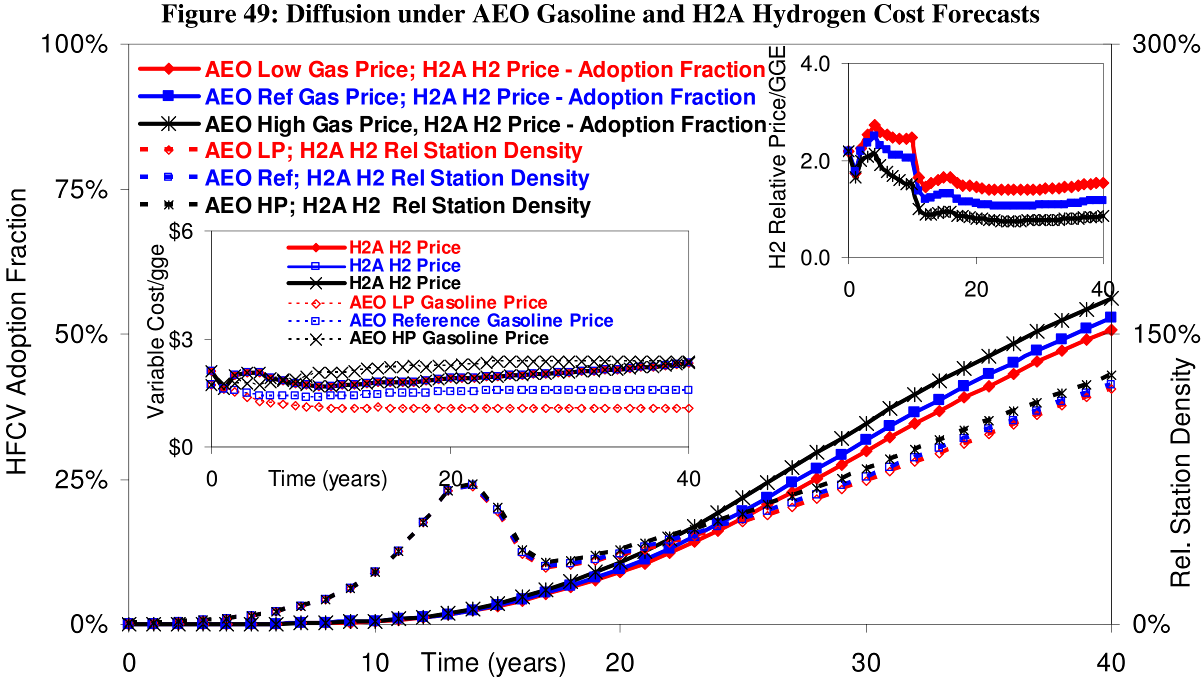
Figure 48: Diffusion under AEO Gasoline Price Scenarios (Hydrogen Variable Cost Tied to Gasoline Prices)



The AEO petroleum product price forecasts include low price and high price scenarios along with EIA's projected business as usual reference scenario. Despite a range of $1.50/gallon between forecasts in retail gasoline prices, variation in the rate of HFCV adoption is small. As the variable costs for the two competing are 50% correlated, this isn't that surprising. The relative retail fuel price of hydrogen does not change much from scenario to scenario.

What if the variable cost of natural gas was unaffected by gasoline price? In Figure 49 the same wholesale gasoline price time series are again drawn from the low, reference, and high price Annual Energy Outlook scenarios. However, this time the hydrogen price is not directly linked to those prices. All three scenarios assume the same hydrogen variable cost price trajectory drawn from the H2A model for the next forty years (note that this model's project is partially derived from the AEO reference forecast). Regardless, the idea of the test is to observe system response when gas prices rise or fall while hydrogen maintains an independent trajectory.

Figure 49: Diffusion under AEO Gasoline and H2A Hydrogen Cost Forecasts



The simulation results show more variation than in the previous case. Diffusion and infrastructure development are both somewhat faster in the scenario where gasoline prices are high (HP) compared to the low gasoline price scenario (LP), as would be expected.

Thus, whatever one's assumptions about how tightly coupled hydrogen variable costs will be to petroleum product prices over the next forty years, the small variation in price included in the three Annual Energy Outlook forecasts does not fundamentally differ the transition story for hydrogen fuel cell vehicles.

Appendix C: Additional Policy Tests

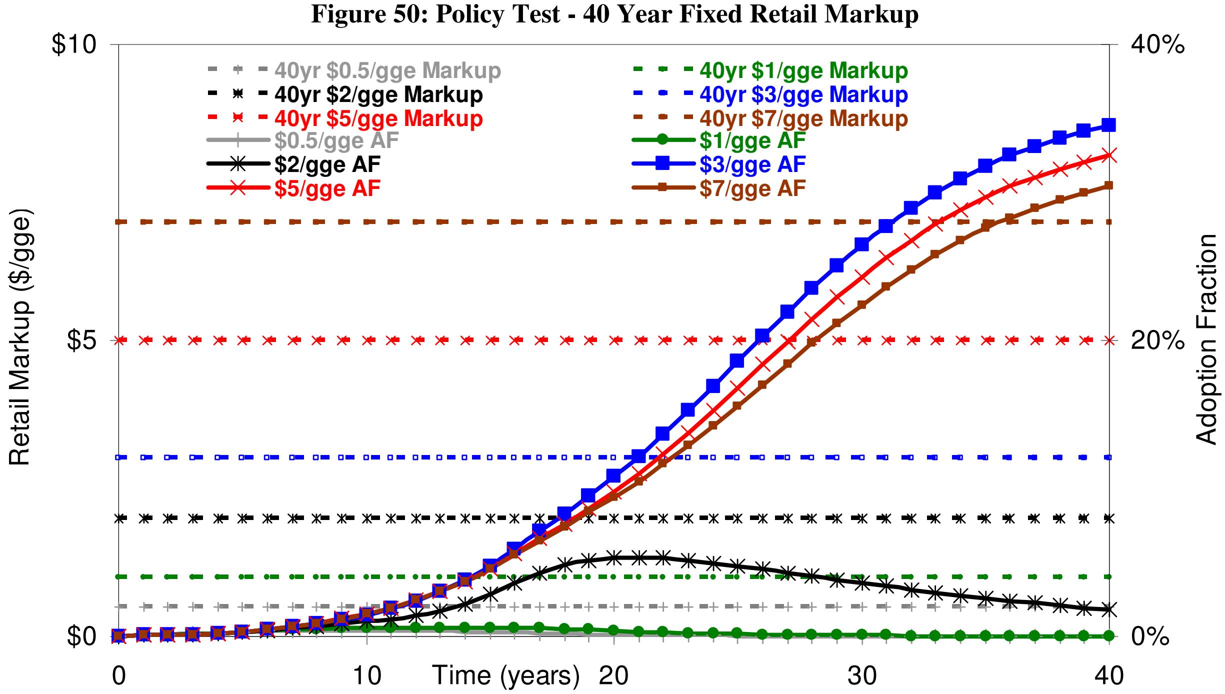
Additional policy tests reinforce insights seen in the Policy Testing section.

<u>40 Year Fixed Retail Markup</u>

Rather than using a 10 year demonstration phase markup on variable cost prior to competitive margin setting by the fuel outlets, here the retail markup is fixed for the entire forty year simulation period. The test again illustrates a sweet spot in the markup optimal for successful transition. The markup must be high enough to support early station profitability and growth, but when too high it suppresses diffusion because the travel cost to drivers for hydrogen fuel is more than that for gasoline.

In comparison to the base run, all of these scenarios are inferior. The implication is that dynamics margins, responding the needs of the market are more effective. What is really needed is a high initial markup that gradually falls as the developing infrastructure creates exponential growth in fuel demand, reduced station costs via economies of scale, and stations become profitable even as margins continue to become more competitive.

Figure 50: Policy Test - 40 Year Fixed Retail Markup



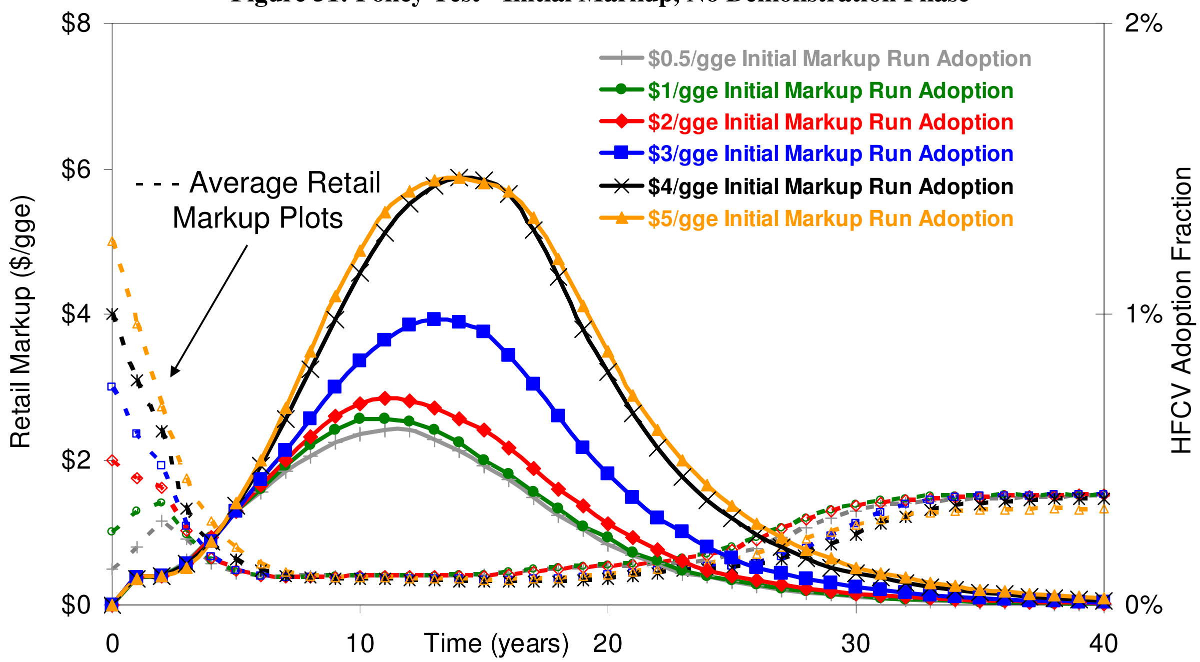
No Demonstration Phase Markups

The demonstration phase markup was included in the base run, but it is relevant to ask what type of system behavior occurs when the markup is immediately modeled as an endogenous function of cost and competitive pressures that factor into the retailer's retail price decision making.

Here the sensitivity of the initial markup at time zero is explored. Because the competitive pressures rapidly bring the markup to low levels, none of these scenarios results in sustained diffusion at any level. The adoption fraction grows no higher than 1.5% of households and eventually the system crashes as the marketing programs end. Higher initial markups do make a small difference in how high adoption peaks because the level of very early station entrance has lasting effects. Yet stations must be able to remain in business for successful diffusion.

This sensitivity test is a good illustration of the power of the markup policy and provides evidence for why it was included in the base run. One also observes that, as vehicle adoption crashes over the last twenty years, station managers do increase retail markups to try to cover costs in the face of falling demand. Balancing loops within the model do lead to intuitive behavior on the part of fuel stations. Yet the markup increases observed, combined with evaporating familiarity, are not nearly sufficient to overcome the significant transition barriers. Non-linear relationships in the system resulting from the network and complementary asset effects lead to market failure. Policy and coordination are imperative.

Figure 51: Policy Test - Initial Markup, No Demonstration Phase



Markup Policy Analysis Under Variations in Fuel Economy

Multivariate sensitivity analysis is used to more deeply understand the relationship of the markup policy, fuel economy, and tank size on adoption over the first twenty years and in equilibrium.

The highly non-linear relationship as markup is increased is clear in all cases. Yet the position of the adoption slope relative to fuel economy depends upon other assumptions such as vehicle tank capacity. Here we see that by decreasing the hydrogen vehicle's tank capacity from 8 kilograms to 6 kilograms, the slopes shift substantially to the left. Notably, at fuel efficiencies between 60-80 miles/gge, another steep gradient is observed in the year 40 adoption fraction plot (lower right) at higher retail markups, demonstrating how vehicle tank size affects the difficulty of the infrastructure development challenge.

Figure 52: Year 20/40 Adoption vs. Markup and Fuel Economy, 8 kg Tank Capacity

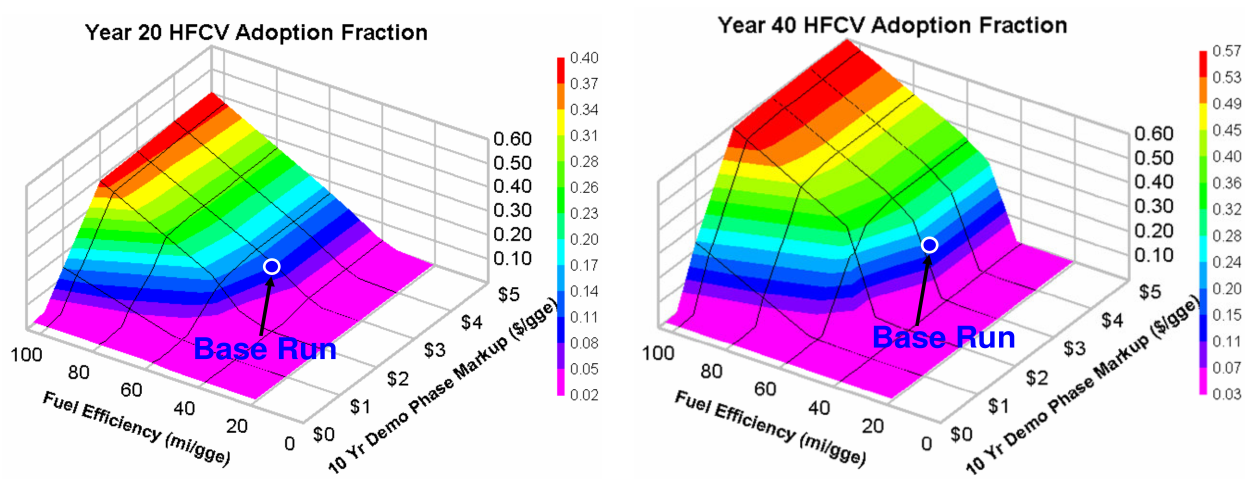
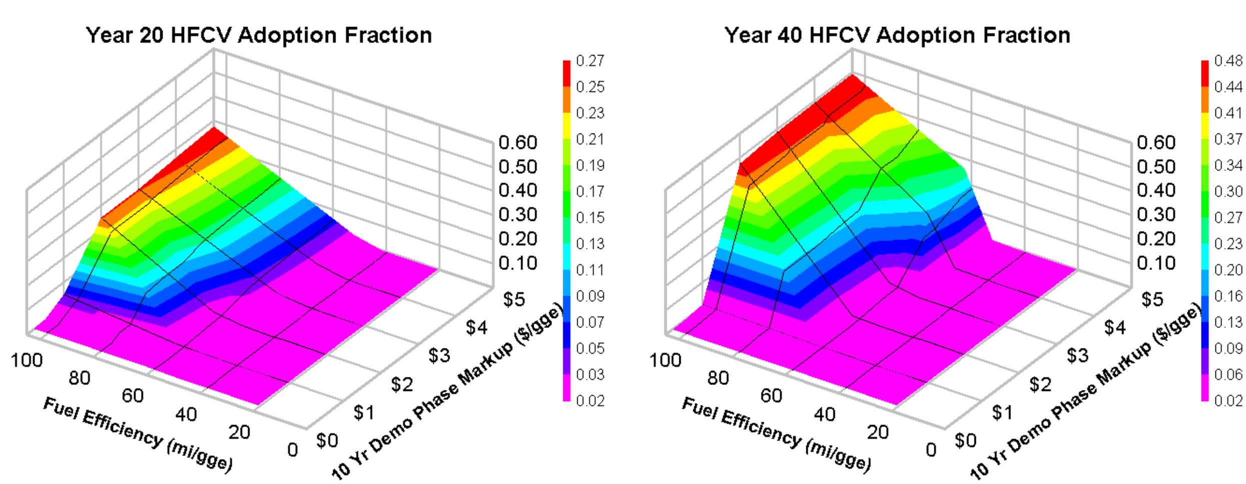


Figure 53: Year 20/40 Adoption vs. Markup and Fuel Economy , 6 kg Tank Capacity



Delayed Vehicle Subsidy Onset Time

Because vehicle subsidies are not effective without sufficient fuel station coverage, one strategy might be to delay vehicle subsidy policies until refueling convenience has improved. In this test, a 15 year subsidy of four thousand dollars per vehicle purchased is employed beginning at year 0 and at year 10, respectively. The cumulative net present value of the two vehicle subsidy programs is around the same order of magnitude. Even in the delayed onset case, however, the vehicle subsidies remain ineffective in boosting the speed of diffusion.

Figure 54: Policy Test - Delayed Onset of Vehicle Subsidy

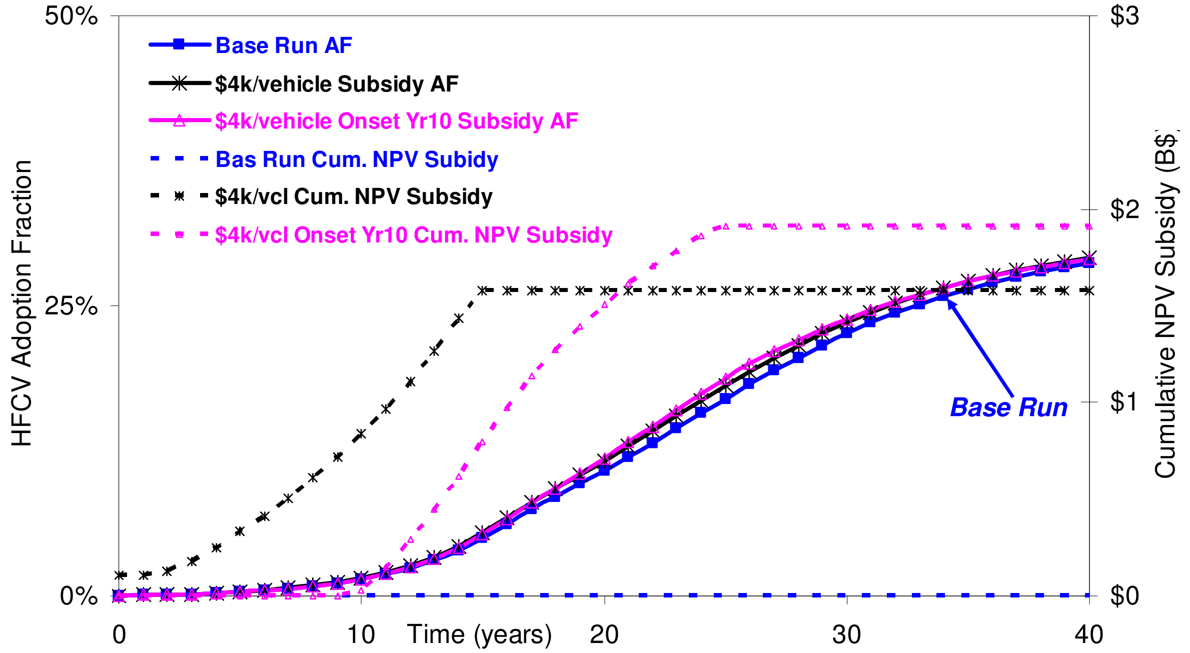
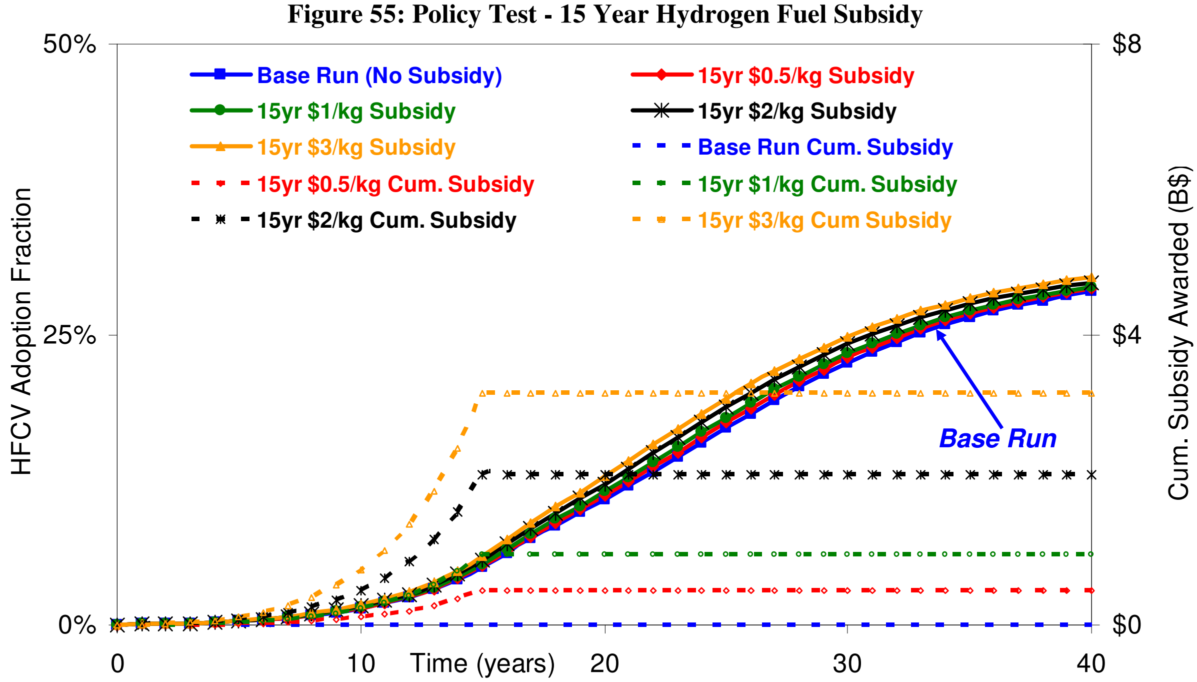


Figure 55: Policy Test - 15 Year Hydrogen Fuel Subsidy



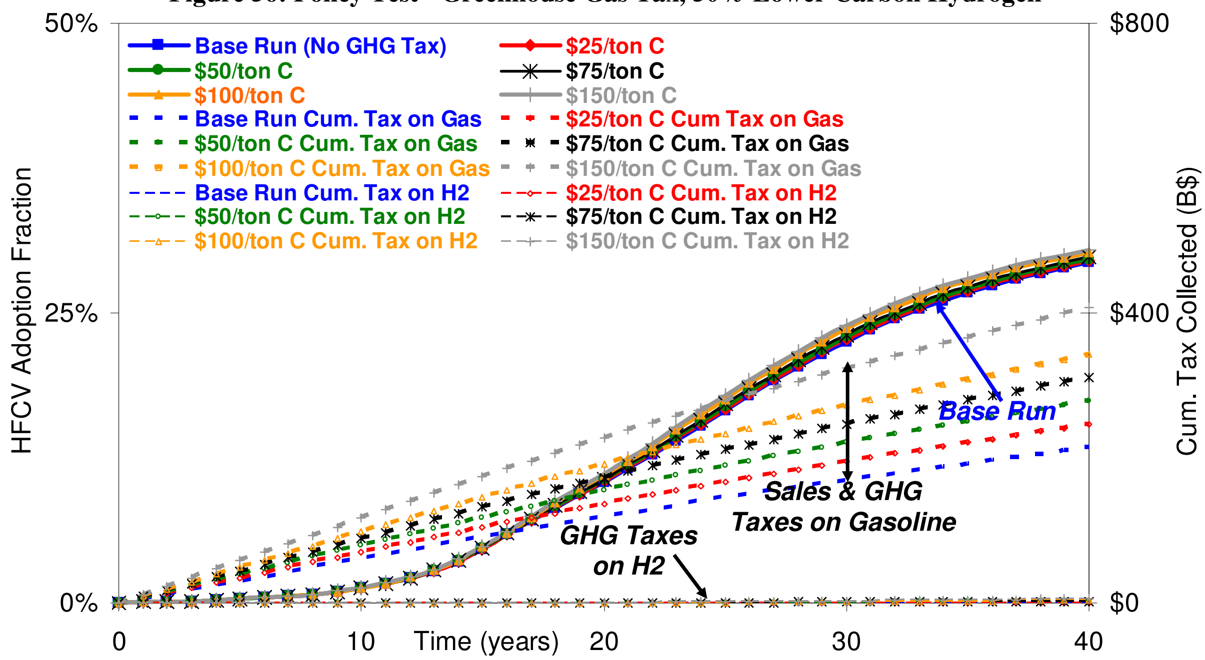
15 Year Hydrogen Fuel Subsidy

Earlier fuel subsidy policy testing portrayed the impacts of stable fuel subsidies over the entire forty year duration of the simulation. Are temporary fuel subsidies effective in accelerating the market beyond self-sustaining thresholds? Figure 58 indicates that the temporary boost provided by such a policy does lead to improved rates of diffusion. However, the subsidy's impact is again diluted by the high fuel economy of the hydrogen fuel cell vehicle. When the policymakers and their public are accustomed to retail transport fuel prices on the order of \$2-\$3/gge, will the idea of fuel subsidies on the order of more than \$3/gge be feasible? Education about energy efficiency is imperative to shift drivers to think of fuel cost in units per typical vehicle mile, rather than price per gallon delivered at the pump.

Greenhouse Gas Tax, Hydrogen with ½ GHG Emission Factor of Gasoline

Under this policy test, the well-to-wheel greenhouse gas emission factor is set at 5.6 kilograms carbon dioxide equivalent per kilogram of hydrogen delivered to the fuel tank. This assumption is much more optimistic than the base run setting informed by the GREET model, yet we also assume no increase in feedstock or capital costs. Even under such optimistic settings, the impact on diffusion of various levels of greenhouse gas taxes remains weak.

Figure 56: Policy Test - Greenhouse Gas Tax, 50% Lower Carbon Hydrogen

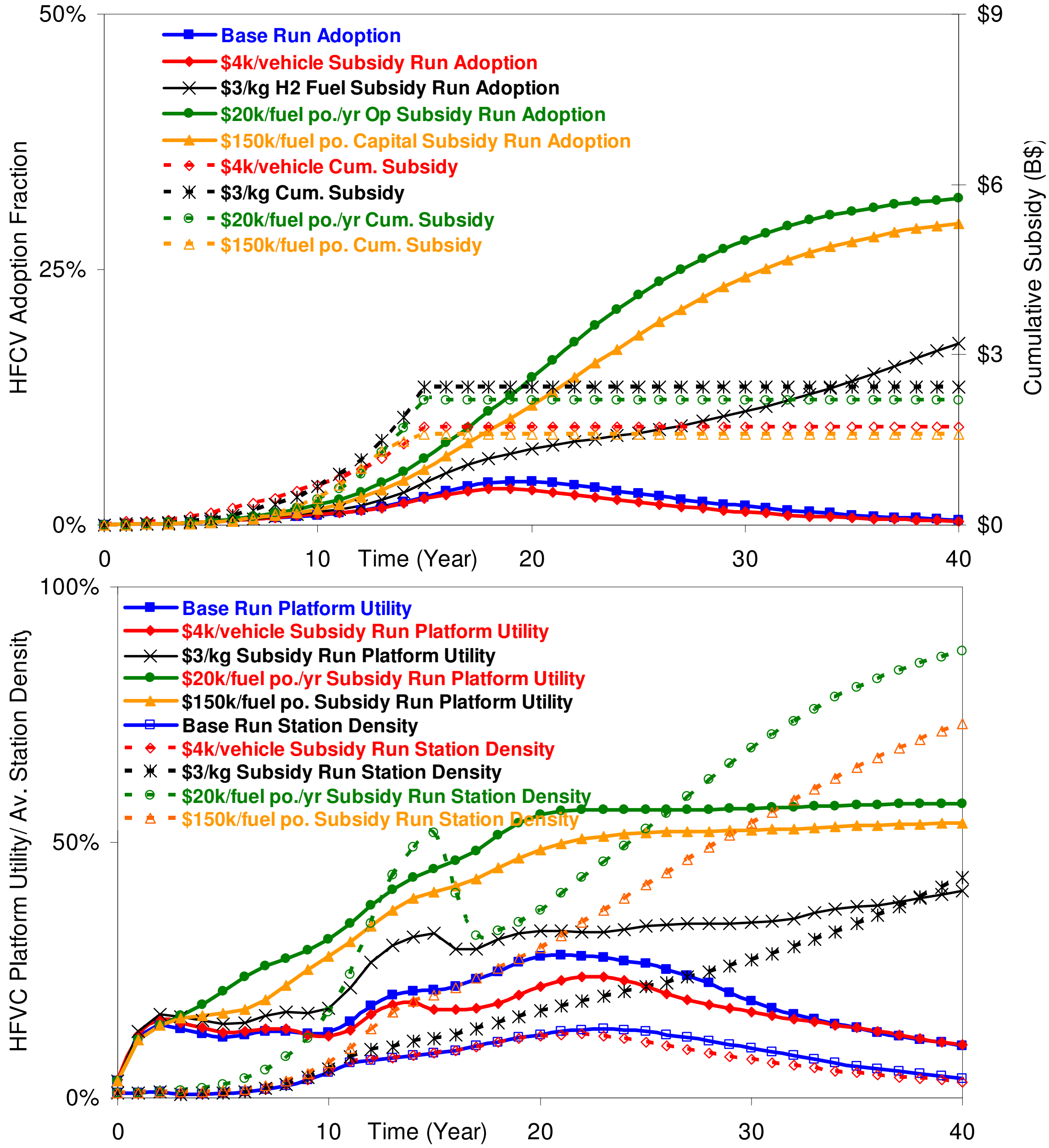


$2/gge Demo Markup "Failure Reference Case"

In the markup policy testing, it was observed that \$2/gge markup was too small, under base run assumptions, to move the system beyond the requisite thresholds for self-sustaining success.

In addition to policy testing using the successful base run a point of reference, it is useful to compare the impact of policies when they are applied upon a new reference base run in which diffusion crashes and fails. Here we apply and compare the same four policies tested in Figure 33. The results confirm earlier findings in the relative effectiveness of these policies. The station operating and capital subsidies bring the failure case to one of successful diffusion. Fuel subsidies do so, but to a much weaker extent. Yet, notably, the vehicle purchase subsidies actually have a chilling effect on adoption under these conditions. As depicted in the plot of platform utility, the vehicle subsidy does in fact result in increased HFCV attractiveness over the first four years compared to the other policies.

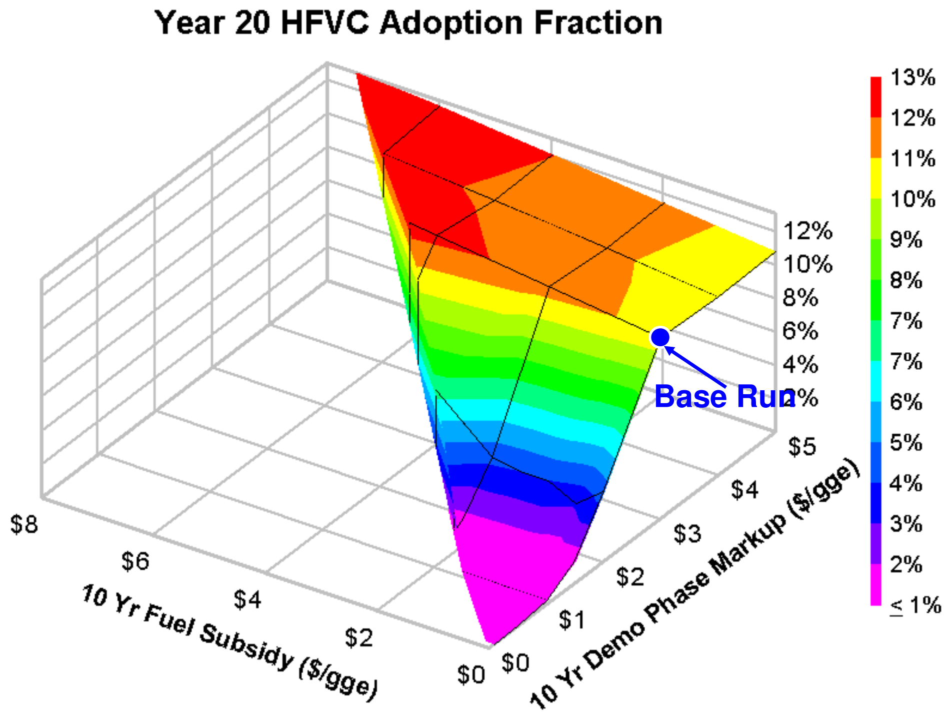
Figure 57: Comparative Policy Analysis, "Failure Reference Case"

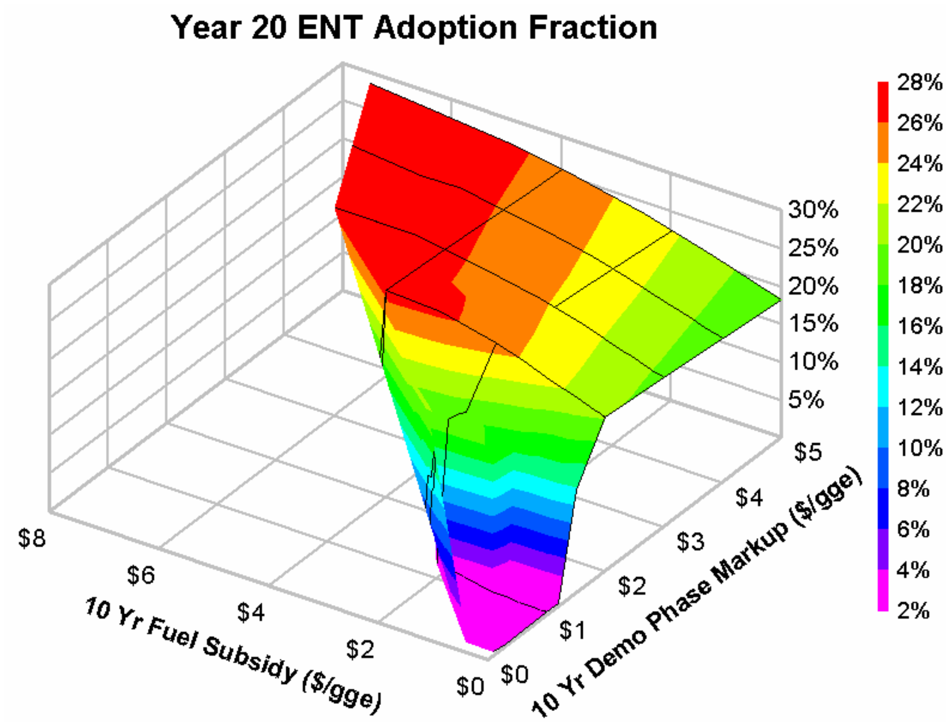


Yet because of the lack of fuel station incentives and development, the utility of the hydrogen vehicle overshoots and drops even below the failure case base run. An early incentive to purchase vehicles without sufficient coordinated efforts to grow fueling infrastructure leads to busier stations, more lines, station closures, unhappy HFCV drivers, and, in a highly path dependent system, actually leaves the market worse off. The coordination of policies to achieve balanced growth in the vehicle fleet and complementary assets is paramount.

In these plots, the multivariate policy sensitivity presented earlier is extended and refined for various conditions. Such visualizations reinforce the highly non-linear effect of the markup and the existence of a sweet spot near the tipping point. In comparing the two technology contexts, ENT's markup tipping point is lower due to the hydrogen vehicles higher fuel economy. For the same reason, ENT adoption falls more quickly as the markup increases beyond the threshold so long as a fuel subsidy is not used to compensate for the increased retail fuel price.

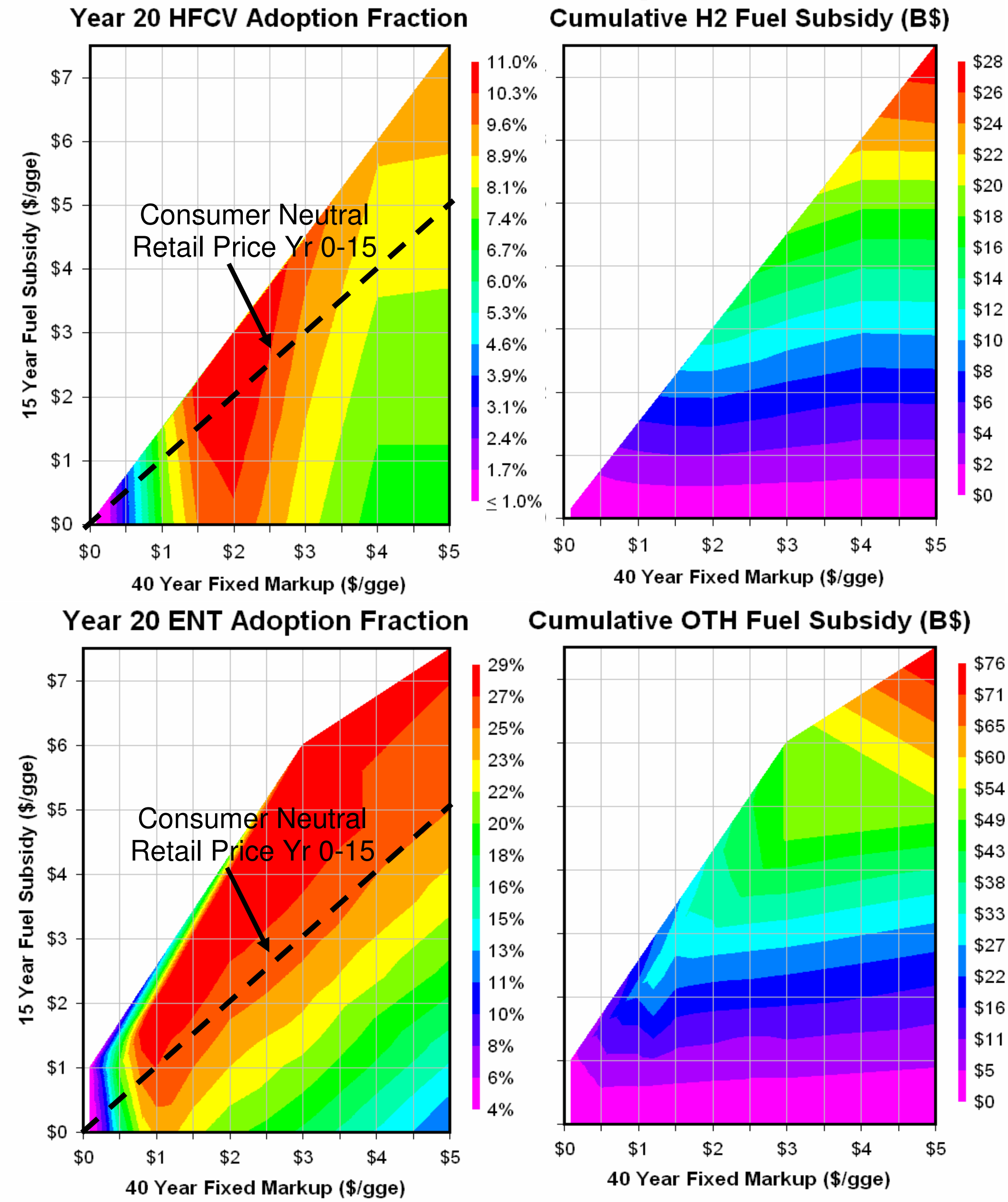
Figure 58: HFCV and ENT Adoption vs. 10 Year Markup and Fuel Subsidy





In this multivariate policy test, the retail markup is held constant for the full simulation duration and the fuel subsidy is in place for fifteen years. Again, subsidies make little difference at low markups. In this case, when the markup gets too high, the year 20 adoption fraction falls because the driver's fuel cost per vehicle mile becomes higher and closer to that of gasoline. As one travels along the dashed line indicating a consumer neutral fuel price during the subsidy, the high markups lead to less adoption because the fuel subsidy ends after year 15.

Figure 59: Multivariate Policy Testing: 40 Year Markup and 15 Year Fuel Subsidy



The pattern changes dramatically for the ICE-equivalent entrant, reinforcing again the lesson that effective policy must recognize and adapt to technology context.