



MIT Sloan School of Management

MIT Sloan Working Paper 4625-06
August 2006

Identifying challenges for sustained adoption of
alternative fuel vehicles and infrastructure

Jeroen Struben

© 2006 Jeroen Struben

All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission, provided that full credit including © notice is given to the source.

This paper also can be downloaded without charge from the
Social Science Research Network Electronic Paper Collection:

<http://ssrn.com/abstract=927012>

Identifying challenges for sustained adoption of alternative fuel vehicles and infrastructure

Jeroen Struben

jjrs@mit.edu

MIT Sloan School of Management, Cambridge MA 02142

August 2006

Abstract

This paper develops a dynamic, behavioral model with an explicit spatial structure to explore the co-evolutionary dynamics between infrastructure supply and vehicle demand. Vehicles and fueling infrastructure are complementarities and their "chicken-egg" dynamics are fundamental to the emergence of a self-sustaining alternative fuel vehicle market, but they are not well understood. The paper explores in-depth the dynamics resulting from local demand-supply interactions with strategically locating fuel-station entrants. The dynamics of vehicle and fuel infrastructure are examined under heterogeneous socio-economic/ demographic conditions. The research reveals the formation of urban adoption clusters as an important mechanism for early market formation. However, while locally speeding diffusion, these same micro-mechanisms can obstruct the emergence of a large, self-sustaining market. Other feedbacks that significantly influence dynamics, such as endogenous topping-off behavior, are discussed. This model can be applied to develop targeted entrance strategies for alternative fuels in transportation. The roles of other powerful positive feedbacks arising from scale and scope economies, R&D, learning by doing, driver experience, and word of mouth are discussed.

Introduction

In response to environmental, economic, and security related pressures on our current energy system, automakers are now developing alternatives to internal combustion engines (ICE). A diverse set of alternatives are considered ranging from promoting existing possibilities that run on alternative fuels, such as compressed natural gas (CNG), bio-fuels (such as E85), and diesel, to radically different hydrogen fuel cell vehicles (HFCVs), and to hybrid forms, such as hybrid electric-ICE vehicles (HEV-ICE). Current perspectives on the possibility of a successful transition to various alternative fuel vehicles (AFVs) are diverse. For example, concerning HFCVs, Lovins and Williams (1999) emphasize their long-term socio-economic advantages, while Romm (2004) stresses the current costs and performance factors that disadvantage hydrogen. Central to these debates are the various so-called chicken-egg dynamics “that need to be overcome” (National Academy of Engineering 2004) For example, drivers will not find HFCVs attractive without ready access to fuel, parts, and repair services, but energy producers, automakers and governments will not invest in HFC technology and infrastructure without the prospect of a large market (e.g. Farrell et al. 2003, National Academy of Engineering 2004). The non-compatibility of an infrastructure with that of the existing gasoline network is a major issue for most alternatives and past introductions of AFVs have yielded mediocre results, despite subsidies and promotions. Ethanol in Brazil, CNG in Argentina, and diesel in Europe are examples of large scale penetration and potentially self-sustaining markets. In contrast diesel in the United States and CNG in Canada and in New Zealand have fizzled after an initial period of sizzle. Most commonly however, whether they are gaseous-, liquid-, or flex-fuel vehicles or electrics (EVs), alternatives

fail to exceed penetration levels of a few percent (Cowan and Hulten 1996; Di Pascoli et al. 2001; Sperling and Cannon 2004; Energy Information Administration 2005).

The underlying dynamics are much more complex than simple chicken-egg analogies suggest. **Table 1** lists various sources for dynamic complexity for AFVs. First, competitive dynamics are determined by the interplay of several feedbacks: a transition towards any AFV, but especially towards HFCVs, involves building of consumer acceptance, automotive learning-by-doing that improves with production experience, co-development of complementarities, especially maintenance and fueling infrastructure, and investment synergies with non-automotive applications. Further, these interactions play out under a system of government incentives, but also in concert with public interest and media attention. Second, the system is distributed in various ways: a multiplicity of stakeholders has varying perceptions and conflicting goals (Bentham 2005); the adoption population is heterogeneous in physical and socio-economic space; and the alternative options for technology deployment are many and diverse. Third, elements in the system change with large time delays. Some of those elements are tangible, such as consumers' vehicle replacement times, while others are more difficult to observe, such as adjustment of consumers' perceptions of value, or of their familiarity with the technologies. Finally, many of these relationships are highly non-linear. For example, in the very early stages when there are few fueling stations, the marginal benefit of one or two additional fueling locations is very low for consumers but increases dramatically as the number of stations increases and returns to zero when stations are found on every corner.

The existence of such dynamic complexity in the early stage of a market formation process suggests that the evolution of new technologies such as these is likely to be strongly path dependent (David 1985; Arthur 1989; Sterman 2000). In such environments policymakers' and strategists' efforts to stimulate adoption can contribute to its failures. Consequently, in order to understand how policy can effectively stimulate adoption on a large scale, it is essential to have a quantitative, integrative, dynamic model with a broad boundary, long time horizon, and realistic representation of decision making by individuals and other key actors. Such a model should take economic, social and cultural, but also technical and physical parts of the system into account. This thesis lays the groundwork for a behavioral, dynamic model to explore the possible transition from ICE to AFVs such as hybrids, CNG, and HFCVs. **Figure 1** shows a conceptual overview of the main feedbacks in the model. The approach emphasizes a broad boundary, endogenously integrating consumer choice, as conditioned by product attributes, driver experience, word of mouth, marketing, and other channels, with scale economies, learning through R&D and experience, innovation spillovers, and infrastructure. The full scope for such a model is discussed in more detail in Struben and Sterman (2006).

In this paper I analyze one of the mechanisms in depth: the dynamics resulting from interactions between AFVs' adoption and the necessary fueling infrastructures. To support my analysis of the critical mechanisms, I develop a dynamic behavioral spatial simulation model. A full policy analysis requires a model that integrates infrastructure dynamics with the other feedbacks. However, such an integrated model will be complex and its behavior difficult to understand. This paper builds an understanding of the

complex dynamics surrounding the infrastructure question as a foundation for an integrated analysis. Similarly, other papers analyze other key feedbacks: Struben 2006a focuses on key interactions between consumer familiarity and adoption; Struben 2006b focuses on the dynamics of performance improvement of alternative fuel vehicles through learning-by-doing and R&D, and spillovers between them. The analysis in this paper as well as in the others provides an understanding of the dynamics that are associated with the integrated framework.

Understanding the dynamics that result from the interdependency of vehicle adoption and development of fueling infrastructure is critical for achieving the successful introduction of various AFVs. Infrastructure development is considered to be one of the biggest challenges for HFCVs (Farrell et al. 2003, National Academy of Engineering 2004, Ogden 2004), but is also central to diffusion of other AFVs, whether CNG (Flynn 2002), prospective bio-fuel vehicles, or even plug-in hybrids. While the dynamics result from demand externalities that lay behind the complementary character of vehicles and their fueling infrastructure, the actual underlying mechanisms are more subtle. Ascertaining when the market can be self-sustaining, or when incentives or coordination are critical - and if so, to what extent, and how - requires knowing how demand for fuel, vehicle adoption multiplied with desired travel behavior, grows with infrastructure as well as the economics of infrastructure supply in the early transition.

An earlier transition, from the horse-driven to the horseless carriage at the turn of the 19th century, with ICE as the eventual winner, can serve as a useful starting point for building

an understanding of the co-evolutionary dynamics between vehicle demand and fueling infrastructure. In those days ICE vehicles and the fueling infrastructure co-evolved gradually over time. Slow evolution was possible because the need for long-distance automotive travel had not developed. First, long-distance travel services were provided by the rail network, while proper roads, especially between settlements were virtually nonexistent. Second, there existed limited experience and familiarity with the idea of driving for pleasure. Third, cars frequently broke down. Together these conditions hardly provided incentives to extend the road network. Further, as touring by individual transport was a novelty in the early days of the automobile, the initial adopters were adventurous and willing to put up with inconveniences, such as the problem of finding fuel. Thus, early on proper refueling facilities were only required in urban settlements. Later, around 1900, gasoline also became available at local retail shops all over the country, allowing, in a period where touring became ever more popular and road construction grew, for a gradual diffusion of demand to more remote areas (Geels 2005). Thus, the emergence of a gasoline fueling network through local pockets that gradually connected to each other was a viable, though slow path for ICE in the early 1900s.

In contrast to this, contemporary consumers are accustomed to a dense, high-performing network of fueling infrastructure. Consumers demand high levels of service along the dimensions of availability, speed and convenience for all their trips. Such demands greatly constrain the viability of an alternative transportation fuel when the infrastructure is developing. Figure 2 (on left) illustrates the feedback that lays behind this, and what policymakers term the “chicken-egg” problem (Farrell et al. 2003). To increase the

attractiveness to drive, the availability of fuel needs to be sufficient, and likewise, without considerable expectations about demand, investors have no confidence to invest in and commit to building and expanding a significant fueling infrastructure. Figure 2 (on right) illustrates the conditions for such a tipping point graphically. It depicts vehicle demand as a function of the number of stations. Starting with only one fueling station, no one is willing to adopt, or drive. When the fueling infrastructure grows, demand grows at increasing rate as more factors favor adoption: initially only short trips for a few are covered, subsequently some people can also make longer trips and trips for those already covered are more convenient. This encourages more adoption and more consumption per vehicle. Demand growth flattens when the average station distance becomes small enough, not bringing significant additional benefits to drivers, and eventually demand becomes irresponsive to an increase in the number of fueling stations. Assuming cumulative industry costs of fuel supply grow linear with infrastructure, the S-shaped demand curve intersects the cost curve at a critical point, above which the industry is profitable and the market is self-sustaining.

In order to test this hypothesis, I analyze the detailed mechanisms underlying the, thus far high-level, concept of chicken-egg dynamics. Rather than treating fuel station development as independent, various sources of dynamic complexity - feedbacks between demand and supply, distributed decision making, time delays and non-linearities are taken into account. Further, it is critical to appreciate that feedback between fuel supply and demand is mediated through interactions that are non-uniformly distributed in space. For example, households in urban areas will not be satisfied with fuel services

limited to their home locations. They also want to make long trips. An urban dweller living in San Francisco, also wants to make an annual trip to the Yosemite national park, or to Las Vegas and they require fueling infrastructure in these distant places. The consumer's utility includes the distribution of stations through space. This interaction in space, across settings with a heterogeneous population distribution, strongly contributes to the non-linear and distributed characteristics of the transition dynamics (Table 1 has the spatial component explicitly listed). In this paper the chicken-and-egg dilemma is explicitly modeled by considering consumers' choice for adoption, driving and refueling, as well as the fuel station entry, exit and capacity adjustments in response to and anticipation of fuel demand developments. These infrastructure developments in turn feedback to change the consumer's trip convenience. ¹

This paper begins with a brief motivation of the modeling approach and an exposition of the conceptual model. Next I present the formulation of the spatial dynamic behavioral model and the analysis that is based on the simulations of the model. While the model is generally applicable, the analysis uses the state of California as a laboratory. I discuss the finding that low adoption levels, with clusters concentrated in urban areas, form a bi-stable equilibrium. I identify and discuss the technical and economic parameters to which the dynamics are particularly sensitive. Finally, the counterintuitive finding that the introduction of more fuel efficient AFVs can yield larger thresholds for a successful

¹ An earlier version Struben (2005) generated the insight of clustering through a one dimensional spatial model with a short patch length. The current model develops a much richer structure, provides deeper insight into the dynamics and the role of various other feedbacks, and explores alternative policies and strategies, including supply/demand side subsidies/taxes. Further, it allows for calibration.

transition is discussed. The analysis demonstrates that the behavioral assumptions are critical to understand such phenomena. In the conclusion and discussion section I suggest that relying on the standard assumptions, such as exogenous demand or supply is problematic. To understand how policy can effectively stimulate AFV adoption on a large scale, a quantitative, integrative, dynamic model with a broad boundary, long time horizon, and realistic representation of decision making by individuals and other key actors is essential. The paper ends with a discussion of implications for policy, in particular for the transition challenges for AFVs, and further work.

Modeling spatial behavioral dynamics

The existence of chicken-egg challenges between AFV adoption and fueling infrastructure development are well known (e.g. Farrell 2003; Ogden 2004; National Academy of Engineering 2004). However, a careful analysis of the co-evolutionary dynamics of market formation of AFVs and fueling infrastructure has not been conducted. I conduct such an analysis. Vehicles and their fueling infrastructure are strong complementarities (Katz and Shapiro 1994). However, their short and long-range interactions result in significantly more complex issues than basic hardware-software analogies justify. Before laying out the conceptual model, I discuss briefly existing approaches to problems that have a spatial, behavioral and/or dynamic character.

Transportation and travel research has a long history of modeling demand and supply in space (e.g. Fotheringham 1983). This research has mainly focused on identification of least cost optima (e.g. Collischonn and Pilar 2000), or equilibrium (e.g. Lefebvre 1958)

distributions, and has grown enormously since Dijkstra (1959) published his shortest path algorithm. However, to allow for a detailed computation of trajectories, there is limited room for dynamics. In most of these studies either the demand or the supply side is assumed to be fixed over time. Such approaches are suitable for problems of more static character - explaining the existence of certain equilibria of travel demand -or to study the effect of an optimal solution to marginal changes within an established system - the impact of a new highway on current traffic flows. This model benefits from particular concepts developed in this literature, such as shortest path algorithms and gravity demand models. However, the market formation processes associated with AFV transitions involve situations of disequilibrium and the potential existence of multiple equilibria requires focus on the dynamic interrelationship of supply and demand.

Interest in the formation of spatial patterns through reinforcing and balancing feedbacks took-off after Turing (1952) introduced physio-chemical diffusion reaction structures, or “Turing Structures”. Such patterns are likely to be found where the movement and range of influence of actors is small compared to the global scale, leading to strong local correlations. With increases in information processing capabilities, problems throughout the sciences including problems in statistical physics (e.g. Ising models), material physics (crystal growth and the process of solidification, or dendrites (Langer 1980)), and organic surface growth (diffusion limited aggregation, (e.g. Witten and Sander 1981)) were addressed. Similar trends are found in the social sciences, for example in aggregation and geographical economics (Krugman 1996).

The field of economic geography has a longstanding history in spatial dynamic problems, appreciating that the actual location of activity deviates from the optimum location (Lösch 1940; Christaller 1966). Modern, formal applications focus on the tension between “centripetal” and “centrifugal” forces regarding geographical concentration (Krugman 1996). While dynamic, these models seek to filter out core mechanisms from each of the two competing forces that are perceived to be dominant (Fujita and Krugman 1999, 2004). With little prior understanding of the dynamics of the system, as is the case with technology transitions as the AFVs, a richer set of behavioral feedbacks needs to be included. In this case, it is the combination of spatial heterogeneity with the detailed behavioral feedbacks that gives rise to the dynamic complexity.

The dynamic behavioral spatial model presented in this paper demonstrates that relaxing the assumption that supply and demand directly adjust to clear the market, and including many of the behavioral aspects, leads to transition dynamics that are more diverse than can otherwise be observed. The model captures endogenous driver behavior including decisions regarding the adoption of AFVs, the mode of transportation (AFV, or other) for each trip, where to refuel, and “topping off” behavior. These decisions are influenced by driver concern for the risk of running out of fuel, service times, and how far one has to go out of one’s way for refueling. Similarly, on the supply side, decisions about fueling stations, entrance, exit, location and expansion decisions are endogenous. These behaviors mediate interactions that are different over short- and long-distance and could drive dynamics that cannot be observed with mean-field approaches.

Figure 3 provides a spatial representation of the model structure and illustrates at a high level how interactions between supply and demand are captured. For illustration a grid structure is shown overlaying an area representing greater Los Angeles. The area is divided into patches, or zones, the darker ones having a larger household density. Households locations are indicated by index z .² Households wish to make trips to various places outside their patch location, for work, leisure, and other purposes. While any set of desired trips can be generated, and thus various types of drivers can be represented, in this paper the distribution of trip destinations z' is assumed to be lognormal in their length l , and randomly distributed in direction θ . I capture boundary constraints properly by disallowing non-feasible trips, such as those that would lead into the ocean. For each zone, the average household's trips are normalized to equal the average vehicle miles of the population. The actual trip choice is endogenous. Drivers will choose whether and how often to travel to a particular location based on their assessment of how difficult the trip will be, including the travel time, the risk of running out of fuel, and the likely extra time and effort involved in finding fuel (the need to go out of their way to find fuel if it is not available on their main route). Similarly, households select between vehicle platforms depending on perceived utility of using it for the trips that they desire to make. The location of fueling infrastructure is also endogenous. Station entry and exit are determined by the expected profitability of each location, for example in zone z' , which, in turn, depends on the demand and expected demand for fuel at that location and the density of competition from nearby stations.

² Throughout this Essay I will use zones and patches interchangeable, the first representing the geographical boundary, and the second being the formal term used in spatial models.

For the analyses, I define the patch sizes such that heterogeneity at the scale of typical trip behavior is captured. For more specific analysis, the model can be setup with a finer grid, and with more technical detail, however this will put significant pressure on scarce resources, as they dramatically increase computation time, make analysis harder. Finally, lower level provides significant data challenges. Most importantly however, as I will justify in the analysis, a finer level of detail contributes noise, but does not change the fundamental dynamics. For the same reasons the model does not include technical details, such as traffic flows, or highly disaggregated agents, representing large variation of consumer types.

Figure 4 shows a conceptual overview of the main feedback loops in the model that result from behavioral assumptions. Feedback (R1) describes the basic chicken-egg dynamics. An increase in the number of stations of platform i in a zone z , lowers refueling efforts for trips to or through z for households living in a nearby zone z' (depending on their normal trips to/through that area). This increases the attractiveness of driving and raises platform i 's market share in that area. A larger number of adopters generates more demand around z , increasing station utilization, sales and finally profitability, contributing to industry-level profits, which increases fuel station entrance for this platform (B1), until fuel station sales and profits are reduced to critical levels. However, those who have already adopted the platform also experience a decrease of trip efforts, induced by a higher number of stations, which leads to an increase of the fraction of trips for which the alternative vehicle is used, rather than a conventional vehicle or

other transport modes (R2). High station utilization is good for profitability, but also leads to increased crowding (B2), requiring an increase in the drivers' efforts to refuel, and thus lowering their adoption, and likewise lowering vehicle miles through that region. Finally, within a zone z , higher profitability also leads to a larger share of the entrants in that particular zone (R3), fewer exits (R4), and capacity expansion (B3) (more pumps), by existing stations. Finally, while not explicitly shown, in response to an inconvenient distribution of fuel along the route, drivers can raise the tank level at which they top off (topping off well before the warning light goes on). For this they trade off an increase in refueling effort for the need to go out of their way to refuel.

These concepts together define the inherent spatial, dynamics between vehicle fleet demand and fueling infrastructure. Combined with other feedbacks, this structure governs the co-evolutionary dynamics among the elements of an alternative-fuel-based transportation system. However, for analytical clarity the model is restricted to the interactions between infrastructure and vehicle demand only.

The Model

In this section I provide an exposition of the model: the demand-side structures for vehicle adoption; the trip, route, and refueling choices. This is followed by a more detailed discussion of the components of trip effort and the supply-side decisions, including entrance, exit, and capacity adjustment.

Adoption

The total number of vehicles for each platform $j = \{1, \dots, n\}$, in region z , V_{jz} , accumulates new vehicle sales, s_{jz} , less discards, d_{jz}

$$\frac{dV_{jz}}{dt} = s_{jz} - d_{jz} \quad (1)$$

Ignoring the age-dependent character of discards, and assuming a total fleet in equilibrium, this implies that purchases only involve replacements:³

$$s_{jz} = \sum_i \sigma_{ijz} d_{iz} \quad (2)$$

where σ_{ijz} is the share of drivers of platform i living in location z replacing their vehicle with platform j .

Consumers base their adoption decision on a range of vehicle attributes: vehicle price; power; operation and maintenance; safety; drive range; effort and cost of driving. I capture this by integrating diffusion models with discrete consumer choice theory (McFadden 1978; Ben-Akiva and Lerman 1985). These are often applied to transport mode choice (Domencich et al. 1975; Small et al. 2005), and automobile purchases (Berry et al. 2004; Train and Winston 2005), including alternative vehicles (Brownstone et al. 2000; Greene 2001). Then, the share switching from i to j depends on the expected utility of platform j as judged by the driver of vehicle i , in location z , u_{ijz}^e . Hence,

$$\sigma_{ijz} = u_{ijz}^e / \sum_j u_{ijz}^e \quad (3)$$

³ See appendix 1a of Essay 1 for the age-dependent structure and appendix 1b of Essay 1 for the initial sales structure.

While drivers may be generally aware that a platform (such as CNGs or HFCVs) exists, they must be sufficiently familiar with that platform for it to enter their consideration set, which I model in Struben 2006a by its degree of familiarity F_{ijz} , with $u_{ijz}^e = F_{ijz} u_{ijz}$, where u_{ijz} is the perceived utility of platform j by a driver of platform i in region z . Further, for those platforms considered, expected utility depends on perceptions regarding the set of vehicle attributes a_{ijlz} which represents the performance of platform j with respect to attribute l , for a driver of platform i in region z . Driver experience with and perceptions about various characteristics of each platform may differ significantly even if individuals have identical preferences. For example, drivers of HFCVs experience the actual availability of hydrogen fueling stations in their local environment. However, drivers of other platforms who consider buying a HFCV have to learn about these services through various indirect channels, and do not know the exact levels of convenience for their trips. Similar issues relate to attributes associated with vehicle performance. This diffusion process of knowledge about attribute performance is discussed in Struben 2006a which shows that it has a significant impact on adoption dynamics. While the socialization dynamics associated with drivers' familiarity and consumers' learning about the performance of the various platforms are important for overall dynamics, here I focus purely on dynamics related to the demand and infrastructure. Therefore I set

$F_{ijz} \equiv 1 \forall i, j, z$ and $a_{ijlz} \equiv a_{jlz} \forall i$, where a_{jlz} is the perceived performance of an attribute l to any consumer in z . Consequently, expected utility is identical for all drivers, and equals utility based on the perceived efforts a_{jlz} part of the set L , $u_{ijz}^e = u_{jz}$.

Appendix 3a of Struben 2006b discusses the general structure capturing the relevant attributes, and their changes, in more depth. Of the many relevant attributes, only the trip convenience is directly affected by the abundance of fuel stations and is thus a central attribute, which yields a utility contribution u_{jz}^t . This component will be discussed in the next section. For arguments of consistency, the model must explicitly capture those attributes that are affected by parameters that vary supply and demand elsewhere in the model. For example, the maximum action radius of a vehicle (which correlates with, but is not identical to, trip convenience), influences not only a consumer's purchase decision, but also influences the number of fuel station visits by drivers, and thus utilization; supply is affected in a non-trivial way. For the same reason, we capture operating cost (which is a function of fuel price that also affects supply) and fuel economy (which affects demand, as well as fuel station visits). We capture these under attributes a_{jlz} . All other attributes by which AFVs may differ, such as vehicle power and footprint, are aggregated under the vehicle-specific term u_{jz}^0 . Using the standard multinomial logit formulation we can now state:

$$u_{jz} = u_{jz}^0 u_{jz}^t \exp \left[\sum_l \beta_l \left(a_{jlz} / a_l^* \right) \right] \quad (4)$$

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

Trip, route, and refueling choice

Consumers not only decide to purchase vehicles but also how to use them – their driving patterns. Drivers wish to take trips to various places around their home for work, leisure, and other purposes. But trip choice is endogenous. Drivers will choose whether and how often to travel to a particular location based on their assessment of the difficulty of

the trip. Drivers select their favorite routes and refueling locations as a function of the availability of fuel.

Determination of refueling effort is explained later. **Figure 5** illustrates how the motivations for consumers' adoption choice, and drivers' trip, route, and refueling choices are captured. The diagram on the left shows the high-level structure: first, as discussed above, consumers in region z , decide on adoption, with share σ_{iz} going to the i -th platform. This share depends, among other factors, on the utility component u_{iz}^t to adopt an AFV. Similarly, the fraction of trips from one's home z to destination z' for which the AFV is used, $\sigma_{izz'}$, conditional upon prior adoption, depends on their utility to make that trip $u_{izz'}$. Further, consumers' aggregate utility to drive u_{iz}^t depends on the utility derived from making each trip, weighted by $w_{zz'}$. Going further down the diagram, for each trip, consumers decide on the route to follow, with share $\sigma_{i\omega_{zz'}}$ depending on the relative utility for each route one might consider taking, $u_{i\omega_{zz'}}$. This route utility, also determines the trip effort of the average consumer in z $u_{izz'}^t$, weighted by its shares. Finally, in a similar fashion, drivers decide where to refuel along the route, $\sigma_{i\omega_{zz's}}$. The refueling effort is determined by other factors that will be explained later.

The right-hand side of **Figure 5** shows the functional forms that determine the share and the effort variables. For each choice type the share is determined through a logit-expression, as listed in column 1. For example, row 1 describes the derivation for the vehicle adoption share and average efforts to drive that have already been discussed.

Columns 1-2 yield exactly equations (3) and (4) for the vehicle choice decision. A driver's trip choice involves a driver i 's decision on the mode of transportation for a trip from z to z' . The fraction of trips that their alternative vehicle is used depends on the utility for that trip, $u_{izz'}^i$, compared to using another mode of transportation that is available $u_{zz'}^o$.

The experienced utility of driving is a non-linear, weighted average of the various trips, as shown by column 3 in **Figure 5**. To represent the effort, several functional forms are possible. The form used and shown in column 3 is the constant elasticity of substitution (CES) function (McFadden 1963; Ben-Akiva and Lerman 1985; see Struben 2006b and its Appendix 2e and Appendix 3a for expansions on this function). Households' total trips from/to an area (trip generation), combining residential and job locations and trip distribution (location of these trips) are constant. This generates a desired trip frequency distribution per household, $T_{zz'}^{\max}$. The utility to drive is a weighted average over the utility derived from each trip that is part of a driver's desired trip set $T_{zz'}^{\max}$. The weight $w_{zz'}$ can be a function of anything, but I assume it increases with frequency and distance. For example, long-distance trips, while less frequent, could be considered very important (see Appendix 4a <http://web.mit.edu/jjrs/www/ThesisDocumentation/Struben2Appendix.pdf>):

$$w_{zz'} = g(r_{zz'}; T_{zz'}^{\max}) / \sum_{z' \in T_z^{\max}} g(r_{zz'}; T_{zz'}^{\max}) \quad (5)$$

The parameter μ^i of the CES function can be interpreted as follows: the case where individual consumers make only one unique type of trip corresponds with $\mu^i \rightarrow 1$, which means that utility captures the weighted average across all trips, and the expression of

vehicle share converges to a standard multinomial logit expression. The case in which individuals make many distinct trips corresponds with $\mu^t < 1$, with the extreme case being $\mu^t \rightarrow \infty$, where perceived utility of driving equals that of the individual trip that is perceived to provide the worst utility (in this case trips can be seen as full complements of each other). In the special case $\mu^t = 0$, the aggregate utility equals the utility of the (weighted) average trip.

Going further down the hierarchy, in **Figure 5**, the modal choice (Small 1992) of each trip is endogenous and depends on the fraction of trips between z and z' that are taken with the alternative fuel platform i , $\sigma_{izz'}$, with the actual frequency of trips for drivers living in z , owning platform i , with destination in z' , with platform i , $T_{izz'} = \sigma_{izz'} T_{zz'}^{\max}$. Small (1992) offers a long list of factors that influence drive effort, including travel time, on-time arrival fraction, operating cost, parking. Here we concentrate on the role of fuel availability. We differentiate i) the normal drive time for a route ω between z and z' , $a_{\omega_{zz'}}^{t0}$, without any refueling; ii) the factors that depend on the availability of fuel, which include the risk of running out of fuel, and the likely extra time and effort involved in finding fuel (the need to go out of one's way to find fuel if it is not available on the main route), which are experienced in the location s where one seeks to refuel, a_{is}^f ; iii) all other factors are aggregated in one effect on trip utility $u_{izz'}^0$.

The share of trips between z and z' taken by platform i is derived through a binomial choice expression, comprising the utility to drive trip $u_{izz'}^t$, of driving trip zz' with platform i , and the combined alternative u_{zz}^o , (capturing alternative modes of transportation and the opportunity cost of not going). A driver's trip utility is the composite over routes that are part of the route set for trips from z to z' , However, in this case, it is assumed that individual drivers have one favorite route (which can be adjusted), and $\mu^\omega \rightarrow 1$. Working our way down **Figure 5**, the perceived effort to drive an individual trip is experienced on the route. The elasticity parameter β^ω represents a driver's sensitivity to changing routes. If the sensitivity would be large, different drivers would tend to take the same route. The average route effort, $a_{i\omega_{zz}'}^t$, is approximated by the sum of the route effort, in absence of refills $a_{\omega_{zz}'}^t$, and the expected refills per trip, $\phi_{i\omega_{zz}'}$, multiplied by the average effort of refueling (see Appendix 3b), which is the sum over refueling at any location, $a_{i\omega_{zz}'}^f = \sum_{s \in \omega_{zz}'} \sigma_{i\omega_{zz}'s} a_{is}^f$, weighted by the refueling share.

Finally, drivers adjust their refueling behavior and driving, based on variation in perceived effort utility of refueling for trip zz' . The refills along the route that locations s receive, with share of the total $\sigma_{i\omega_{zz}'s}$, depends on the length of the route that passes through an area $r_{\omega_{zz}'}$, but also on the effort it takes to refuel, within each location.

The ability to select more convenient locations depends critically on refueling behavior. Frequently running the tank down close to empty implies the consumer constrains

himself to refueling at locations available when the tank is empty, which would imply refueling shares are constrained to be according to the relative distance that is driven through each location. Such behavior works well when stations are abundant everywhere, as is currently the case with gasoline, and reduces the frequency, and thus total effort, of refueling. At the other extreme, however, when topping-off occurs at extremely higher tank levels (before the warning light goes on), the freedom of choice for refueling becomes limited again. When top-off levels are between these two extremes, the freedom to select those locations that are most attractive for refueling is larger (at the expense of increased refueling frequency). The tank level (converted to miles) available when consumers refill is referred to as the buffer. The number of miles driven between a full tank and top-off is referred to as the effective range (see Figure 6).

More formally, the effective range between two refills r_{iz}^f equals the maximum range r_i^f minus the average buffer that remains when refueling, r_{iz}^b :

$$r_{iz}^f = r_i^f - r_{iz}^b \quad (6)$$

where $r_i^f = \eta_i^f q_i$, with η_i^f the fuel efficiency and q_i the energy storage capacity of a tank. The refueling sensitivity parameter β^f determines the sensitivity of refueling shares that go to the various locations to a change in the consumers perceived utility to refuel. (see **Figure 5**). Running the tank always empty does not give any freedom of choice to select a more favorable location, thus, $r_{iz}^b \rightarrow 0 \Rightarrow \beta^f \rightarrow 0$. Reducing the effective tank range too much provide the same constraints, $r_{iz}^b \rightarrow r_i^f \Rightarrow \beta^f \rightarrow 0$. However, when the

buffer and effective range are on the order of the trip length, the freedom of choice is

large, or, $r_{iz}^f / r_{i\omega_{zz}}^t \wedge r_{iz}^b / r_{i\omega_{zz}}^t \cong 1 \Rightarrow \beta^f \rightarrow \beta_{ref}^f$. Then we can state:

$$\beta^f = \beta_{ref}^f g\left(r_{iz}^b / r_{i\omega_{zz}}^t\right) h\left(\left[r_{iz}^f - r_{iz}^b\right] / r_{i\omega_{zz}}^t\right); \begin{cases} g(0) = 0; g(1) = 1; g' \geq 0 \\ h(0) = 0; h(1) = 1; h' \geq 0 \end{cases} \quad (7)$$

Where β_{ref}^f is determined by the physical constraints of refueling elsewhere. Typically, the functions h and g can be expected to be concave because of the increasing effect of the physical constraint of refueling. Appendix 2a provides the functional forms used in the model.

Finally, the length of trip equals the sum of the normal route and average distance when refilling, which equals the refills per trip, $\phi_{i\omega_{zz}}$, multiplied by the average distance one is required to go out of the way for refueling,

$$r_{i\omega_{zz}}^t = r_{\omega_{zz}}^t + \phi_{i\omega_{zz}} \sum_{s \in \omega_{zz}} \sigma_{i\omega_{zz},s}^f r_s^f \quad (8)$$

See Appendix 3c for the derivation of the refills per trip. This completes the formulation of the consumer decision-making processes regarding adoption, trip choice, route choice, and refueling location. The endogenous component that affects all of these is the trip effort explained below.

Components of trip effort

The normal effort for a route is expressed in time units and is given as

$$a_{\omega_{zz}}^{t0} = \tau_{\omega_{zz}}^d = \sum_u r_{\omega_{zz},u}^t / v_u \quad (9)$$

The speed may depend on the region, for example, the drive time associated with driving an extra mile in a congested urban area is much longer than on a rural highway.

We model the experienced refueling effort in each location as a weighted sum of: (i) the effort to find fuel a_{is}^d , which depends on the time spent driving out of one's way to reach a fuel station; (ii) the risk of running out of fuel a_{izs}^r , which depends on vehicle range and the location of fuel stations relative to the driver's desired refueling needs; and (iii) servicing time a_{izs}^x , which depends on wait times resulting from local demand being higher than the refill capacity at fuel stations. The experienced trip effort in location s is the weighted sum of each of these three components:

$$a_{izs}^f = w^d a_{is}^d + w^r a_{izs}^r + w^x a_{izs}^x \quad (10)$$

The relative value of the weights w^d , w^r and w^x can be interpreted as the relative sensitivity of a driver's utility to a change in these effort components. The out-of-fuel risk involves a cost and time component. The drive and service time both involve time components, but the experience of time is not necessarily the same in each case. A large body of transportation research is devoted to how commuters and other travelers value their time (e.g. Steinmetz and Brownstone 2005); reliability (e.g. Brownstone and Small 2005); and related attributes (e.g. Small 1992; McFadden 1998; Small et al. 2005). The perception of time or cost associated with additional trip efforts may vary considerably by type of trips (recreational, business), individual, and activity (waiting in line to refuel vs. driving to a station). This explicit formulation allows taking the valuing of time into consideration, if it is deemed to be importantly influencing the dynamics. Appendix 5a provides a discussion of the elasticity of utility to a change in the various components.

The effort to find fuel is expressed as the search time, which is the average distance to a station divided by the average driving velocity in region s :

$$a_{is}^d = \langle r_{is}^d \rangle / v_s \quad (11)$$

The value of $\langle r_{is}^d \rangle$ depends on fuel station density and can be analytically derived, which is done in appendix 3d.

The second component of driving effort, the perceived risk of running out of fuel within region s can be captured by assuming that a combination of experiences and individual assessments yield results that are qualitatively similar to the expected out-of-fuels per refill $\langle o \rangle_{isz}$ within a region s :

$$a_{isz}^r = \langle o_{isz} \rangle \quad (12)$$

Expected out-of-fuels is found by integrating over the probability of not reaching a station within its range, with the refueling buffer r_{iz}^b being the average. The probability further decreases with station density in region s , and increases with the required distance driven through that region s . Its full derivation is provided in appendix 3e.

Finally, the service component of the effort attribute is determined by the average servicing time at the station

$$a_{isz}^x = \tau_{isz}^x \quad (13)$$

Figure 7 shows the main idea of the structure for servicing time. This expression comprises waiting in line, which depends on station utilization, and the actual refueling time:

$$\tau_{izs}^x = \tau_{izs}^w + \tau_{izs}^f \quad (14)$$

The refueling time has a variable component of actually operating the pump and a fixed component (including paying and purchasing ancillary products), $\tau_{izs}^f = \tau_{izs}^p + \tau_i^0$. The variable component is a function of the quantity demanded and the capacity of the pumps:

$$\tau_{izs}^p = q_{iz} / k_i^p \quad (15)$$

Average quantity demanded depends on tank capacity, adjusted for the effective top-off levels (see Equation(6)):

$$q_{iz} = q_i \left(r_{iz}^f / r_i^f \right) \quad (16)$$

The wait component in equation (14) depends on the average demand versus capacity.

The expected time that customers must wait depends very non-linearly on the station utilization and the number of pumps, as suggested in **Figure 7**. When the number of pumps is relatively high, say 8, the average wait time will remain low, even for reasonably high utilization. This is because the expected number of empty service points upon arrival remains high. However, when stations have only one or two pumps, for the same station utilization, we are less likely to find an empty pump. Thus, in this case the average wait time for service can be large, even at reasonably low levels of utilization. Representing this relationship is important, especially when we realize that in initial stages, and in particular in those regions where demand is critically low, we might expect

stations to be small. This is captured using a simple queuing theory. The wait time depends on the average refill time for that location, τ_{is}^f , given by the mix of demand and equations (15)-(16), the station utilization ν_{is}^f , and the number of pumps per station, y_{is} (discussed below). The resulting mean waiting time is

$$\langle \tau_{is}^w \rangle = \frac{P_{is}^q}{y_{is} (1 - \nu_{is}^f)} \tau_{is}^f \quad (17)$$

where P_{is}^q is the probability of finding all pumps busy (which is itself a highly non-linear function of average refill time, the utilization, and the arrival rate). Details of how the mean waiting time is derived through application of basic queuing theory and the station utilization are provided in Appendix 3f.

It is noteworthy to mention that all expected values and averages expressed in equations (11)-(17) are derived through probabilistic calculus, as functions of station concentration or demand in each region and do not involve additional assumptions or parameters (Appendix 3).

Search time, out-of-fuel risk and service time are based on perceived values of station density (for search time and out-of-fuel risk), and the wait time at the pump. They adjust to the actual values with time delay τ^s .

The total vehicle miles driven per year by drivers of platform i equal,

$$m_{iz}^v = \sum_{z's} \phi_{i\omega_{z,s}} m_{izz}^v T_{izz} (v_{iz_u} d_{iz_u} / k_{iz_u}) \quad (18)$$

with utilization v_{is} and demand d_{is} as derived in Appendix 3f, in the derivation of the mean waiting time for service. This completes the consumer segment of the model and the description of how the distribution of fueling stations is influenced by consumers' decision to adopt a vehicle that is compatible with the fueling infrastructure, as well as their trip, route, and refueling choices. Supply formation which occurs partly in response to existing demand is described in the next section.

Fuel Station economics

Before discussing the supply-side decisions, I first set up the basic fuel station economics. Next, the decisions made by the (potential) fuel station owners, which include entrance, expansion, and exiting are examined. Stations can serve consumers with various product mixes. For example, a station with 8 pumps can have 8 gasoline pumps or 6 gasoline and 2 diesel pumps. Throughout this paper, for the purpose of analytical clarity, I ignore explicit modeling of multi-fuel stations and therefore can distinguish stations by the fuel they serve, indexed by v . This is reasonable as a first order approximation, as most of the scale economies do not apply across fuel type. The role of multi-fuel stations will be discussed in later work. Average profits for stations of type v in region s equal revenues r_{vs} minus total cost c_{vs} :

$$\pi_{vs} = r_{vs} - c_{vs} \quad (19)$$

Revenues equal sales from fuel multiplied by price p_{vs} , and revenues from (net) ancillary sales r_{vs}^a are given by:

$$r_{vs} = p_{vs} S_{vs} + r_{vs}^a \quad (20)$$

Ancillary sales mainly involve convenience-store items and can account for up to 50% of profits. It might be that ancillary sales opportunities vary by platform. For example, hydrogen fuel stations might be seeking a wider set of services through complementarities with stationary applications, motivated by higher initial capital cost. This is possible for hydrogen because many services, such as maintenance, are not specialized enough, or because of complements with stationary applications. This would, of course, only work in populated areas. In all simulations ancillary sales will be set to a fixed amount per gallon consumed.

Station costs include a fixed, capacity-dependent component, c_{vs}^k , that represents such categories as land rent, equipment, and capital depreciation and a variable component that increases with sales, having unit cost c_{vs}^u . The unit cost comprises feedstock cost c_{vs}^f ; and “other” c_{vs}^o that include electricity, labor, and taxes. Ignoring sunk costs (of starting a station) and adjustment costs:

$$c_{vs} = s_{vs} c_{vs}^u + c_{vs}^k; \quad c_{vs}^u = c_{vs}^f + c_{vs}^o \quad (21)$$

Both fixed cost and unit cost can differ considerably by location, because of the large contribution of rent, especially in urban areas. Unit cost can be different, because of gradients in distribution costs. Fixed costs increase with capacity k_{vz} and are equal to $c_{vs}^{k,ref}$ when the number of pumps y_{vs} are equal to y^{ref} :

$$c_{vs}^k = c_{vs}^{k,ref} f^k \left(y_{vs} / y^{ref} \right); f(0) > 0; f(1) = 1; f' > 0; f'' < 0 \quad (22)$$

Scale economies are concave in the number of pumps (see Appendix 2b).

Sales are determined by station capacity and utilization ν_{is} ,

$$s_{vs} = v_{is} k_{vs} \quad (23)$$

with station capacity being the product of the number of pumps and pump capacity

$$k_{vs} = y_{vs} k_v^p .$$

To complete the fuel station economics, price is set at fuel stock cost plus markup:

$$p_{vs} = (1 + m_{vs}) c_{vs}^f \quad (24)$$

For simplicity we assume that fuel stock markups are constant.⁴

Supply decisions

Potential station owners also make decisions. **Figure 8** shows the entrance and exit behavior of stations. Potential entrants decide to enter the market based on perceived industry return on investment. Next, entrepreneurs decide where to locate, after which a permitting procedure results in construction and, finally, actual operation. Following this overview, we track the total number of fuel stations F_{vs} of type v , in region s which integrates entrance e_{vs} less exits x_{vs} :

$$\frac{dF_{vs}}{dt} = e_{vs} - x_{vs} \quad (25)$$

⁴ Empirical data between 1960 and 2000 show that the average markups remain virtually constant, they were reduced only after the first oil shock, when cost of fuel increased dramatically, suggesting a very slow anchoring and adjustment process. (Sources: U.S. Wholesale Gasoline Price, US Bureau of the Census, Statistical Abstracts of the United States 1950 & 1976 & 1980 & 1994 & 2005; U.S. Retail Gasoline Price, 1949-2004 Annual Energy Review 2004 Report No. DOE/EIA-0384(2004) Accessed August 15, 2005 <http://www.eia.doe.gov/emeu/aer/petro.html>).

While the higher-order process is captured in the model, in this exposition I collapse the process of location selection, permitting, and construction into one, with aggregate entry time τ_e . Then, new-to-industry stations in region s , F_{vs}^n , enter the market as:⁵

$$e_{vs} = F_{vs}^n / \tau^e, \quad (26)$$

Where the indicated new-to-industry stations equal the new-to-industry capacity intended for region s , divided by the desired fuel station capacity k_{vs}^* ,

$$F_{vs}^n = K_{vs}^n / k_{vs}^* \quad (27)$$

Location s receives share σ_{vs}^k of the total new-to-industry capacity:

$$K_{vs}^n = \sigma_{vs}^k K_v^n \quad (28)$$

High returns at the industry level lead to expansion of existing capacity, $K_v \equiv \sum_s k_{vs} F_{vs}$.

The total market for fuel v grows at rate g_v^k , which increases with industry profits:

$$\begin{aligned} K_v^n &= g_v^k K_v \\ g_v^k &= g_v^{k0} f^g(\bar{\pi}_v^e); f(\ll 0) = 0; f(0) = 1; f' \geq 0; f'(\gg 1) = 0; \end{aligned} \quad (29)$$

where $\bar{\pi}_v^e$ is the perceived returns minus the desired, normalized to the desired

$\bar{\pi}_v^e \equiv (\pi_v^e - \pi_v^0) / \pi_v^0$. The constraints imply, first, that the growth rate equals g_v^{k0} when

perceived returns on investment equal desired returns; second, that the growth rate

increases with return on investment, which could differ by fuel, because of potential

variation in constraints. Further, the shape is bounded, at zero, for extremely negative

⁵ The model includes the higher-order entrance process and allows for varying the extent to which the supply line is taken into account.

profits, and, at some finite value, for extremely high returns. The most general shape that satisfies these conditions is an S-shape (see appendix 2c for the exact functional form).

Finally, region s 's share of total new capacity is a function of the expected relative return on investment within each region, π_{vs}^β , compared to that of alternative regions. A logit-expression is sensible, given the noise in the relevant information for those who have to decide what area to locate in:

$$\sigma_{vs}^k = \exp\left(\beta^k \bar{\pi}_{vs}^\beta\right) / \sum_z \exp\left(\beta^k \bar{\pi}_{vs}^\beta\right) \quad (30)$$

where β^k is the sensitivity, which depends on the accuracy of information on differences in profitability. Expected return on investment is derived through a net present value calculation of future profits streams π_{vs}^β , compared to the desired return on investment, $\bar{\pi}_{vs}^\beta \equiv (\pi_{vs}^\beta - \pi_v^0) / \pi_v^0$. Entrepreneurs use heuristics to estimate how much demand would be induced by their entrance., based on reference demand generated by existing transport patterns (see appendix 2d).

Exits are driven by recent station performance and follow a standard hazard formulation, where the hazard rate λ^x is a function of anticipated return on investment, $\bar{\pi}_{vs}^x$, compared to a required profitability, π_s^x , $\bar{\pi}_{vs}^x \equiv (\pi_{vs}^x - \pi_s^x) / \pi_s^x$:

$$\begin{aligned} x_{vs} &= \lambda^x F_{vs}^x; \\ \lambda^x &= \lambda^{x0} f^x\left(\bar{\pi}_{vs}^x\right); f(0) = 1; f \geq 0; f' \leq 0; f'' > 0 \end{aligned} \quad (31)$$

where λ^{x0} is the exit rate when recent profits equal desired profits. A general shape that satisfies these conditions is an S-shape, such as the logistic curve (see appendix 2c for the exact functional form).

To determine their own anticipated return on investment π_{vs}^x , mature stations rely on recent performance π_{vs} ; new to industry stations use their expected return on investment figures, π_{vs}^β . The different emphasis is captured by the weight w_{vs}^m given to the recent profits streams, which increases with the average station maturity:

$$\pi_{vs}^x = w_{vs}^m \pi_{vs} + (1 - w_{vs}^m) \text{Max}[\pi_{vs}^\beta, \pi_{vs}] \quad (32)$$

where the weight increase is zero for entirely new to industry stations, and equals one for old stations. A reasonable form is an S-shaped form, centered around the age m^* ,

$$\bar{m}_{vs} \equiv m_{vs} / m^* :$$

$$w_{vs}^m = f(\bar{m}_{vs}); f(\infty) = 1; f(1) = 1/2; f(0) = 0; f' \leq 0 \quad (33)$$

Station maturity is derived through a simple age co-flow function (Sterman 2000) that tracks the average age of fuel stations. Appendix 2e provides the selected functional form. Appendix 2c of Struben 2006a describes the formulation of co-flow structures.

The final decisions to be described are decisions within industry to alter capacity of fuel stations. Existing stations adjust capacity, in terms of the number of pumps, to the desired level y_{vs}^* over an adjustment time τ_{vs}^k , accounting for both the time to actually learn about the optimal size, as well as the time to alter capacity, which can differ by region.

$$\frac{dy_{vs}}{dt} = (y_{vs}^* - y_{vs}) / \tau_{vs}^k \quad (34)$$

where the desired number of pumps allows the utilization to reach its desired level:

$$y_{vs}^* = (v_{vs}^k / v_{vs}^{k*}) y_{vs} \quad (35)$$

where v_{vs}^{k*} is desired utilization. Stations desire high utilization, as profits increase with utilization; however, very high utilization will lead to congestion at stations and customer defection. Thus, desired utilization is well below 1. A heuristic estimate, observing fuel stations gives utilization levels on the order of 0.2, that is, well below maximum utilization .⁶

This finalizes the model structure. Key decisions on the supply side were: market entry decisions that were based on expected NPV; exit decisions, in response to realized profits; fuel station location decisions, based on relative expected profitability between different locations; and finally, capacity adjustment, in response to utilization.

Analysis

The analysis begins with consistency tests, illustrated through a comparison with empirical data based on the state of California. Next key insights of the basic behavior of

⁶ The desired utilization is therefore linked to the wait time in equation (17), with a likely optimum at the point where its slope begins to increase sharply, which is also well below full utilization. For less regular demand patterns, or fewer pumps, desired utilization would be lower. On the other hand, adjustment constraints can lead to a utilization that is higher than desired, while competition effects can render it lower.

the model found by analyzing the introduction of a hypothetical AFV in California are discussed. Given these understandings, I discuss the generality of these results and explore the value of relaxing technical and behavioral assumptions. Finally, I analyze implications when technical and economic parameters are varied and discuss implications for the introduction of various types of AFVs.

I use the state of California as a reference region for analysis. That is, the demographic, economic, and technical parameter settings as well as the reference data, are equivalent to those typically found in California. **Table 2** provides a summary of the relevant statistics. The default parameters in the model are provided in Table 3, and are used for the simulations, unless otherwise stated. Parameter settings for particular simulations are discussed in the text for each figure. To determine behavioral parameters, such as the consumer sensitivity parameters, or those that relate to station entrance and exit, a combination of heuristics, published empirical findings, sensitivity analysis, and calibration are used to select reasonable values. To simplify analysis and dynamics, one type of consumer is assumed: households that generate trips conforming to a frequency distribution $T_{zz'}^{\max}$ that is generated by a lognormal in distance with average trip length of 20 miles and θ , with a uniform distribution of the direction, subject to boundary conditions. If all trips would be made by vehicles, it generates the maximum 15,000 vehicle-miles per person per year.

Fundamental behavior

Several partial model tests, sensitivity analyses, and calibrations have been carried out to confirm behavioral consistency and heuristic parameter settings. Figure 9 shows, as an example, the results of a partial model test, which was to replicate the distribution and total number of ICE gasoline stations in California. Figure 9a shows the actual gasoline fuel station distribution in California in 2003 (N=7949) on a 625 patch grid. For the stations we used actual GIS data provided by the National Renewable Energy Laboratory. Throughout these simulations vehicle ownership was held fixed at 2003 levels (17.126e6) with a distribution identical to that of the population, with an adoption fraction equal to 0.91 throughout. For each trip destination, the desired fraction of trips to be performed with an ICE/gasoline vehicle was 0.8, which would yield the average of 12,000 miles per vehicle, if realized. Simulations began with 10% of current stations, uniformly distributed, with 8 pumps per station. Supply was subsequently allowed to adjust over time through entry, exit, and capacity adjustment. **Figure 9b** shows the simulated results based on the heuristic parameters, obtained without optimization.

Without relying on detailed data inputs regarding items such as traffic flows, the model performs quite well, though there are a few regions that over or underestimate the number of stations. For example, the model places some stations in mountainous regions, or deserts, while it ignores a disproportionately high number of stations in big transit hubs, e.g., to Las Vegas. While these deviations are small, it is easy to correct for such deviations, without much additional data being required. This is discussed later. On a final note, the model performs much better, compared with simulations where the number

of pumps per station was held fixed at the average of 8, illustrating the relevance of such additional behavioral feedbacks.

Now we perform an analysis in which both supply and demand are endogenous. **Figure 10** shows the base case simulation. In the base case, the initial ICE fleet and infrastructure size and distribution are set to 2003 California values: 15.5 million vehicles and 7949 gas stations. In the base case, to emphasize the spatial co-evolution of vehicles and infrastructure, we assume full familiarity with AFVs and set AFV economic and technical parameters of merit equal to those of ICE. The simulation begins with an AFV adoption fraction of 0.1% and 200 fueling stations (these numbers approximate station values for CNG in California in 2002, including private fleets and fueling stations). We assume, optimistically, that all AFV fuel stations are accessible to the public. Initially, investors and other partners will be committed to and collaborate to achieve a successful launch and hence they attempt to keep stations open, even when making losses. We capture this by subsidizing, on average, 90% of a station's losses for the first 10 years. This scheme disproportionately favors those stations that are in more vulnerable locations and receive more support.

Figure 10 shows the alternative fuel stations and fleet. The top graph shows the simulated adoption fraction, stations, and fuel consumption, relative to normal, over time. The bottom graph shows the geographical distribution of the adoption fraction and number of fuel stations at time $t=45$. Qualitatively, three important results are revealed. First, despite performance equal to ICE/gasoline and full familiarity with the AFV, overall diffusion is very low, especially in the early phase. Net fuel station growth initially lags that of the fleet.

Second, many stations are forced to exit when subsidies expire, while entry ceases somewhat earlier, as the expected value from subsidies starts to decline. Average capacity

increases strongly after the shakeout (see number of pumps, right axis) because of two effects: a selection effect is that those who exit are generally the smaller stations; in addition, those that remain in business experience increased demand, which drives their capacity expansion. For the same reason average profitability increases dramatically. However, these effects have a limited effect on the overall demand growth. Eventually, with the gradual increase of demand and constraints in capacity expansion, station entrance accelerates.

Note that the growth of fuel consumption lags adoption, especially earlier in the simulation. This is because of the limit on the destinations that can be reached with the AFV because of absence of stations in rural areas and overcrowding in urban areas. Time to adopt and settle is much longer than one might expect from the time delays in vehicle replacement and station entrance only, which total up to 12 years for this simulation. This behavior is a result of closing the feedback between the interdependent relationship of vehicle demand and infrastructure development, each of which only gradually increases to an indicated level, as shaped by the other, and thereby also only slowly adjusts the goal for the other.

Third, the end state that emerges shows a spatially bi-stable equilibrium in which essentially all AFVs and fueling stations are concentrated in the major urban centers. Miles driven per year and actual consumption for the typical AFV are also far less than for ICE vehicles. Limited diffusion is a stable equilibrium in the cities, because high population density means fuel stations can profitably serve the alternative fleet, and low refueling effort induces enough people to drive the alternative vehicles. **Figure 11** shows the underlying hypothesis. Both urban and rural demand is subject to chicken-and-egg

dynamics (R1, B1). For metropolitan areas, potential demand would be sufficient if all demand would be generated from within and to within; however, rural areas would never be able to generate a self-sustaining market. Though AFV fuel stations do locate in rural areas during the period they are subsidized, rural stations remain sparse, so rural residents and city dwellers needing to travel through rural areas find AFVs unattractive (demand spillover, R2). Further, urban adopters, facing low fuel availability outside the cities, use their AFVs in town, but curtail long trips (demand spread R3). Consequently, demand for alternative fuel in rural areas never develops, preventing a profitable market for fuel infrastructure from emerging, which, in turn, suppresses AFV adoption and use outside the cities.

Consideration of relaxing assumptions

The benefits and costs of expanding the model boundary are discussed in this section and provide further support for the insights. Central to the model structure is its ability to capture the dynamics of supply and demand that interacting through space. Therefore I discuss first the appropriateness of the level of spatial detail. The AFV introductory scenario that was discussed earlier is used as the basis. Figure 12a illustrates the sensitivity of the model behavior to changes of the patch length (the square root of the patch area). To control for large rounding errors with very large patches, population density is kept fixed at the California average (109 households/sqmi). Tracing the equilibrium adoption as a function of patch length, the results show: no self-sustaining fuel demand for the alternative when patch length are above 200 miles; equilibrium demand peaking when patch length is about 100 miles; and convergence for patch length below

30 miles. The variation in the equilibrium demand for larger patches is explained as follows: the extreme case of one single patch corresponds to assuming a uniformly distributed population. This assumption does not bring out strategic location incentives on the supply side, and, even under rich behavioral assumptions, will yield demand /supply responses that correspond with the qualitative sketch in **Figure 2**, where demand is adjusted for the number platforms. The single patch dynamics will therefore result in a limited amount stable equilibria of which the number depends on the number of competing platforms. In the case of two platforms, as here, there are at most three stable equilibria. Two equilibria provide full adoption of either platform, and zero for the other. Whether a third equilibrium allows for both platforms to be self-sustaining depends if, in the case of equivalent platforms, if 50% of the demand yields a profitable market (see appendix 4b that this is indeed the case). Whether such equilibrium is actually achieved, depends on whether the subsidy schemes can bring the adoption/fuel stations past the boundary separating the low and the 50% equilibrium. We see that in this case this did not yield enough adoption for take-off towards the 50% adoption fraction. At more moderate patch length of say 100 miles, some patches capture major urban clusters, but also their hinter land. Within such patches, average potential demand is large enough to yield the penetration to 50%. Further, virtually all trips of drivers are covered within that area, resulting in more adoption and demand.

Under such assumptions of regional uniformity, expected distance to a station is identical from all locations within that region, however, the fraction of long trips fulfilled relative to short trips differs slightly. This is mostly because of the varying dependence of effort

and out of fuel risk, for short and long trips. In sum, this level of granularity brings out bi-stable character, associated with adoption clustering, but not the coupling between the different regions (as indicated by the demand spread and demand spillovers loops in Figure 10).

AFV demand and fueling infrastructure supply exhibit more subtle long distance interdependency that drives dynamics. Decreasing the patch length further brings the feedbacks associated with the long-range interactions into consideration. The explicit consideration of the existence of vast rural areas outside, and between urban regions, results in a reduction of demand as compared to the coarser grid, which is also illustrated by a lower ratio of large to small trip fulfillment for these patches. Decreasing patch length from here on, allows capturing population level and demand fluctuations, but does not affect the overall patterns of demand and supply. However, as simulation run time increases exponentially with the number of patches, computational constraints become another factor of consideration. The current patch length of 18 miles falls within the region where dynamics are insensitive to a change in its length. This example further illustrates that the current analysis not only allows exploration of behavioral explanations of why take-off might stall, or of what policies might lead to success, but uncovers fundamentally different dynamics and equilibria, compared to assumptions that ignore the spatial heterogeneity, or that only focus on local supply and demand interactions. Studies of symmetry breaking in spatially distributed systems are more and more appearing in biological research (e.g. Sayama et al. 2000). In this particular case the consumer and supplier behaviors mediated interactions that are different over short- and

long-distance and drive dynamics that cannot be observed with mean-field approaches. Finally, it is expected that dynamics are not affected by disaggregating other parameters, such as consumer types, for reasons similar to those arguing against reducing the patch size.

A second assumption to explore in more depth involves that of randomly distributed trip destinations. Such an assumption greatly limits data and modeling requirements and is certainly useful for shorter trips. However, long-distance travel occurs at least partly over highways and is thus considerably more concentrated. The impact of relaxing the assumption of undirected travel for longer trips on the overall dynamics is not straightforward. Highway travel creates corridors that reduce the effective dimensionality for parts of the long-distance trips. This lowers the effective distance between stations and thus, holding actual stations constant, has a declining effect on driving effort. On the other hand, including road travel increases the typical length for the same absolute distance, and thus the required total number of stations per trip. Further, availability of sufficient fuel stations throughout a trip is imperative for drivers' willingness to adopt and drive, but long-distance travel is a relatively low contributor of the total demand volume and provides limited potential for revenues, especially in the less high-volume regions (even for gasoline competitive highway stations are frequently more than 30 miles apart).

I address these considerations in a simulation that generates different driving patterns with a different treatment for short and long distance trips. Short trips with random directionality, distributed following the same assumptions as in the previous analysis are generated. The concept of gravitational models (e.g. Fotheringham 1983) is used to generate long-distance trip destinations as a function of the population density, with populated areas serving as the main destinations. Next, the repertoire of highly frequented destinations is expanded by including several destination hotspots, such as Las Vegas, Lake Tahoe, and the north east border, Crescent City.⁷ In the model, the high density traffic between cities and to hotspots form natural corridors for demand and serve as a useful proxy for directed trips. We perform a simulation that is further, where possible identical, to Figure 10, in terms of parameter settings, initial conditions and subsidy scenario for the entrant equivalent to ICE. However, to conserve computational efforts, I limit the simulated area. I choose one that includes the complete LA region, until the Mexican border, including Lake Tahoe towards the North-East, and San Jose on the North-West. The average population density for the selected region is 30% higher than the California average. Details are provided in appendix 4c.

Figure 12b shows the results. We see, first, that adoption attains a low level equilibrium, only slightly higher than in Figure 10. Further, there is a strong discrepancy between urban and rural adoption. Comparing these results with a simulated equilibrium of ICE in absence of the equivalent entrant (ICE equilibrium), illustrates that a high equilibrium with stations throughout, can be achieved. Performing analysis at this more disaggregated

⁷ Even though such hotspots may lie outside the modeled grid area, their drivers destined for these locations generate demand within the modeled grid.

level requires careful calibration and more work is needed to confirm these results.

However, the results are strong: the assumptions for this simulation strongly favor take-off: besides the higher average population density any station that appears along the corridors is easily accessible for regional demand. This favors especially rural stations.

Adding more behavioral detail does matter. An analysis of the role of endogenous topping-off behavior illustrates this. Drivers can adjust their topping-off level, trading off the frequency of refueling for a reduction in needing to go out of the way, crowding and out-of-fuel risks, by selecting more convenient locations before the actual need appears. To test the implications, we represent the endogenous topping-off level relative to the normal topping-off buffer r_{i0}^b , that adjusts to the indicated level r_{iz}^{b*} , which is a function of the average utility of driving, which can be seen to represent the certainty of availability of fuel and service:

$$r_{iz}^{b*} = f(u_{iz}^t) r_{i0}^b; f' \leq 0; f(0) = r_{\max}^b / r_{i0}^b; f(1) = 1; f(\infty) = r_{\min}^b / r_{i0}^b$$

The relative top-off buffer increases with decreasing utility, but stabilizes at r_{\max}^b for very low utility, as drivers will not want to be constrained by refilling on average too early.⁸

Further, when drivers are fully confident, they will reduce their buffer to r_{\min}^b , which can be below the indicated level by the warning sign, r_0^b . The exact form, yielding one

sensitivity parameter α^f , is derived in Appendix 4d, also including a graphical

representation. When the value of the sensitivity parameter α^f equals 0, the topping-off

⁸ This level depends on the physical constraint of refueling elsewhere; see also equation (7) and Figure (5). From this behavioral reasonable parameters could be derived.

buffer remains constant for all utility parameters, when it is equal to 1, the buffer changes linearly with utility. The reference topping-off buffer is $r_{i0}^b = 40$ miles (10% of the total range), $r_{\max}^b = 200$ miles (50% of the total tank range), and $r_{\min}^b = 20$ miles.

Figure 13 illustrates the results. Respective simulations involve increasingly sophisticated assumptions about refueling behavior. Varying α^f , and β_{ref}^f , a measure for refueling location sensitivity to a change in the relative effort in refueling, I show 1) the case of responsive behavior, for which the topping-off buffer is held fixed and drivers are assumed to always start searching for fuel when they reach their buffer ($\beta_{ref}^f = 0; \alpha^f = 0$). In this case, within each trip, the refueling location shares $\sigma_{i\omega_{zs},s}$ is exactly equivalent to the share of driving through the various locations; 2) balancing behavior, in which drivers hold their topping-off buffer fixed, but are allowed to select refueling sites, based on the ($\beta_{ref}^f = 2; \alpha^f = 0$);⁹ iii) adjusting behavior, in which drivers endogenously adjust the effective tank range ($\beta_{ref}^f = 2; \alpha^f = 0.5$). We see from the results that endogenous topping-off does not stimulate, but hinders adoption. Ignoring other effects, facing an increase of uncertainty of fuel availability, a driver's adjustment of its topping-off buffer can improve her utility, from being able to locate at more favorable locations, at the cost of a little increased frequency. However, once that happens, two major reinforcing feedback loops become active: first, drivers contribute to an increase in crowding, because of their lower effective range, without increasing net consumption,

⁹ These parameter settings correspond with the assumptions for all other simulations

this further triggers upward adjustment of buffers, leading to more crowding. Second, the reallocation of demand for fuel implies that more fuel goes to more favorable locations. This further reduces demand in already ill-served areas, contributing to more station exits, increasing uncertainty and reducing further demand in those areas. This last feedback is intrinsic to the urban-rural inequality, as well as the behavioral and disequilibrium character of this system.

Varying AFV characteristics

How is adoption affected when AFVs differ from the incumbent technology, ICE, along technical and economic dimensions of merit? To answer this question using simulations, use more favorable conditions than before to generate a successful take-off in the reference case that represents the ICE-equivalent AFV. Besides high station and vehicle subsidies, favorable assumptions regarding vehicle/fuel performance, cost parity, awareness and acceptance of the alternative technology - already assumed in the previous simulation – are used. In addition, lower consumer sensitivity to the additional effort/risk associated with low station coverage is included. In **Figure 14**, the blue line (highest penetration) shows the reference case, a successful penetration. The left axis shows adoption, with a value of 0.5 corresponding to a 50% share of the market, which is expected to be the maximum equilibrium situation for an ICE equivalent. Equilibrium market penetration still saturates at a level lower than that of the status quo due to a high degree of clustering near metropolitan centers.

Particular starting assumptions are relaxed step-by-step to allow for a comparison of three other fictitious AFVs that are also shown in **Figure 14**. The parameters that are varied

and their values for each run are shown in Appendix 4e . To illustrate the role of increased efficiency, the red line shows the dynamics for scenario 2, representing a fuel-efficient fictitious AFV with fuel efficiency three times that of the reference case and total vehicle driving range held constant, as compared to the reference case (to achieve this, the tank size is set to equal 1/3 of the reference case's). This scenario could represent the introduction of small fuel-efficient AFV vehicles, at first sight an attractive candidate for early adopters. While adoption takes off fast, it stagnates early; surprisingly, more efficient vehicles are not necessarily more successful. **Figure 14**, right, shows that the supply collapses after the subsidies come to an end. The increased demand is not sufficient to make up for lower revenues, and no self-sustaining market emerges at low levels of penetration. Thus, this counterintuitive result illustrates a large trade-off between the end goal of increasing fuel efficiency and diffusion: on the one hand, there is efficiency, which reduces the environmental footprint (the energy dependence of transportation), and may drive adoption; on the other hand, we see the importance of rapid supply growth to achieving successful diffusion.

Dispensing capacity is expected to be a constraint for many alternatives, especially gaseous fuels (CNG, hydrogen), and EVs. Scenario 3 (the green line in **Figure 14**) illustrates the role of dispensing rate on the dynamics. It shows the dynamics for parameters similar to scenario 2, except for an assumption of dispensing capacities being 25% as compared to the reference. Entrant technologies also have the burden of limited performance. In this case, adoption is suppressed directly as well. Due to the significant overcrowding at stations, which has a very non-linear response to station/pump utilization

levels, attractiveness for potential adopters remains low. On the other hand, stations have limited incentives to expand or enter in places where utilization does not achieve very high levels. When fuel efficiency is lower, fueling frequency and crowding go up considerably. This dramatically increases the refueling time, making the effect even stronger. The final simulation represents early stage HFCVs, with DOE's 2015 targets for HFCVs as a reference for the parameters (Table 3, case 4). Importantly to stress, without sophisticated introduction policies and under the current model assumptions, these parameters result, in no take-off at all. To point of this last simulation is not to show expected failure for HFCV, but to illustrate that for different configurations, dynamics can be disproportionately influenced.

Different technologies result in different challenges. For example, introduction of hybrid vehicles, that use an infrastructure that is compatible with gasoline, and further have lower fuel consumption, will lead to fast penetration (ignoring other feedbacks that relate to familiarity, technology learning and policies). In this model, if utility from hybrid vehicles equals that of gasoline vehicles, 25% of the market share is attained in 5.5 years, and 40% in 11 years, solely constrained by replacement dynamics of vehicles. The infrastructure can easily absorb the reduced demand, while still providing fuel throughout. However, for most of the alternative technologies, for which the infrastructure is not compatible, the dynamics as discussed above will be critical.

Bi-fuel and flex-fuel vehicles will exhibit a significantly reduced out-of-fuel risk, compared to alternative fuels, such as CNGs and HFCVs, as they can rely on pure

gasoline as backup, while they can select the cheapest vehicle. But for hybrid solutions, there are inherent tradeoffs. This is illustrated by the case of CNG-gasoline vehicles. The fixed cost is higher, while vehicle performance and space are compromised. More importantly, the spatial dynamics of bi- and flex-fuel vehicles might play out quite differently than is the case for a mono-fuel: the reduced dependence of drivers on availability of remote stations reduces demand in the low-volume regions even further, which further reduces incentives for a widespread network to build up. Plug-in EVs also pose challenges. Charging at home solves part of the service time challenge of EVs. However, a side-effect is that the demand volume outside the home location is virtually non-existent, again providing little incentive for infrastructure to build up. In summary, for bi-fuel vehicles, the low-demand bi-stable equilibrium might emerge more easily and quickly, but the gap with full-scale penetration can become even larger than is the case for mono-fuel vehicles that depend on an infrastructure that is incompatible with gasoline.

This analysis also brings to mind the coordination and standardization challenge that stakeholders, fuel suppliers, automotive manufacturers, and governments face. Similar coordination issues contributed heavily to the stalling of the EV infrastructure in the early 20th century. Not until it was too late were inventors, entrepreneurs, owners of central electricity stations, and policy makers able to coordinate on a viable infrastructure solution by providing large-scale, low-cost, off-peak refueling opportunities at central stations; sufficient coordination did not occur despite many viable ideas that were

proposed early, included battery change services, leasing by central stations, and curbside pump networks stations (Schiffer 1994).

Also here, choice to seek early standardization occurs at several levels: across AFV portfolio choice, such as internal combustion hydrogen versus hydrogen fuel cells; within an AF technology, such as forms of on-board storage (comprising a variety of gaseous low- and high pressure, liquid, Nanotube solutions); with respect to individual technologies; or, regarding practices and regulations, such as on-site fuel storage modes, or the dispensing process. While technology diversity may be beneficial to the innovation rate of the technologies involved, absence of standards produces many difficulties. First, this greatly increases incompatibility for users. For example, different forms of on-board storage require different dispensing technologies. From the preceding analysis, one can readily interpret the dramatic negative impact this would have on the early market formation. Similarly, for fuel stations absence of standards implies higher cost and increased space constraints. Further, different technologies that share much lower volumes have less learning and cost-reduction. Finally, absence of standards, rules, and legislation greatly increases permitting time for fuel stations.

Discussion and conclusion

Modern economies and settlement patterns have co-evolved around the automobile, internal combustion, and petroleum. The successful introduction and diffusion of alternative fuel vehicles is more difficult and complex than for many products. The dynamics are conditioned by a broad array of positive and negative feedbacks, including

word of mouth, social exposure, marketing, scale and scope economies, learning from experience, R&D, innovation spillovers, complementary assets including fuel and service infrastructure, and interactions with fuel supply chains and other industries. A wide range of alternative vehicle technologies – hybrids, biodiesel, fuel cells – compete for dominance.

This paper focuses on only one interaction: the co-evolution between alternative fuel vehicle demand and the refueling infrastructure. I developed a dynamic behavioral model, with explicit spatial structure. The behavioral elements in the model included drivers' decisions to adopt an AFV, their trip choices, and their decisions to go out of the way to find fuel, as well as their topping-off behavior in response to the uncertainty of finding fuel. The responses to fuel availability included the effort involved in searching or getting to a station, the risk of running out of fuel, and the service time (as a function of supply and demand), and number of service points. The supply-side decisions included station entry and location decisions, exit, and capacity adjustment.

The local scale, but long-distance correlation of interactions is paramount in this dynamic and behavioral setup. Fuel availability differs for each driver based on their location and driving patterns relative to the location of fuel stations. Often labeled as “chicken-and-egg” dynamics, these co-evolutionary dynamics are much more complex. The increasing interest for spatial symmetry breaking in biological systems (e.g. Sayama et al. 2000) is also justified for the complementary interactions between vehicle demand and its fueling infrastructure. Analysis of local adoption and stagnation provides an explanation for

persistent clustering phenomena, with low levels of adoption and usage, for AFVs that are introduced in the market. For example, in Italy, with a CNG penetration of 1% in 2005, 65% of the CNG vehicles and 50% of the CNG fuel stations are concentrated in 3 of the 20 regions (Emilio-Romagna, Veneto, and Marche), together accounting for about one-sixth of the population and area (Di Pascoli et al. 2001). In Argentina, the largest bi-fuel CNG market with a penetration of 20%, 55% of the adopters live in Buenos Aires and 85% in the biggest metro poles. Similarly, in the beginning of the 20th century, EVs remained clustered in urban areas, with virtual absence of recharging locations outside urban areas (Schiffer et al. 1994). Many attempts to introduce AFVs collapsed after government support, subsidies, or tax credits were abandoned, for example with bi-fuel CNG/gasoline in Canada and New Zealand (Flynn 2002). While islands of limited diffusion might be sustained in the cities, as can be seen in Argentina, broad adoption of AFVs can easily flounder even if their performance equals that of ICE. The acknowledgement of different relative “tipping points” for rural and urban markets and their interdependency can inform the evaluation of different hydrogen transition strategies and policies. The clustering and stagnation behavior is significantly different than the basic chicken-egg dynamics suggests, or than can be inferred from standard economic analysis of complementarities. Modeling the behavioral decision making and the spatial aspects dynamically is essential for revealing these patterns of low penetration.

This model is in the early stages of development and requires more intense calibration, validation, and extensions. Yet current analysis considerably enhances our understanding of previous alternative fuel experiences and future alternative fuel transition strategies.

The tight coupling between components of the system that are physical (such as typical replacement time and the spatial characteristics), behavioral (trip choice, sensitivity to availability of fuel), or technical/economic (e.g., fuel economy, tank size, fuel price) influence the dynamics. The analysis illustrates a bi-stable equilibrium with urban adoption clusters and limited aggregate demand. This fully dynamic perspective illustrates some counterintuitive results: more efficient vehicles are not necessarily improve the transition dynamics, for the emergence of a self-sustaining market, and can in fact harm it. More generally, the analysis illustrates the trade-off between the long-term goal of low consumption and emission vehicles and the necessary market take-off.

The behavioral character of the model, within the spatial context, provides significant insights with driver behavior, for instance fuel station capacity adjustment, being endogenous. For example, the number and length of trips increases as fuel availability rises, and only then demand spillovers from urban to local regions, allowing for sufficient demand for take-off in those regions. Finally, we saw that dynamics were critically impacted when we allowed topping-off levels to be endogenously adjusted. Drivers who perceive refueling effort to be high - say, because some fuel stations are distant or crowded - will seek to refuel before their tanks are near empty, balancing increased efforts from more frequent refueling stops against reduced out-of-fuel risk. However, the side effects of increased crowding, and reallocation of demand to the higher volume regions, set in work self-fulfilling prophecies of the uncertainty of supply. More generally, including these behavioral aspects highlights the distributed nature of the system. The local adjustments of supply and demand can easily be absorbed in a well

established high volume system and provides increased adaptability and efficiency that can thus be expected to improve successful transitions. However early in the transition the negative side effects of such adjustments can and lead to a failed transition.

The analysis focused on the impact of supply-demand interactions relevant for aggregate diffusion dynamics. This model's finite element approach suggests several research directions. For example, one could focus on specific state-level location strategies, by reducing patch size and incorporating detailed data such as traffic flow information. However, we saw that for the transition dynamics, capturing heterogeneity at the scale below the typical trip length, in combination with the behavioral feedbacks, was critical to obtaining the results, but the high-frequency noise from smaller-scale fluctuations could be ignored. In addition, we saw that the fundamental conclusions are not changed, when relaxing the assumptions of randomly directed trips. Assuming random directions saved scarce resources for computation and analysis, and critically reduced data requirements. Also, analysis at a higher level of aggregation allows including more behavioral feedbacks that, as we saw throughout, but in particular with the topping-off dynamics, contribute significantly to the aggregate dynamics.

Transition challenges are different for different AFVs. Successful introduction of hybrid vehicles poses much fewer and smaller challenges than achieving this for HFCVs. It is valuable to think how the dynamics observed here would interact with other elements of the socio-technical system. For example, suppressed diffusion also limits the

accumulation of knowledge that is critical for improving AFV performance. Further, automotive OEMs are likely to respond to the observed demand patterns for AFVs that favor cars for city-dwellers. In response, their portfolios would come to consist mainly of small, efficient, inexpensive models, adapted for commuting but ill suited for touring. Such behavior further reduces their attractiveness in rural areas, and likely restricts adoption to affluent households who can afford an AFV for commuting and an ICE vehicle for weekend excursions. These feedbacks can further constrain diffusion.

Taking a broad system perspective allows exploring at high leverage interventions. As we discussed with hybrid vehicles, a transition is certainly possible. For example, in Struben 2006a I focus on the role of social exposure dynamics: as vehicles are complex, and emotions, norms and cultural values play an important role, social exposure dynamics will have significant influence on the transition dynamics. Combining the partially local diffusion aspects with the spatial infrastructure dynamics will provide more insights into challenges and levers for adoption. As an “inverse” analogy to ring vaccination policies (designed to contain viruses), peripheral dotting of metropolitan regions at edges between urban and rural areas might be used to bridge demand for drivers towards more remote regions, thereby lowering uncertainty in demand. This robustness of this policy can be further tested with this model.

Other policy levers lie in the collective action problem that is deeply rooted in AFV transition dynamics. Without coordination between automakers, fuel suppliers, and

governments, adoption will not take off. First, there is the challenge of coordination on strategic investment. As we saw above, if AFs are initially only introduced in light, compact, efficient cars, there might be little incentive for the supply side to roll out a large infrastructure. On the other hand, if the benefits are too little from the consumer perspective, demand will not develop. This suggests high leverage can be found in coordination across stakeholders on issues such as pilot region selection, target market, vehicle portfolio selection, asymmetric incentives for urban and rural stations, other incentive packages, and standardization. Second, governments' policies need to be aligned with those of the industry: a gasoline tax alone might spur demand for other fuels, but it might take a long time before good alternatives became available. Further, as we saw, if the alternative does not provide incentives for suppliers to build fuel stations or for automakers to build alternative vehicles, impact will be small. Finally, the lack of standardization is a strong cause and effect of the coordination problem. Further application of the present model can reveal high-leverage coordination policies between these (and other) stakeholders. Subsequent research will be targeted at such questions.

The observations in this discussion suggest that, for exploration of robust alternative fuel transition strategies, full policy analysis, and development of incentives of proper kind and duration, other feedbacks need to be included as well. Inclusion of other feedbacks -- such as scale and scope economies, R&D, learning by doing, technology spillovers, familiarity through word of mouth and driver experience, and production/distribution of fuels and other complementary assets -- are crucial for understanding the transition challenges. Initially, the technologies of AFVs will perform much worse than ICE,

significantly increasing the threshold for the formation of a self-sustaining market. The strong dependency of model behavior on economic/technical characteristics suggests that full inclusion of these feedbacks is critical. Building towards this, Struben 2006b discusses the inclusion of learning and technology spillovers. Finally, full analysis must include various alternatives at the same time also competing with each other.

The variety of success and failures of AFV market formation in the past suggests strongly that our understanding was unguided by reliable insight. This paper demonstrates the importance of dynamic models – when they incorporate behaviorally rich detail and focus on those factors that increase the dynamic complexity – for understanding the dynamics of market formation that involves consumers, producers, regulators, and producers of supporting infrastructure.

References

- Abernathy, W. and J. Utterback (1978). "Patterns of Industrial Innovation." *Technology Review* **80**(7): 40-47.
- Arthur, W. (1989). "Competing Technologies, Increasing Returns, and Lock-in by Historical Events." *Economic Journal* **99**(394): 116-131.
- Bass, F. (1969). "A New Product Growth Model for Consumer Durables." *Marketing Science* **15**(5): 215-227.
- Ben-Akiva, M. and S. Lerman (1985). *Discrete choice analysis: theory and application to travel demand*. Cambridge, Mass., MIT Press.
- Bentham, J. (2005). CEO Shell Hydrogen Testimony to the U.S. Senate Subcommittee on Energy.
- Berry, S., J. Levinsohn, and A. Pakes. (2004). "Differentiated products demand systems from a combination of micro and macro data: The new car market." *Journal of Political Economy* **112**(1): 68-105.
- Brownstone, D., D. Bunch, and K. Train. (2000). "Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles." *Transportation Research Part B-Methodological* **34**(5): 315-338.
- Brownstone, D. and K. A. Small (2005). "Valuing time and reliability: assessing the evidence from road pricing demonstrations." *Transportation Research Part a-Policy and Practice* **39**(4): 279-293.
- Centola, D. and M. W. Macy (2005). "Complex Contagion and the Weakness of Long Ties." Under review, *American Journal of Sociology*.
- Collischonn, W. and J. V. Pilar (2000). "A direction dependent least-cost-path algorithm for roads and canals." *International Journal of Geographical Information Science* **14**(4): 397-406.
- Cowan, R. and S. Hulten (1996). "Escaping lock-in: The case of the electric vehicle."

- Technological Forecasting and Social Change 53(1): 61-79.
- David, P. A. (1985). "Clio and the Economics of Qwerty." *American Economic Review* 75(2): 332-337.
- Di Pascoli, S., A. Femia, et al. (2001). "Natural gas, cars and the environment. A (relatively) 'clean' and cheap fuel looking for users." *Ecological Economics* 38(2): 179-189.
- Domencich, T. A., D. McFadden, et al. (1975). Urban travel demand : a behavioral analysis : a Charles River Associates research study. AmsterdamNew York, North-Holland Pub. Co. ;American Elsevier.
- DOE (2006). Department of Energy Hydrogen Program - H2A Analysis
http://www.hydrogen.energy.gov/h2a_analysis.html.
- Dijkstra, E. W. (1959). "A Note on Two Problems in Connexion with Graphs." *Numerische Mathematik* 1: 269-271.
- Energy Information Administration (2005). Alternative Fuel Reports, Analyses 1993-2003. Energy Information Administration Accessed 11-20-2005.
<http://tonto.eia.doe.gov/reports/reportsD.asp?type=Alternative%20Fuel>
- Farrell, A. E., D. W. Keith, et al. (2003). "A strategy for introducing hydrogen into transportation." *Energy Policy* 31(13): 1357-1367.
- Flynn, P. C. (2002). "Commercializing an alternate vehicle fuel: lessons learned from natural gas for vehicles." *Energy Policy* 30(7): 613-619.
- Fotheringham, A. S. (1983). "A New Set of Spatial-Interaction Models - the Theory of Competing Destinations." *Environment and Planning A* 15(1): 15-36.
- Fujita, M. and P. Krugman (2004). "The new economic geography: Past, present and the future." *Papers in Regional Science* 83(1): 139-164.
- Fujita, M., P. Krugman, et al. (1999). "On the evolution of hierarchical urban systems." *European Economic Review* 43(2): 209-251.
- Geels, F. W. (2005). Technological Transitions and Systems Innovations - A Co-evolutionary and Socio-Technical Analysis. Northampton, MA, Edward Elgar.

- Greene, D. (2001). TAFV: Alternative fuels and vehicle choice model documentation. Center for Transportation Analysis, Oak Ridge National Laboratory report ORNL/TM-2001/134.
- Gnedenko, B. V. and I. B. N. Kovalenko (1989). Introduction to queueing theory. Boston, Birkhäuser.
- Katz, M. L. and C. Shapiro (1994). "Systems Competition and Network Effects." *Journal of Economic Perspectives* **8**(2): 93-115.
- Keeling, M. (1999). Spatial Models of Interacting Populations (Ch3). *Advanced ecological theory: principles and applications*. J. M. McGlade. Malden, Mass., Blackwell Science: xvii, 353.
- Klepper, S. (1996). "Entry, exit, growth, and innovation over the product life cycle." *American Economic Review* **86**(3): 562-583.
- Krugman, P. (1996). The Self-Organizing Economy. Birmingham, Blackwell Publishers.
- Langer, J. S. (1980). "Instabilities and Pattern-Formation in Crystal-Growth." *Reviews of Modern Physics* **52**(1): 1-28.
- Lefebvre, L. (1958). Allocation in space; production, transport, and industrial location. Amsterdam, North-Holland Pub. Co.
- Lösch, A. (1940). The economics of location. New Haven, Connecticut, English translation: Yale University Press.
- Lovins, A. and D. Cramer (2004). "Hypercars((R)), hydrogen, and the automotive transition." *International Journal of Vehicle Design* **35**(1-2): 50-85.
- Lovins, A. and B. Williams (1999). A Strategy for the Hydrogen Transition. Tenth Annual US Hydrogen Meeting.
- McFadden, D. (1963). "Constant Elasticity of Substitution Production Functions." *The Review of Economic Studies* **30**(2): 73-83.
- McFadden, D. (1978). Econometric Models of Probabilistic Choice. In *Structural Analysis of Discrete Data with Econometric Applications*. C. Manski and D. McFadden (eds.). Cambridge, MA, MIT Press.

- McFadden, D., Ed. (1998). *Measuring Willingness-to-Pay for Transportation Improvements. Theoretical Foundations of Travel Choice Modeling*. Amsterdam, Elsevier Science.
- National Academy of Engineering (2004). *The Hydrogen Economy: Opportunities, Costs, Barriers, and R&D Needs*. Washington D.C., National Academy Press.
- Ogden, J. (2004). Where will the Hydrogen Come From? System Considerations and Hydrogen Supply. *The Hydrogen Economy Transition: Moving Toward the Post Petroleum Age in Transportation*. D. Sperling and J. Cannon (eds.) Amsterdam, Elsevier Academic Press.
- Romm, J. (2004). "The hype about hydrogen." *Issues in Science and Technology* **20**(3): 74-81.
- Sayama, H., L. Kaufman, and Y. Bar-Yam (2000). "Symmetry breaking and coarsening in spatially distributed evolutionary processes including sexual reproduction and disruptive selection." *Physical Review E* **62**(5): 7065-7069.
- Schiffer, M. B., T. C. Butts, et al. (1994). *Taking charge: the electric automobile in America*. Washington, Smithsonian Institution Press.
- Small, K. A. (1992). *Urban transportation economics*. Chur, Switzerland ; Reading, Harwood Academic Publishers.
- Small, K. A., C. Winston, et al. (2005). "Uncovering the distribution of motorists' preferences for travel time and reliability." *Econometrica* **73**(4): 1367-1382.
- Steinmetz, S. S. C. and D. Brownstone (2005). "Estimating commuters' "value of time" with noisy data: a multiple imputation approach." *Transportation Research Part B*
- Sterman, J. (2000). *Business dynamics: systems thinking and modeling for a complex world*. Boston, Irwin/McGraw-Hill.
- Struben, J. (2005). Space matters too! Mutualistic dynamics between hydrogen fuel cell vehicle demand and fueling infrastructure. 23rd International System Dynamics Conference, Boston, MA.
- Struben (2006a). *Essays on transition challenges for alternative propulsion vehicles and*

transportation systems – Essay 1. Sloan School of Management, Massachusetts Institute of Technology.

Struben (2006b). *Essays on transition challenges for alternative propulsion vehicles and transportation systems – Essay 3.* Sloan School of Management, Massachusetts Institute of Technology.

Struben, J., and J. Sterman (2006) "Transition Challenges for Alternative Fuel Vehicle and Transportation Systems". *MIT Sloan Research Paper* No. **4587-06** Available at SSRN: <http://ssrn.com/abstract=881800>

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

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

Turing, A. M. (1952). "The Chemical Basis of Morphogenesis." Philosophical Transactions of the Royal Society **B237**: 37-72.

Witten, T. A. and L. M. Sander (1981). "Diffusion-Limited Aggregation, a Kinetic Critical Phenomenon." *Physical Review Letters* **47**(19): 1400-1403.

Figures

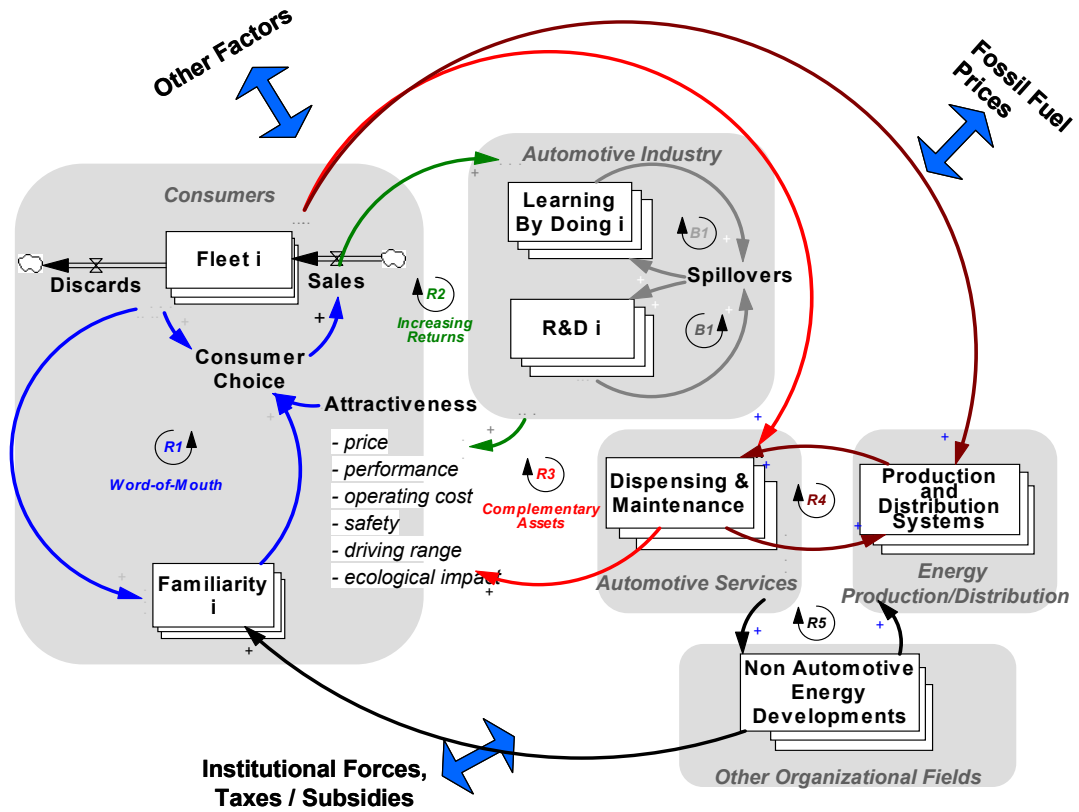


Figure 1 Full model boundary.

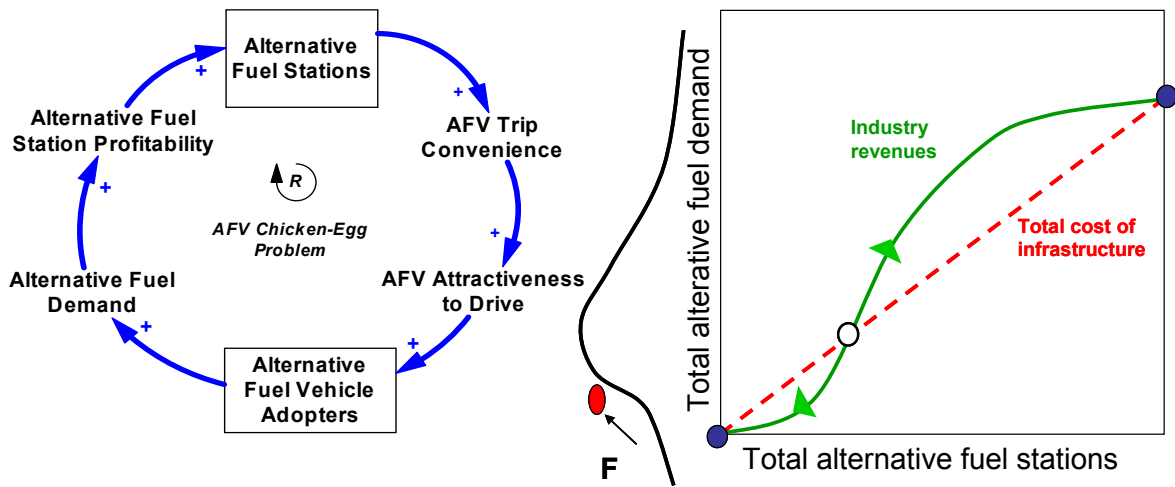


Figure 2 Rudimentary hypothesis for chicken-and-egg dynamics.

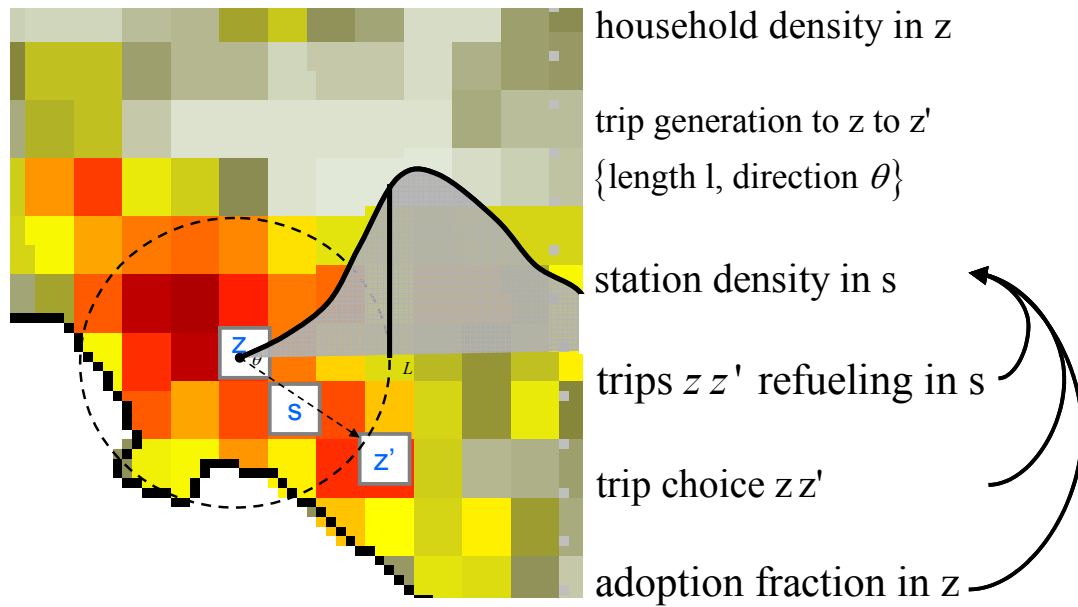


Figure 3 Spatial representation of model concept: demand and supply are subject to short and long-range interactions; demand decisions involve adoption, trip-choice, and refueling locations, and topping-off behavior; supply decisions involve entrance, exit, location selection and capacity adjustments.

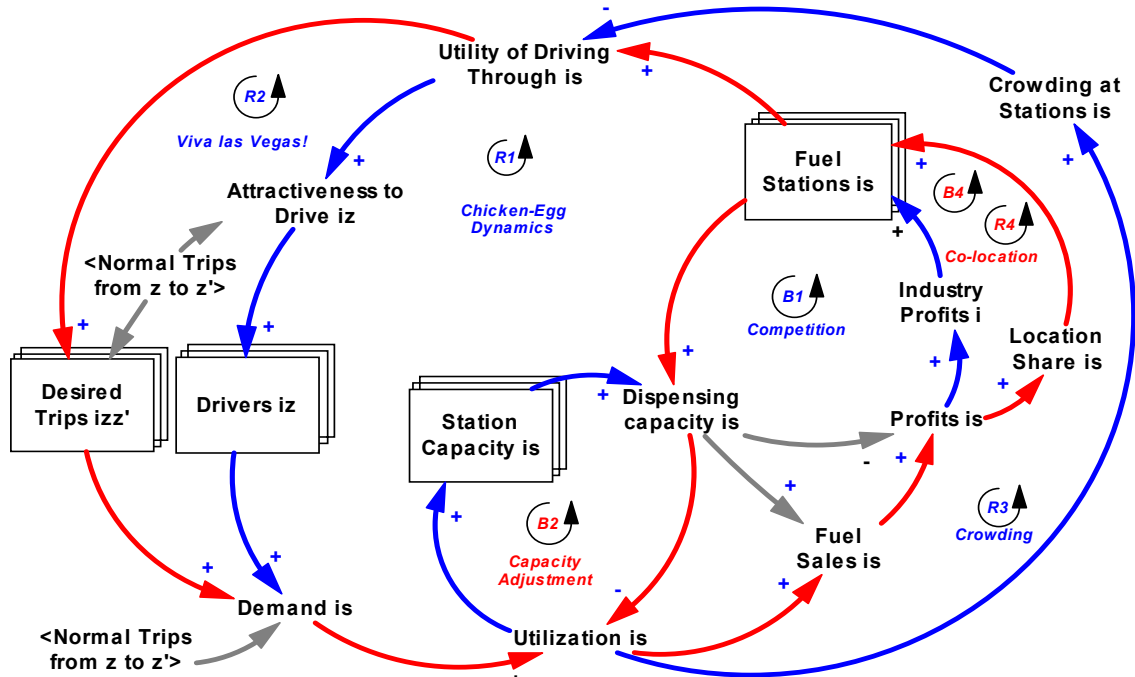


Figure 4 Principle feedbacks governing the co-evolutionary dynamics between vehicle fleet and fueling infrastructure.

Overview of decision structure	choice function (MNL)	aggregate utility and effort function (CES)
	$\sigma_{iz} = \frac{u_{iz}}{\sum_j u_{jz}}$ $u_{iz} = u_{iz}^0 u_{iz}^t e^{\sum \beta_i \frac{a_{iz}}{a_i^*}}$	$u_{iz}^t = \left(\sum_{z' \in Z} w_{zz'} u_{izz'}^{\mu^t} \right)^{\frac{1}{\mu^t}}$
	$\sigma_{izz'} = \frac{u_{izz'}^t}{u_{izz'}^t + u_{zz'}^o}$ $u_{izz'}^t = u_{izz'}^0 u_{izz'}^t$	$u_{izz'}^t = \left(\sum_{\omega_{zz'} \in \Omega_{zz'}} \sigma_{\omega_{zz'}} u_{i\omega_{zz'}}^t \mu^{\omega} \right)^{\frac{1}{\mu^{\omega}}}$
	$\sigma_{i\omega_{zz'}} = \frac{u_{i\omega_{zz'}}}{\sum_{\omega_{zz'} \in \Omega_{zz'}} u_{i\omega_{zz'}}$ $u_{i\omega_{zz'}}^t = e^{\beta^{\omega} \frac{a_{i\omega_{zz'}}^t}{a_{zz'}^*}}$	$a_{i\omega_{zz'}}^t = a_{\omega_{zz'}}^{t0} + \phi_{i\omega_{zz'}} a_{i\omega_{zz'}}^f$ $a_{i\omega_{zz'}}^f = \sum_{s \in \omega_{zz'}} \sigma_{i\omega_{zz'},s} a_{is}^f$
	$\sigma_{i\omega_{zz'},s} = \frac{\varphi_{i\omega_{zz'},s}}{\sum_{s' \in \omega_{zz'}} \varphi_{i\omega_{zz'},s'}}$ $\varphi_{i\omega_{zz'},s} = r_{\omega_{zz'},s} e^{\beta^f \frac{a_{is}^f}{a_{zz'}^*}}$	a_{is}^f

Figure 5 Consumer choice decision tree: left, diagrammatic representation; right, functional forms used for choice structure (multinomial logit (MNL)), and utility and effort structure (non-linear weighted average (CES)).

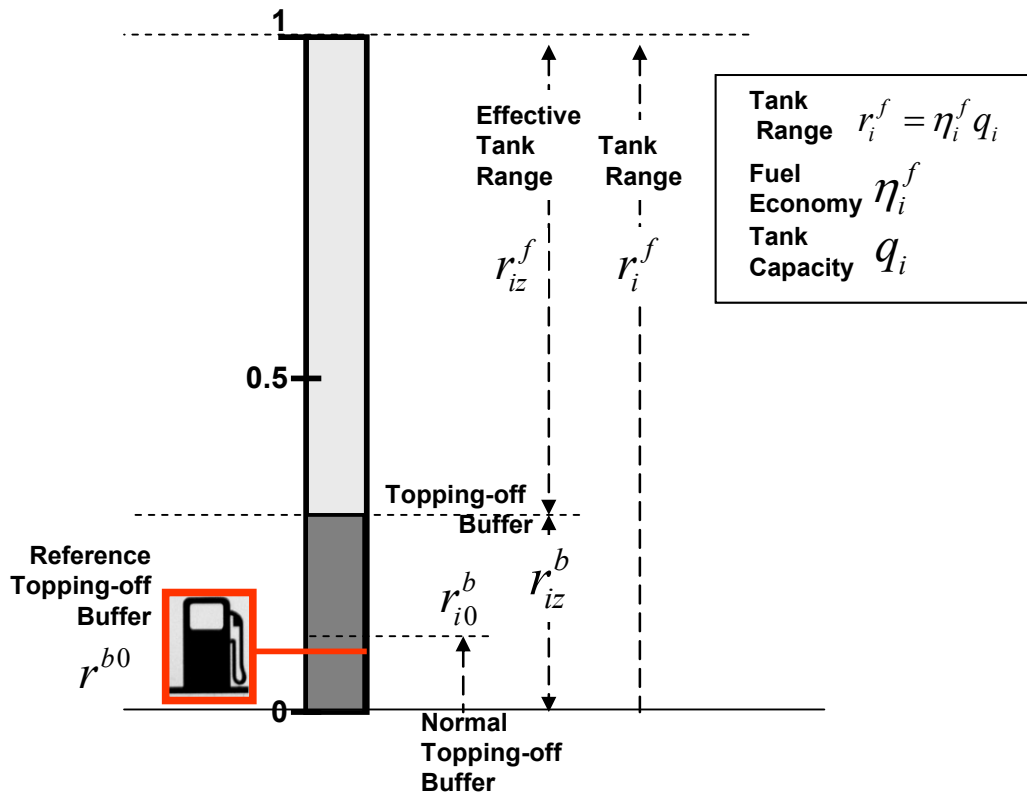


Figure 6 Tank range and topping-off parameters.

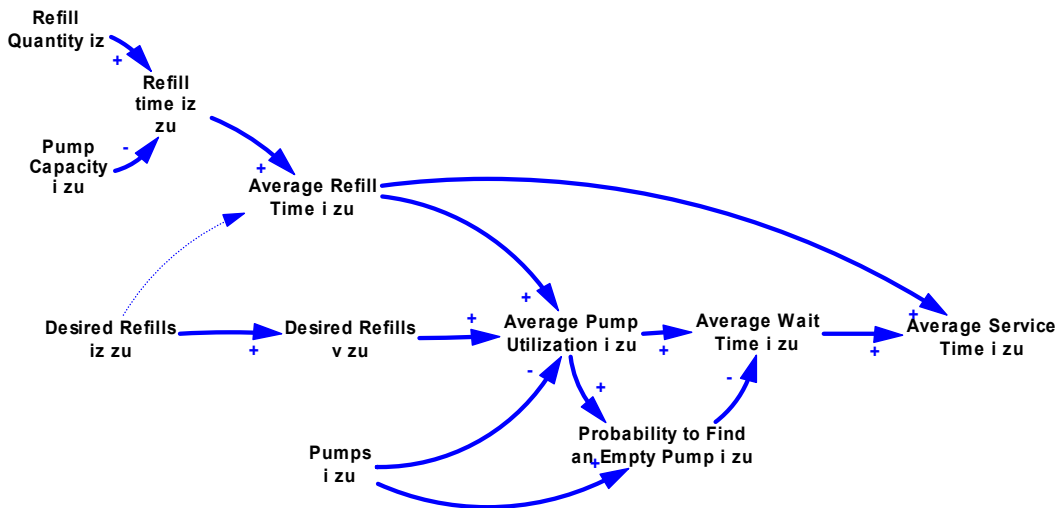


Figure 7 Station utilization and servicing time.

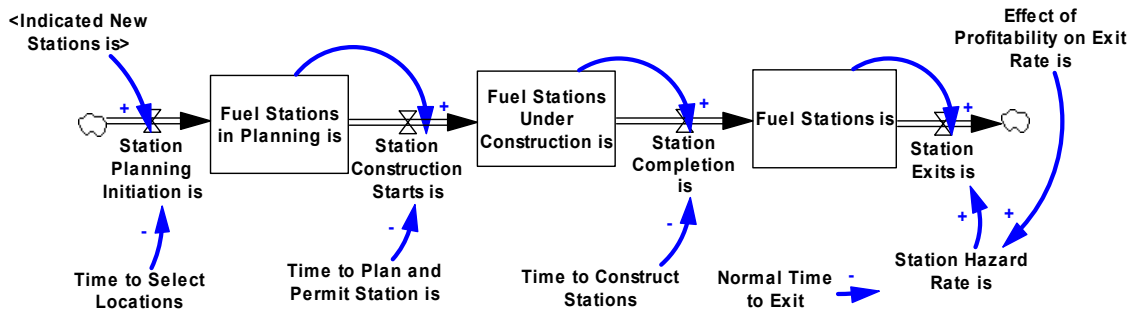


Figure 8 Fuel station entrance and exit process.

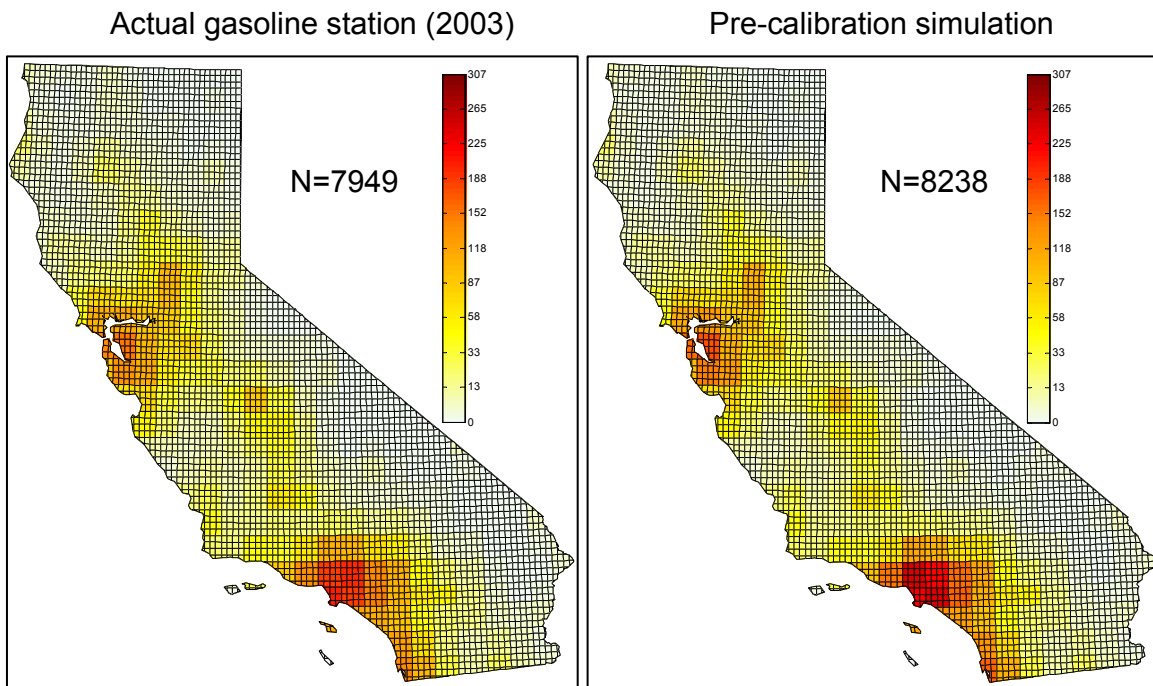


Figure 9 Pre-calibration performance test of station entrance behavior: a) Actual California station distribution; b) Simulated under fixed adoption.

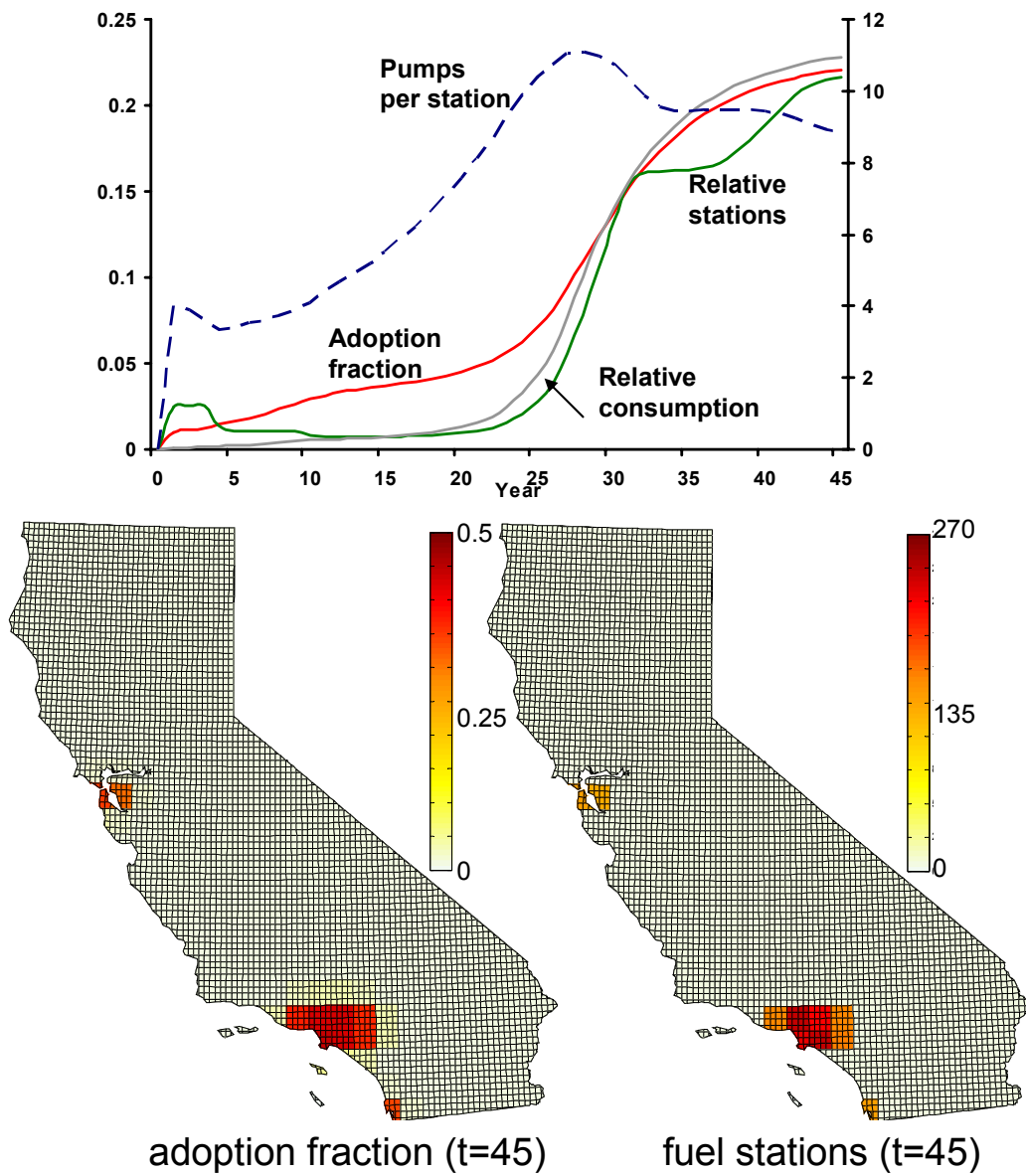


Figure 10 Behavior of spatially disaggregated model calibrated for California.

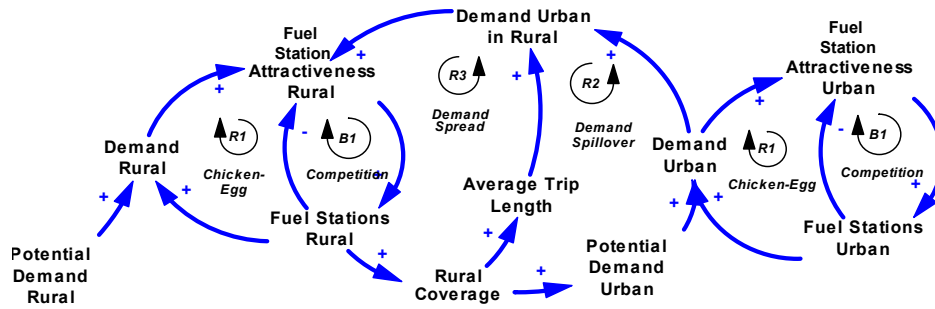
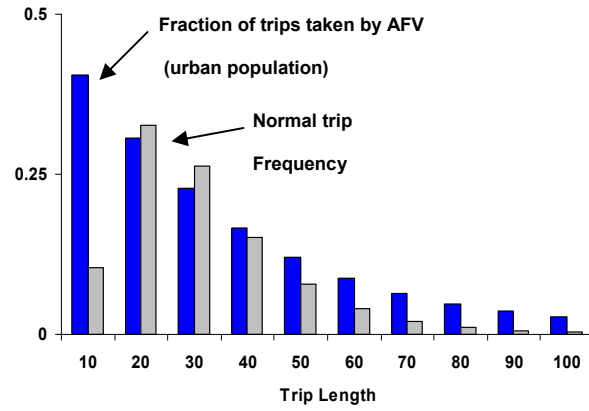


Figure 11 Hypothesis for bi-stable equilibrium with low level adoption and urban clusters.

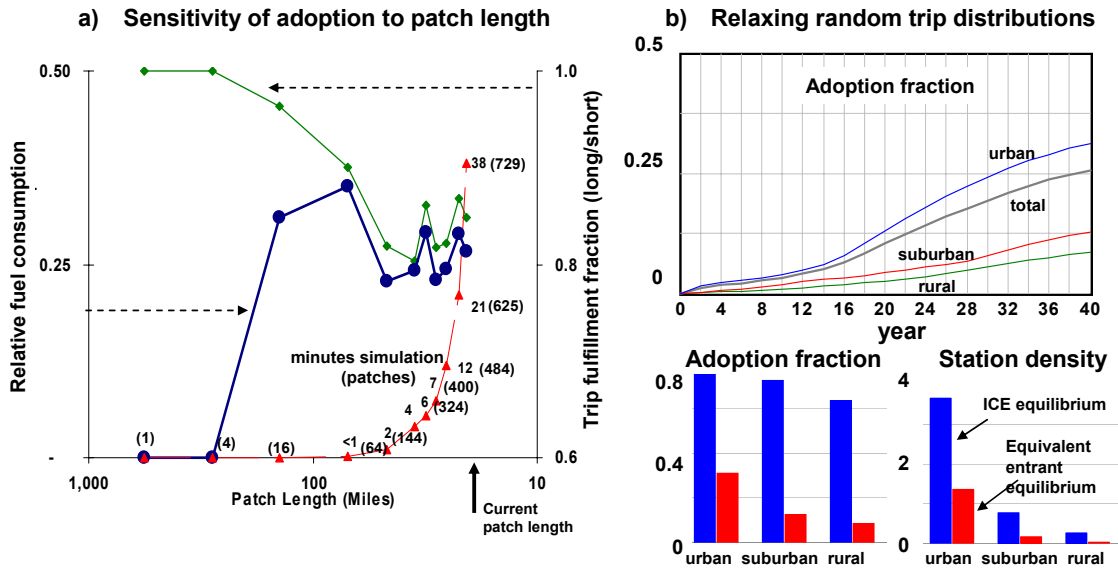


Figure 12 Model sensitivity to spatial detail: a) sensitivity of equilibrium behavior to patch length, with equilibrium fuel consumption (left axis), relative trip fulfillment short versus long trips (right), and simulation time (number of patches) as function of patch length; b) relaxing the assumption of randomly distributed long-distance trips, with adoption fraction over time (top) and the equilibrium adoption fraction for urban, suburban and rural, compared to the results for a simulation of ICE.

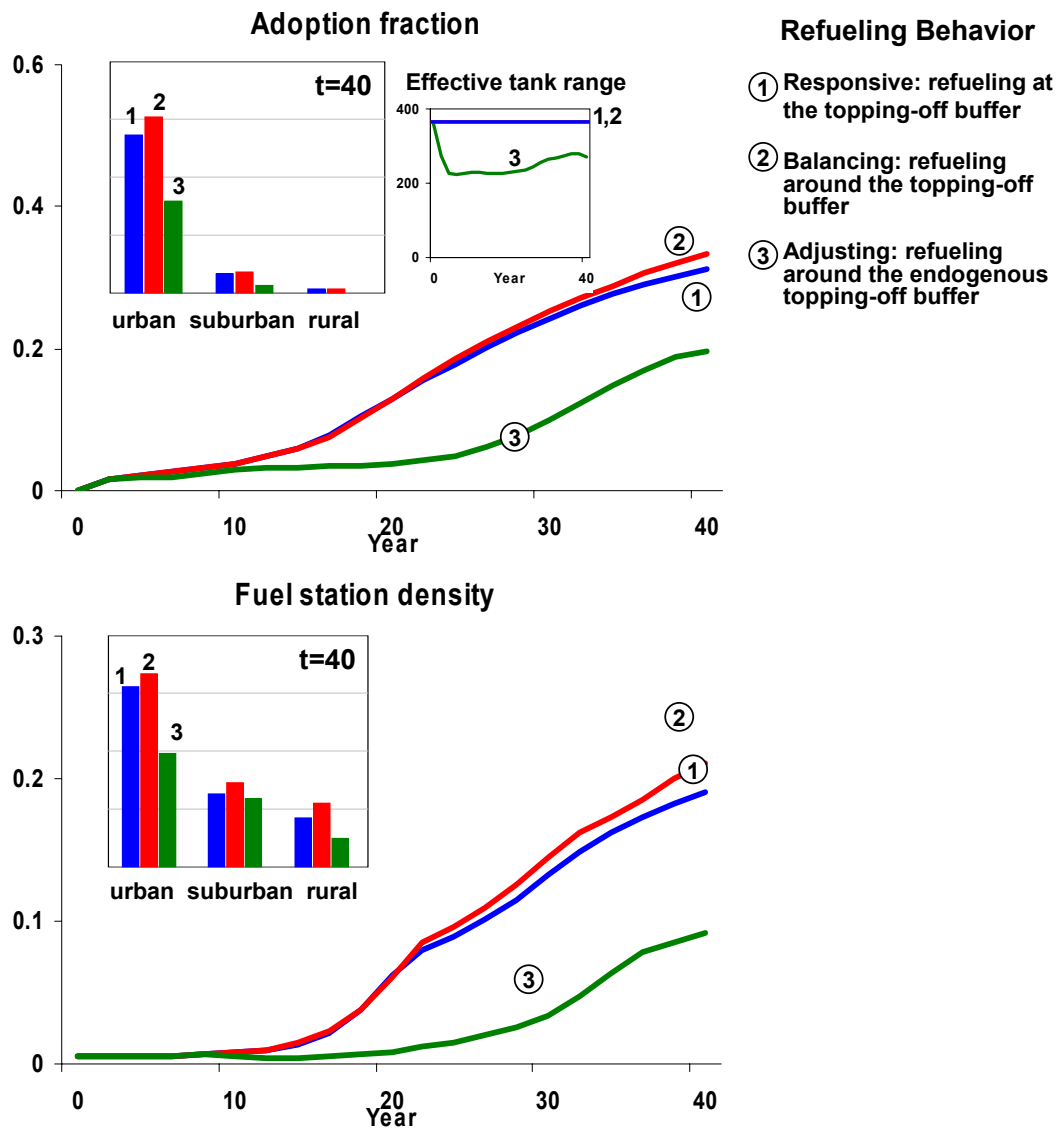


Figure 13 Sensitivity to topping-off behavior: adoption fraction (top) and fuel station density (bottom) for increasingly behavioral assumptions: 1) responsive, drivers always start searching when they reach their topping-off buffer; 2) balancing, drivers refuel on average at their topping-off buffer, allowing some flexibility to refuel at more favorable locations 3) adjustment: topping-off buffers are adjusted in response to changes in the uncertainty of availability of fuel. Left insets show the adoption fraction and fuel station density at $t=40$ for urban, suburban and rural populations. The right inset shows the effective tank range. For simulation 3 the effective tank range adjusts over time.

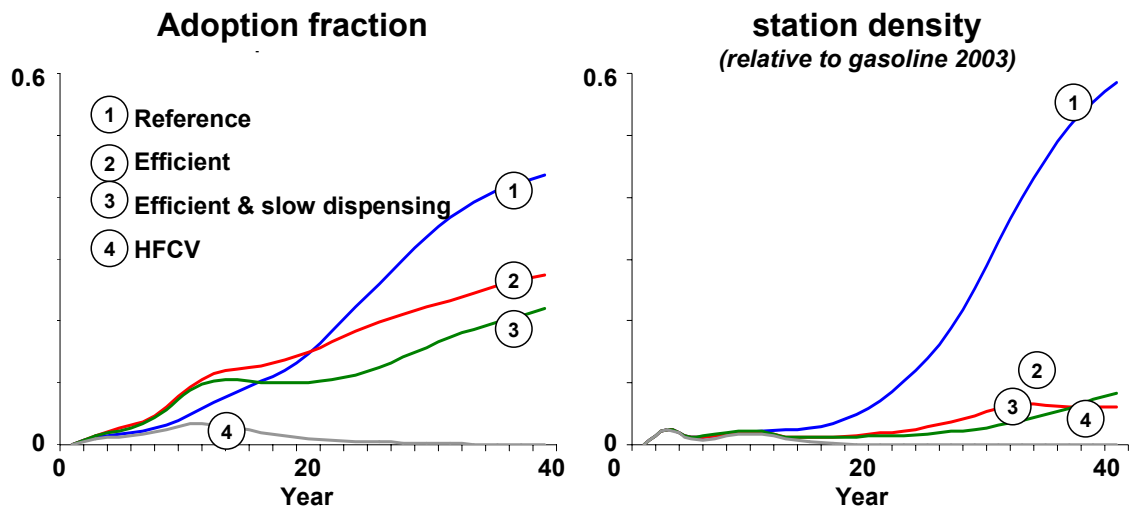


Figure 14 Introductions of hypothetical alternative fuels; details in **Table 3**. Run 2 shows a failure of a more efficient vehicle relative to the reference.

Tables

Table 1 Sources of dynamic complexity of market formation for alternative fuel vehicles.

Characteristic	AFV market formation example
Dynamics / time scale of change	Vehicle turnover; technological progress; infrastructure replacement.
Multiple stakeholders	Consumers; automotive companies; energy companies; fuel cell developers; policy makers; media.
Multiple feedbacks	learning from R&D- and user experience, and by doing; word-of-mouth, technology spillovers; complementarities (fueling infrastructure).
History dependent	Cumulative knowledge; efficacy- and safety perceptions; oil infrastructure.
Nonlinear	Effect of fuel availability on trip effort.
Spatial heterogeneity	Urban/rural asymmetries; short haul/long haul trips; station locating strategies

Table 2 Summary statistics for the state of California.

Statistic	value	Unit	Source
Population	35,537,438	People	US Census 2000
Households	50.2%	Dmnl	US Census 2000
Land area	155,959	Miles^2	US Census 2000
Fraction population metropolitan	84	Dmnl	US Census 1996
Fraction land metropolitan	0.08	Dmnl	US Census 1996
Registered automobiles	17,3e6	Vehicles	Bureau of Transportation Statistics http://www.bts.gov/publications/state_transportation_profiles/california/html/fast_facts.html
Gasoline fuel stations	7,949	Fuel stations	Provided by National Renewable Energy Lab (year = 2003)
Mean travel time to work	27.2	Minutes/ trip	US Census 2000
Annual vehicle miles	12,000	Miles/ year	Average US

Table 3 Default parameter settings; defaults not listed here have been specified in elaboration sections in Appendix 2.

Short	Description	Value	Units	Source/Motivation
Demand - Consumer Choice				
τ^d	Time to discard a vehicle	8	Years	Close to Census values
u^*	Reference Utility	1	Dmnl	Free choice
u_{zz}^o	Utility of alternative to drive	0.25	Dmnl	Heuristic
μ^t	Trip distribution parameter	-2	Dmnl	See discussion in text
β^t	Route choice sensitivity	∞	Dmnl	Simplifying dynamics
μ^ω	Route distribution parameter	1	Dmnl	
β^c	Elasticity of Utility to Cost	-0.5	Dmnl/ (\$/trip)	Used to compare (coarsely) across elasticity
v^t	Value of Time	40	\$/Hour	See research by e.g. Train (2005). Used to specify value of elasticity parameters, including refueling
v^r	Value out of Fuel	200	\$/Empty Tank	Used to calculate w^f
γ^s	Relative Value of Time Service	1	Dmnl	Used to calculate w^x
γ^f	Acceptable refueling effort as fraction of trip effort	0.25	Dmnl	
v_u	Average drive speed	40	Miles/hour	
τ^s	Time to observe station density and wait time	1	Dmnl	As close as possible to 3 Months, simulation time constraints
r^{b0}	Reference Topping-off buffer	0.1	Dmnl	
Demand - Platform specific				
q_i	Storage capacity per Tank	20	Gallon Equivalent	Equivalent to typical ICE
η_i^f	Vehicle fuel Efficiency	20	Miles/Gallon Equivalent	Equivalent to typical ICE
Station Economics				
c_{vz}^f	Whole sale fuel price	1.65	\$/gallon	Typical for US
c_{vz}^o	Non Fuel Variable Cost	0.6	\$/gallon	Typical for US
f_{vz}^a	Ancillary revenues as fraction of value of 1 gasoline gallon equivalent consumed	0.2	Dmnl	Typical for US
m_{vz}	Fuel margin	0.5	dmnl	Typical for US

Short	Description	Value	Units	Source/Motivation
π_v^0	Reference Profitability	0.1	dmnl	
y_{iz_u}	Reference number of pumps per station	8	Pumps/station	Typical for US (Gasoline)
$k_{iz_u}^p$	Normal Pump Capacity	400	Gallons/hour	Average for California (Gasoline)
Station Behavior				
τ_{iz}^{ep}	Time to Permit Stations	1	Year	Part of τ^e
τ_{iz}^{el}	Time to Select Locations	1	Years	Part of τ^e
τ_{iz}^{ec}	Time to Construct Stations	2	Years	Part of τ^e
λ_{ref}^x	Normal station hazard rate (station hazard rate at zero ROI)	0.1	Dmnl/year	
β^k	Sensitivity of Entry to Local Profits	1	Dmnl	
τ_{vz}^k	Time to adjust capacity	1	Year	Though longer when population density is larger.

Technical Appendix

The technical Appendix can be downloaded from:

<http://web.mit.edu/jjrs/www/ThesisDocumentation/Struben2Appendix.pdf>