Alternative fuel vehicles turning the corner?: A product lifecycle model with heterogeneous technologies

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Abstract

The automotive industry may be on the verge of a technological disruption as different alternative fuel vehicles are expected to enter the market. Industry evolution theories are not unified in suggesting the conditions under which different types of entrant technologies can be successful. In particular, the competitive dynamics among a variety of technologies with varying potential for spillovers are not well understood. This paper introduces a product life cycle model used to analyze the competitive dynamics among alternative fuel vehicles, with explicit and endogenous product innovation, learning-by-doing, and spillovers across the technologies. The model enables in particular the exploration of the spillover dynamics between technologies that are heterogeneous. I explore how interaction among learning and spillovers, scale economies, and consumer choice behavior impacts technology trajectories of competing incumbents, hybrids, and radical entrants. I find that the existence of learning and spillover dynamics greatly increases path dependence. Superior radical technologies may fail, even when introduced simultaneously with inferior hybrid technologies. I discuss the implications for the prospective transition to alternative fuels in transportation. While the dynamics are discussed in relation to the automobile industry, the model is general in the sense that it can be calibrated for different industries with specific market, technology, and organizational characteristics.

Introduction

Mounting economic, environmental, and security-related concerns put long-term pressure on a largely oil-based transportation system. In response, automakers are developing alternative technologies, such as hydrogen fuel cell vehicles (HFCVs), to transition away from the petroleum-guzzling internal combustion engine (ICE) vehicle fleet. A central and hotly debated issue among stakeholders is the feasibility of various transition paths towards a vehicle fleet powered by renewable energy. For instance, according to some, HFCVs are a radical innovation with long-term socio-economic advantages and are therefore bound to replace current automobiles (Lovins and Williams 1999). On the other hand, current cost and performance factors disadvantage hydrogen relative to the established ICE-gasoline system, creating large barriers to entry (Romm 2004).

Adding to the complication is the plurality and diversity of other alternatives being considered. Besides leapfrogging to HFCVs or electric vehicles (EVs), some automakers are focused on increasing the efficiency of the current ICE technology. Others emphasize shifting to alternative fuels, such as compressed natural gas or blends of bio- and fossil fuels or are exploring various combinations of these alternative technologies, such as ICE-electric hybrids (ICE-HEVs), diesel-electric hybrids, or hydrogen-ICE (MacLean and Lave 2003). Beyond the fact that each technology trajectory involves large upfront investments, an alternative fuel transport system will drastically transform the social, economic, and organizational landscapes, with implications well beyond the automotive industry. With so much at stake, a thorough understanding of the transition dynamics is crucial.

How do different technologies come to be, gain traction, and sustain themselves? The general pattern dominating the post-industrial perspective regarding technological innovation is the S-shaped diffusion path of superior or novel technologies (e.g., Griliches 1957). This diffusion pattern is currently considered a stylized fact (Jovanovic and Lach 1989), with numerous documented examples including: end products such as motor cars (Nakicenovic 1986) and laser printers (Christensen 2000); process technologies (Karshenas and Stoneman 1993); enabling products such as turbo jet engines (Mowery and Rosenberg 1981) and mini mills (Tushman and Anderson 1986); ideas and forms of social organization (Strang and Soule 1998). While a powerful for ex-post finding, this transition concept is useful for the dynamics of prospective transitions if we have a thorough and detailed understanding of the mechanisms underlying the outcomes[1].

Examination of the mechanisms underlying transitions is required, first, because several hypotheses about the mechanisms underlying the S-curve pattern co-exist (Geroski 2000). For example, while the role of word-of-mouth is emphasized in diffusion models (Bass 1969), game-theoretic models emphasize the process of learning-by-doing and spillovers as fundamental (Jovanovic and Lach 1989). Furthermore, many diffusion patterns deviate from the typical S-shape. Henderson (1995) records unexpectedly long lifecycles for lithographical technologies while other technologies, such as

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[1] The S-curve literature is guilty of selection bias: successful technologies are the focus of explanation. Yet failures (instant or fizzle) are surely numerous.

supercomputers and nuclear energy, have saturated at low levels. Also, as Homer showed, diffusion is often much more complex, with a boom-bust-recovery being common (Homer 1987, Homer 1983). In line with this, the empirical literature increasingly identifies cases of diffusion challenges for new technologies across a wide range of complex environments, such as medical applications (Gelijns et al. 2001), renewable energy (Kemp 2001; Garud and Karnoe 2001), or automotive industry (Geels 2005).

The reason for such a high degree of heterogeneity in hypotheses and outcome is due in part to the differences in potential performance and productivity of individual technologies across cases. Further, the literatures emphasize different drivers of diffusion. The marketing literature emphasizes social dynamics and consumer choice, while the literature on industry dynamics emphasizes the technological S-curve. In each system, both are present, but their influence differs across cases. In several cases it is justified to filter out the most dominant mechanisms; however, this is not always true. However, other critical factors can make similar, or stronger, contributions to the dynamics: a technology transition includes network effects, scale economies and other increasing returns to scale, co-evolution with complementary systems, consumer behavior and learning, public rules and regulations, and competing technologies.

It is such interplay within and with its context that makes a technological trajectory path-dependent. Such path dependency is a particularly important consideration for the evolution of the automotive industry. Figure 1 illustrates the evolution of the installed base of various fuel technologies between 1880 and 2005. ICE vehicles displaced the horse-drawn carriage as the dominant mode of transport through a very rich set of interactions that included the competitive development of various types of platforms (that is, vehicles defined by the technology but also their complimentary and institutional elements) with technological innovations for each that partly spilled over between them, but also competitive and synergistic interactions with other emerging modes of transportation, such as trolleys and railways. Furthermore, co-evolution of fueling and maintenance infrastructure, roads, and driving habits played a large role in the adoption dynamics (e.g., Geels 2005). In the first decades there was little agreement on what the outcome of the transition would be. For example, around 1900 EVs were very much in competition with steam and internal combustion engines (ICE): they held the world speed record of 61 mph in 1899 (Flink 1988); their performance was superior in many other key attributes (e.g., simplicity, cleanliness, noise); they had strong support from leaders in industry, including Thomas Edison. However, soon after, sales of automobiles powered by ICE surpassed electrics and ICE became the dominant design (see Struben 2006a for a more detailed discussion).

With the prospective transition challenges within the automobile industry in mind, we develop a model that captures a broad scope. In other papers, the role of feedbacks related to consumer familiarity (Struben 2006a) and to infrastructure complementarities (Struben 2006b) are analyzed in depth. This paper focuses on the mechanisms that involve technological innovation, learning, standardization, and spillovers among various technologies. Technology spillovers are a central contributor to advancement of technology throughout industries (Jovanovic and Lach1989). For example, a critical invention for the advancement of ICE vehicles was the electric starter. Its idea, built on the use of a battery and dynamo, was derived from the EV. The experience with the EVs was fundamental to its successful implementation in ICE vehicles the dynamo, wiring, non-standardized batteries, and starter system all needed to be adjusted properly to each other.

The power of spillover is also illustrated by the emergence of the wind-power industry. In the early 1980s, two drastically different approaches competed with each other. First, a US-based approach was founded on superior and top-down design, based on aerospace fundamentals, and backed by fundamental R&D. In contrast, the Danish wind industry supported development of diverse alternatives, by individual entrepreneurs, and was geared to stimulate spillovers among them. It was the low-investment, large-spillover approach that out-competed the superior designs (e.g., Karnoe 1999).

One key question to understand in relation to such technology competition is, Under what conditions is leapfrogging, rather than gradual change, more likely to lead to success? A related question is whether broad deployment of competing alternatives constrains or enables a transition. Radically different technologies will experience limited exchange of knowledge with incumbents. For example, HFCVs can share part of the gains in body weight with ICE/gasoline vehicles, and vice versa, but their fuel-cell stacks and electric motors will not benefit from the 100 years of experience with ICE. On the other hand, contemporary HEVs can learn from experience with both ICE and HFCVs.

While strategic and policy implications are enormous, the concept of spillovers has been treated explicitly in only a few models (notable exceptions are Klepper 1996, Jovanovic and Macdonald 1994, Cohen and Levinthal 1989). Here I introduce and explore a model with endogenous innovation, learning and spillover, and resource allocation. This model contrasts with the traditional models regarding three critical aspects. First, this model explicitly captures the notion of variation in the substitutability of knowledge across platforms. Second, advances within an entrant technology can spill over to the market leader. That is, market leading and technology advances are decoupled. Third, the model includes scale effects that are external to the technology and analyzed in interaction with the spillover dynamics.

These differences will permit focus on the specific challenges related to technology transitions. The first two distinctions imply relaxing the implicit assumption of technology convergence to one standard. The third will be shown to have significant implications for the dynamics, even when weak in isolation. Further, we can examine the competitive dynamics between entrants, hybrids, and more radical technologies.

I begin with a short discussion of the literature on technological change patterns. Next I will provide an overview of the model. Thereafter I present the model structure. In the analysis I demonstrate the possibility of superior technologies failing in competition with inferior ones. In addition, while the isolated effects of spillovers and scale effects can be limited, their interaction can dramatically influence the dynamics and reduce the take-off opportunities for more radical technologies. I also point to the path dependency of multiplatform competition. In the final section, I state conclusions and discuss implications for the AFV transitions.

Modeling competitive dynamics between heterogeneous technologies

This section provides an overview of the central factors affecting "technology trajectories" and next describes the model boundary and scope.

The literature on technological change patterns

" In product life cycle (PLC) theories, radically different technologies start with an initial low level of agreement about the key dimensions of merit on the producer side, along with limited attention to the technology from consumers (Abernathy and Utterback 1978). A subsequent rise of entrants with different ideas drives up product innovations. As industry and average firm size grow, and an increase in capital intensity forms barriers to entry, benefits from engaging in process innovations increase, which lowers cost. A shakeout results in a reduction of variety and total product innovation, stabilizing the standard product (Klepper 1996), or, alternatively, a dominant design results in stabilization and shakeout through subsequent process improvement (Abernathy and Utterback 1978). Ultimately, market shares of firms' products stabilize, indicating the final stage of the PLC. Table 1 presents an impressionistic overview of the evolution of the automobile industry, novel in 1890, infant around 1910, and mature by 1960, corresponding with the general PLC observations. The industry is currently experiencing a period of change.

Disruptive innovations are hard to establish in a mature and oligopolistic market. Barriers to change are formed: first, because incumbents can deter entry through preemptive patenting out of fears of cannibalization of existing market share (Gilbert and Newbery 1982, Arrow 1962); and, second, because of the existence of various increasing returns to adoption economies (Arthur 1988). Others describe conditions under which disruption is possible, for example, under sufficient uncertainty of the timing and impact of the innovation (Reinganum 1983).

Addressing the issues of barriers from increasing returns, the literature builds on Dosi (1982), who distinguishes market-performance attributes, organizations' value networks, and technology cost structures. For example, Tushman and Anderson (1986) distinguish capability-enhancing and capability-destroying disruptions: that is, cumulative experience and scale can either help or hinder incumbents producing the old technologies, but not entrants. This asymmetry allows barriers for development of a new technology to be broken down either because incumbents have an incentive to rely on scale economies and experience or because the entrants are not locked-in to the sunk cost and experience of the old technology. Incumbents have inertia because of cost in adjusting their channels (Henderson and Clark 1990) or because of cognitive biases (March 1991; Tripsas and Gavetti 2002). Christensen (1997) notes that disruptive technologies can emerge in a neighboring market and compete on dimensions of merit previously ignored. For the incumbent it is not attractive to invest in a small infant market product, but they can fend off threats by shifting upward in the market. However, as the experience of the entrant grows, its superior performance in the new attributes allows the entrant to outplay the incumbent.

While the unit of analysis of these studies is the firm, when the focus shifts to technology entrant and incumbent, the conclusions are similar. Firm capabilities are built up around particular technologies. Learning and accumulation of experience are central in the study of technological change. Four types of channels are usually distinguished: product innovation through R&D, learning by doing (often equated with process innovation) (Arrow 1962; Zangwill and Kantor 1998), learning by using (Mowery and Rosenberg 1989), and spillovers (e.g., Cohen and Levinthal 1989). Developments in each channel can be tightly interdependent. For example, tasks (processes) depend on design (product). To what extent this is the case depends on technology design characteristics, such as its complexity and modularity (Clark 1985; Sanchez and Mahoney 1996; Baldwin and Clark 2000) and its vertical integration (Henderson and Clark 1990; Christensen and Rosenbloom 1995; Ulrich 1995; Fine 1998).

The window of opportunity for a disruption is discussed by Tushman and Rosenkopf (1992). They expand the “dominant design” model to incorporate the social dynamics by which networks of power rearrange during the ferment period, subsequentially changing the institutional structures and driving the next process towards standardization. Holling (2001) provides a similar ecological view of succession. On the other hand, Basalla

(1988) describes a much more evolutionary process of change. Finally, the invention and progress rate depends also on potential rates of discovery (Aghion and Howitt 1992; Aghion et al. 2001), technological characteristics (Iansiti 1995), firm goals and perceptions of the technology potential (Henderson 1995). The relevance of these different observations depends on industry specific parameters and the stage of the industry.

Technological innovations spill over between technologies. The effect increases with the gap between laggards and leaders (Jovanovic and Macdonald 1994; Aghion et al. 2001), and with the capability to extract knowledge from the outside (Cohen and Levinthal 1989). At the industry level, competence building is a social, distributed process of bricolage (Garud and Karnoe 2003). This view emphasizes the value of technological diversity as was discussed for the emergence of wind energy by (Karnoe 1999; Kemp 2001; Garud and Karnoe 2003). Whether innovations of a potential entrant will generally trigger increased R&D activity and performance increases of incumbents, the so-called sailing-ship effect (Rosenberg 1976), has also been observed in the automobile industry (Snow 2004). It is these combinations of interactions that suggest that hybrid technologies can serve as temporal intermediate bridges between an incumbent and a radical innovation (Utterback 1996).

Other dynamic factors are early uncertainty about the efficacy and safety of new technology, the role of complementary assets, economies of scale, scope, and other market externalities. They drive increasing returns to scale (Arthur 1989) and network externalities (Katz and Shapiro 1985) that play a central role in the emergence of a standard designs (David 1985; Sterman 2000; Klepper 1996).

Model Boundary and scope

The model represents the evolution of an industry's technology over time and is in spirit similar to the product life cycle model of Klepper (1996) that is based on the concepts of industry evolution (Nelson and Winter 1982). The current formulation captures the new and replacement sales of semi-durable goods. The model is discussed in the light of the vehicle market. Klepper focuses on interactions between market structure (patterns of firm entry, exit, and concentration) and innovation, with heterogeneity in capabilities of firms as a main driver of dynamics. In this paper the unit of analysis is the technology rather than the firm. Figure shows the boundary of the model. Layers indicate different platforms. Further, as with other PLC models, this model captures learning-by doing and R&D, and endogenous allocation of resources that are adjusted with the relative productivity of the production inputs. Technological diversity evolve over time and substitutability between variants explicitly and endogenously. However, central to this analysis is the assumption that technology is inherently multidimensional. This means, first, that spillovers can also flow to the market leader, as platforms lead at some aspects of technology, but lag at others. Second, technologies can be non-uniform across platforms. Finally, to explore the dynamics, the model allows examining the interaction with other scale effects, external to the technology.

Figure 3 shows the principal feedbacks that drive technological change. Sufficient attractiveness of a product increases its market share and sales and allows for allocation of resources for R&D that in turn improves the knowledge and technology, and subsequently the product attractiveness. This further increases market share (R1, *learning by R&D*), as well as *learning-by-doing* (R2) through accumulation of production experience. The first results in product improvement, the second mostly in process improvement. Improvements occur with *diminishing returns* (B1). On the other hand, resources can be allocated to absorb *knowledge spillovers* (B3) from other platforms. Resources are allocated to those activities with the highest perceived *productivity* (R3). While not shown explicitly in this high-level overview product and process improvement is separately represented in the model. Also not shown, but included, are several increasing returns to scale. Without a priori assumptions that impose conversion of technologies to one standard, we can explore here under what conditions these dynamics benefit or harm different technologies.

The model

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

$$\pi_j = \pi_j^n - C_j^k - C_j^{RD} \tag{1}$$

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

$$\pi_j^n = \left(p_j - c_j\right)s_j = m_j c_j s_j \tag{2}$$

A key structure in the model is how experience and revenues feedback to improve knowledge, technology and then consumer choice and sales. Figure 4 shows the modeled chain of operations that connects the producers' resource allocation decisions to the consumers' purchase decisions, through knowledge accumulation and technological improvement. The chain is comprised of three main segments: consumer choice, effective technology and knowledge accumulation, and resource allocation. The consumer's choice of platform j, $j \in \{1,...,N\}$, depends on the utility u_j that consumers derive from platform j, and is determined using a multinomial logit function. Utility is derived from two attributes a_l, $l \in \{\text{performance,price}\}$ that are a function of the state of the effective technology associated respectively with cost and technology performance. There are two types of activity, $w \in \{\text{product,process}\}$, that each determine the state of technology. To simplify the analysis, I assume that the state of technology associated with product improvement yields performance improvements and those with process improvements yield solely cost improvements. The technology frontier moves with an increase in the effective knowledge, with diminishing returns. Effective knowledge aggregates knowledge from all sources *i* that contribute to the state of the technology and that are associated with activity *w*, this is done through a constant elasticity of substitution (CES) function. Knowledge of platform j accumulates, through internal learning-by-doing and product improvement $(i = j)$, or through spillovers $(i \neq j)$. The third section comprises resource allocation decisions made to maximize marginal returns.

This structure rests upon several significant simplifications. While the key arguments of this paper do not rest on the current level of detail, a more detailed transition exploration of the transition dynamics would benefit from relaxing some assumptions. Four are especially important to highlight at this point. First, I collapsed several consumer choice attributes into two that map on to cost and performance. However, consumers base their choice on a series of attributes (price, operating cost, convenience, reliability, driving range, power, etc…). Capturing these details can be important, for example because complementarities from fueling infrastructure affect attractiveness at this level, but can differ by platform. Second, I map cost and performance one on one onto respectively process and product innovations. In reality both process and product innovations contribute to both performance and cost. Third, vehicles comprise different modules (powertrain, body, brake-system, electrics). It is at this level that spillovers and improvements occur, and the degree of this depends very much on the specific module. Thus, an analysis of transition dynamics for specific AFVs should rest on a structure at the module level. Fourth, product and process improvements are tightly coupled due to the design/task interdependencies of complex products. For example, the unit production cost of technologies may increase temporarily after a product innovation cycle. This is because product innovations partly render previous process improvements obsolete. Appendix 3a (http://web.mit.edu/jjrs/www/ThesisDocumentation/Struben3Appendix.pdf) describes the generalization of the model that includes these more general formulations.

This expanded model allows testing of the extent to which the key dynamics hold when the boundary is expanded. It also allows for the exploration of dynamics within a larger set of environments.

I proceed here with an exposition of the core model. In the next section I provide the functional relationships for the central parts of the model: technology, and knowledge accumulation. Thereafter I discuss the resource allocation process. I end the exposition with notes on consumer choice and accounting that includes the elasticity of substitution between the various sources of knowledge, effective technology, and the input factors.

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

$$c_j = c^f + c^v \big/ \theta_{j2} \tag{3}$$

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

$$T_{jw}^* = T_{jw}^0 \left(K_{jw}^e \big/ K_w^0 \right)^{\eta_w^k} \tag{4}$$

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

Much of the knowledge that is accumulated within one platform can spill over to others. One firm and platform may lead on certain aspects of technology and lag on others, simultaneously being both the source and beneficiary of spillovers. To allow for varying substitution possibilities, the knowledge base for each platform is a constant elasticity of substitution (CES) function of the platform's own knowledge K_{jjw}, and the knowledge, spilled over from other platforms, K_{ijw}, depending on the spillover effectiveness κ_{ijw}:[2]

$$K_{jw}^{e} = \left[\kappa_{jjw} \left(K_{jjw} / K_{w}^{0} \right)^{-\rho_{jw}^{k}} + \sum_{i \neq j} \kappa_{ijw} \left(K_{ijw} / K_{w}^{0} \right)^{-\rho_{jw}^{k}} \right]^{-1/\rho_{jw}^{k}} \tag{5}$$

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

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

Further, $\rho_{jw}^{k} = \left(1-\varsigma_{jw}^{k}\right) \big/ \varsigma_{jw}^{k}$ is defined as the substitution parameter, with its transformed value ς_{jw}^{k} being a measure of the elasticity of substitution between the various knowledge sources for platform j.[3] For such technologies $1 < \varsigma_{jw}^{k} < \infty$. Further, we see that one way for the effective knowledge to be equal to the normal knowledge is when internal knowledge equals the mature knowledge K_{w}^{0} in absence of any spillover knowledge.

Accumulation of knowledge

Knowledge accumulates through four distinct processes: product improvement through R&D, process improvement through learning-by-doing, and spillovers of both product and process knowledge. Knowledge production occurs through directed search (trials) (Simon 1969) and following standard search models, actors take random draws from a large pool of potential ideas (Levinthal and March 1981). Product improvement trials can be undertaken with increased R&D. Process improvements accumulate through learning-by-doing, increasing with production rates and investment (Arrow 1962; Zangwill and Kantor 1998). Knowledge production grows with diminishing returns in the number of resources, reflecting the several organizational and time constraints in doing more trials.

More formally, product innovation and process improvement knowledge accumulate at a rate Γ_{w} when resources are equal a normal value R_{0}. The accumulation rate increases

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

with allocation of resources, an endogenous productivity effect ε^i_{jw}, and relative resource allocation:

$$\frac{dK_{jjw}}{dt} = \varepsilon^i_{jw} \left(R_{jw} / R_0 \right)^{\eta^i_w} \Gamma_w \tag{6}$$

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

For product improvement the productivity effect is constant, $\varepsilon^i_{j1} = 1$. Process improvement is subject to learning-by-doing effects and the effectiveness is a concave function of the relative resources per volume produced: [4]

$$\varepsilon^i_{j2} = \left(s_j / s_0 \right)^{\eta^s} \tag{7}$$

with $0 \le \eta^s_j \le 1$. The unit of analysis is the platform. Capturing learning-by-doing at this level is justified for that knowledge that can flow easily between firms with similar technologies are fast relative to the industry evolution time scale). However this is certainly not true for all knowledge. As the typical number of firms that are active in an industry can change significantly over time, this also means the learning-by-doing effectiveness can do so. This is discussed in Appendix 2d.

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[4] We can arrive at the combined effect of equations (6)and (7) following a different train of thought: process knowledge grows linear with sales, holding resources per unit produced equal to its reference value, while reference resources per unit produced increase with sales (as it is harder to capture all the benefits); and finally, the productivity of resources per unit produced has diminishing returns Thus:
$dK_{jj2} / dt = s_j \left[\left(s_j / R_j \right) / \left(s_0 / R^s \right) \right]^{-\eta^i_2} \Gamma_1 ; R^s = \left(s_j / s_0 \right)^{\eta^s} R_0$, with constraints:
$-1 \le -\eta^r_2 - \eta^s \le 0$ guaranteeing diminishing returns in sales following this expression, and
$0 \le \eta^r_2, \eta^s \le 1$, because of the interpretation in the main text.

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

$$\frac{dK_{ijw}}{dt} = g_w^o \left(K_{\tilde{ijw}} - K_{ijw} \right) \left(R_{jw} / R_0 \right)^{\eta_w^o} \tag{8}$$

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

Supply decisions

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

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

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

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

$$\sigma^{r*}_{ijw} = R^*_{ijw} \Big/ \sum_{i' \notin j} R^*_{i'jw} \tag{9}$$

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

$$R^*_{ijw} = f\left(\varsigma^{r*}_{ijw} \big/ \varsigma^k\right) R^r_{ijw}; f' \geq 0; f \geq 0; f\left(1\right) = 1 \tag{10}$$

Returns are measured in relation to the relevant lowest level performance indicator that is perceived to be fully influenced by the decision, capturing the essence of local decision making. The planning horizon over which the expected performance is estimated is τ^p. In the case of resources for spillovers across platforms, the reference indicator is total spillover knowledge, $K_{\sim jw}$, with $K_{\sim jw} \equiv \left[\sum_{i \neq j} \kappa_{ijw} \left(K_{ijw} \big/ K^0_w\right)^{-\rho^k_{jw}}\right]^{-1/\rho^k_{jw}}$, which follows from equation (4).

In Appendix 3c show that when the expected returns on effort, ς_{ijw}^{r*}, equal marginal returns on effort, the resource allocation is locally optimal. Here I assume, optimistically, that decision makers understand the structure that drives marginal returns on effort and that they can learn this, with perception delays, under the local conditions of holding current resources and all outside conditions constant (see Appendix 2b for a detailed motivation and example).

A final set of decisions involve entry and exit. Entry decisions are conditional on realization of discovery of a particular technology. Entry depends further on expected return on investment (ROI), which follows similar heuristics as outlined here for the resource allocation process. Expected ROI depends on the spillover effectiveness with incumbents, on the current state of the industry, the initial experience that platforms are endowed with, the initial state of their technology, and on the size and duration of seed funding. Platforms exit when profits fall below a reference value. This will be discussed more in the analysis

Platform sales

The total number of vehicles for each platform $j = \{1,...,n\}$, V_j, accumulates new vehicle sales, s_j, less discards, d_j:[5]

$$\frac{dV_j}{dt} = s_j - d_j \tag{11}$$

[5] I ignore the age-dependent character of discards in this discussion (see for this Appendix 2a in Essay1).

Total potential sales going to platform j equal considered sales from non drivers adopting at rate s^n and all discards from all platforms, multiplied by the share going to platform j, σ_j :

$$s_j = \sigma_j \left(s^n + \sum_i d_i \right) \tag{12}$$

The replacement decision involves a choice of whether to adopt or not, and conditional upon adoption, platform selection. This is captured through a nested logit-model (Ben-Akiva 1973). Further, Struben (2006a) discusses the social factors influencing utility such as familiarity and experience from driving, as well as perceptions of attributes' state as input. Appendix 2e provides the detailed nested-logit formulation, and how familiarity and perceived utility are integrated in the nested-logit formulation. In the model exposition here we proceed with an extreme case of the nested form: the normal multinomial form in which all alternatives are compared at par:

$$\sigma_j = u_j \Big/ \left(u^o + \sum_{j'} u_{j'} \right) \tag{13}$$

For non-drivers, the total purchase rate, in the absence of capacity constraints, equals:

$$s^n = N / \tau^a \tag{14}$$

Where, $N = H - V; V = \sum V_j$ are the non-drivers, with H being the total number of households, while τ^a is the average time between two adoption considerations.[6]

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[6] The proper interpretation of a "share" that is allocated based on relative utility is thus defined as individuals' allocation between two alternatives at a decision point, rather than a fixed fraction of the population adopting or not. The steady state total adoption fraction depends thus on the consideration time. For instance, if $u_j = u^* \forall j$ and non-drivers, the total adoption fraction equals $\tau^a \Big/ \left(\tau^a + \tau^d \right)$, and is therefore not necessarily 50%.

The perceived utility of a platform captures the aggregate of experience across various dimensions of merit. Ignoring variation in perceptions for drivers of different platforms, we can write $u_{ij} = u_i \, \forall i$. Further, with utility being equal to the reference value u^* all attributes equal their reference value, we have:

$$u_j = u^* \exp\left[\sum_l \beta_l \left(a_{jl} / a^* - 1\right)\right] \tag{15}$$

where β_l is the sensitivity of utility to a change in the attribute $l \in \{1, 2\}$. The first attribute captures the performance, and thus state of the production technology, $a_{j1} = \theta_{j1}$. The second attribute captures price $a_{j2} = p_j$, where price is an indirect function of the state of the process technology, θ_{j2}, discussed above.

This concludes the fundamental structure of the model, relevant and sufficient for explaining the key insights of this paper. The model has been subjected to its robustness by testing the role of other factors. None of them have critical impact on key insights of this paper, however, those that I include in Appendix 4 do allow studying a richer variety of contexts and also serve for detailed testing of the conditions under which the key insights hold. Besides the expanded structure regarding technology accumulation, discussed above, additional boundary conditioning structures that I subjected the model to are: i) endogenous elasticity of substitution, which allows capturing consistently spillover dynamics of multiple endogenously platforms over long time horizons; ii) interaction effects between different activities, which traces the effective technology more closely; iii) spillover potential ; iv) endogenous capacity adjustment, constraining the sales growth rate after sudden technology shocks. So far we ignored that demand and actual sales can become decoupled through capacity constraints, accumulating backlogs. v) backlogs and churn, which properly deals with demand responses to supply shortages; vi) adjustment of markups, which allows one to proxy different market structure and competitive effects; vii) scale economies within a platform, which allows to distinguish these effects, that are not prone to spillovers, from learning by doing.

Analysis

We will first explore the basic behavior by testing basic PLC dynamics for two extreme cases: i) a single platform, without spillovers; ii) multiple platforms that enter endogenously, and are subject to complex spillover interactions. Next we analyze the spillover mechanisms in detail by examining the isolated case of two competitive dynamics between two platforms. To understand how these mechanisms play out in a richer context, we also explore the role of scale effects. With the insights from these analyses, we will study implications for AFV transitions and focus in particular on competitive interactions between three heterogeneous platform.

Testing basic model behavior

I first test whether the model is able to generate the stylized patterns of behavior we should expect from a PLC model. Figure 5 shows the product lifecycle dynamics generated by the model, representing the introduction of a new technology in isolation, such as the basic technology related dynamics of the emergence of the automobile industry. Parameter settings for this and other simulations are provided in **Table** . Discovery probabilities for all but one technology are set to zero, while this technology is introduced at t=0. The installed base reaches 90% of the potential market over time (utility of not adopting, u^o equals 0.1). The improvement rate of product technology precedes that of process technology. Vehicle performance improves initially very steeply, while costs rise after initialization, because of the inexperience with the new products. After year 5 costs start to decline rapidly as well due to the rapid increase in scale, spurring learning-by-doing effects. After year 13 the improvement rate of process technology dominates benefits from the increased scale. From then on, costs fall over 50 percent, while vehicle performance improves marginally. Investment in R&D increases rapidly, due to considerable returns on investment and larger scale, but decays gradually subsequently, as ROI evaporates when a reasonable large market share is reached.[7] However, ultimately, rapid experience overcomes this. At the same time, the scale is large enough that net cost reductions remain positive. Clearly, other modes of behavior can be generated depending on these assumptions and on the initial experience of product and process innovation. However, by using typical parameter settings, the fundamental PLC patterns are well represented by the model.

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[7] In these simulations we have ignored the number of firms within a platforms and their effect of the market concentration on scale economies (see Klepper 1996). This will be treated in later versions. See also Appendix 2c.

The PLC scenario in **Figure** 5 represents the aggregate behavior of a market that in reality is comprised of multiple technologies that compete, enter, and exit with various degrees of spillover among them. As the goal is to understand inter platform competition, it is imperative that this model can also reproduce such dynamics deriving from a lower level of disaggregating, in which entrance is endogenous. I analyze here if and how competitive and multiple platform dynamics lead to stabilized market concentration and performance. To do this I explore simulations in which platform entrance is a stochastic process. I first discuss the setup for these simulations and then discuss typical results. The results comply with robustness requirements of the model. In the subsequent section I explore the underlying drivers for spillovers dynamics in depth.

The expected entrance rate for a platform depends on the expected returns and on the normal entrance rate, which can be seen to represent the aggregate barriers to entry due to various factors such as technological complexity, economic barriers, rules and regulations. Expected returns $\varsigma_i^{\pi *}$ are compared to the required returns ς_{ref}^{π} :

$$\left\langle e_i \right\rangle = f\left(\varsigma_i^{\pi} / \varsigma_{ref}^{\pi}\right) / \tau^e ; f\left(1\right) = 1; f\,' \geq 0; f \geq 0; f\left(\infty\right) = f^{\max}; \tag{16}$$

Expected returns depend on the type of current platforms in the market, their market shares and the distribution of knowledge across the various platforms. Expected returns will vary by the technology potential as perceived by those who consider to enter, In this simulation I assume that potential entrants have the same information about the market as actual entrants. Potential entrants are endowed with, and take into consideration, additional seed funding of 5 years of 1.5 Billion $ (equal to 1% of normal industry revenues). Expected entrance increases with expected profits, but saturates for large profits. I use the logistic curve for this, with sensitivity parameter $\beta^e = 1$. To represent the distribution of technologies available for the market, I vary the distribution of spillover effectiveness between technologies, κ_{ij1} and the technology potential, T^0_{j1}. For spillover potential I define $\kappa_{ij1} = \alpha \left| i - j \right|^{(\upsilon - 1)/\upsilon}$, for $i \neq j$ $\left(\kappa_{ii1} = 1 \forall i\right)$, where α is a scaling parameter for spillover strength, and υ is the uniformity index for the available technologies in the market, with $0 \leq \upsilon \leq 1$. When υ is close to zero, the spillover potential between technologies approaches zero very fast over different platforms, representing a more heterogeneous market. While υ equal to 1 implies that spillover across platforms is equal to the maximum α for all platforms. The technology potential is varied randomly across platforms, with an average of 1 and standard deviation of 0.5.

I am interested in the competitive dynamics between the various platforms over time, and the market behavior with respect to knowledge accumulation and performance. To analyze the competition over time, I use the Herfindahl index, which measures the market concentration and is defined as: $H = \sum_{i=1}^{N} \sigma_i^2$

The Herfindahl Index (H) has a value that is always smaller than one. A small index indicates a competitive industry with no dominant platforms. If all platforms have an equal share the reciprocal of the index shows the number of platforms in the industry. When platforms have unequal shares, the reciprocal of the index indicates the "equivalent" number of platforms in the industry. Generally an H index below 0.1 indicates an unconcentrated market (market shares are distributed equally across technologies). An H index between 0.1 to 0.18 indicates moderate concentration, An H index above 0.18 indicates high concentration (most of the market share is held by one or two platforms).

Figure 6 shows representative results. Different simulations each start with 16 potential entrants. Across simulations I vary the technology heterogeneity, with $\alpha = 0.75$ for each, and for simulation $s \in \{1,...,7\}$, $\upsilon \in \{0.91, 0.83, 0.67, 0.5, 0.33.25, 0.1\}$. Figure 6a shows the average spillover potential κ across platforms, weighted by market share in equilibrium (*t=100*). Technology heterogeneity in equilibrium corresponds with the distribution of technologies available in the market. Further, an increase in the spillover potential also results in increased resources being allocated to spillovers. Aggregate behavior of all simulations is consistent (Figure 6b). Figure 6c shows the Herfindahl index over time. First, we see, that for these simulations the market can only support a limited amount of platforms (in equilibrium, $H_{\min} \sim 0.15$, or 5-6 firms). This is in absence of any scale effects that are not related to R&D and learning. We also see that concentration increases with the uniformity of the technologies. Absent any potential for spillovers, entrants can partly catch up, despite initial experience deficit. This holds especially true for those platforms that have superior technology potential. The spillover dynamics work in favor of more superior technologies that have for example, more resources available, providing scale economies associated with learning by doing. [8] Note that these dynamics do not reflect the concept of niche formation, as performance is a scalar. Including additional increasing returns to scale will reinforce this significantly.

[8] An additional analysis to separate micro effects from macro effects would be to look at the seniority of those who have an advantage.

Figure 6d shows that the increased spillovers also lead to a greater attractiveness of the average platform in the market (weighted by market share), in the capacitated market. Attractiveness behaves properly, with diminishing returns. The aggregate market dynamics are robust and intuitive.

Reducing the barriers to entry for new platforms, which can be emulated by lowering τ^e, results in an increase in the number of entrant attempts throughout. The result is that increased spillovers compete with a more intense competition, but before hand it is not clear which effects are stronger. Doubling the normal entrance rate for these simulations has no significant effects on the Herfindahl, and on average a 5-10% increase in the market attractiveness. Increasing the barrier to entry leads to a 5-20% increase in the Herfindahl and a 10-25% decrease in market attractiveness, in all cases with diminishing returns. The results of endogenous entry dynamics illustrate the consistency and robustness of the model behavior over a wide range of contexts. However, a deeper understanding of the dynamics should come from various levels of analysis. I now concentrate on a deeper understanding of the spillover dynamics.

Analysis of spillover dynamics

To understand the basic spillover dynamics, I analyze the competition between the incumbent I_1 and one alternative entrant platform E_2. Figure 7 shows simulated adoption over time for cases with varying, but symmetric, spillover effectiveness across platforms, $\kappa_\Delta \equiv \kappa_{i,i+1} \in [0, 0.1, ..., 1]$. Technology potential is identical. The adoption rate for the entrant and its equilibrium adoption fraction increase with spillover effectiveness: when all platform technology of each platform is fully appropriable, $\kappa_\Delta = 0$, the entrant reaches about 10% of the installed base. However, the entrant can catch up fully, reaching 50% of the market, when spillover effectiveness equals 1. However, note that it takes 40 years to reach the equilibrium, even under maximum spillover effectiveness, while the technology replacement time is 10 years. Figure 7b) and 7c) show the allocation of resources to R&D for two cases of very low, and very high spillover effectiveness, $\kappa_\Delta = \{0.1, 0.9\}$. Figure 7b) shows total resources that are allocated to R&D. The entrant technology, being less mature and having a lower market share, invests heavily as it can capture significant returns on its R&D, especially in the high spillover case. Note that returns and thus investment in R&D would be considerably suppressed in the presence of scale effects. The incumbent experiences several effects. A first order effect is that reduced revenues also lower R&D spending. However, other effects lead to an increase in spending: irrespective of any spillover, demand elasticity to innovation increases when market share is reduced. This effect is however stronger for the high spillover cases, as these are the scenarios under which the entrant captures a larger market share. This effect is combined with an effect that is directly a function of spillover strength: as the entrant develops its technology, so does the spillover potential for the incumbent. These two second order effects lead to an increase in R&D investment by the incumbent and are different manifestations of the sailing-ship effect (Rosenberg 1976; Snow 2004). Further (Figure 7c), after entrance, both parties dedicate indeed the largest portion of their resources to spillovers. Once the core technology has been established it becomes much more beneficial for the entrant to improve technology through internal R&D.

In summary, dynamics between various technologies in a market unfold with three competing effects at work: first, there are competition effects that distribute the market shares; second, there are the learning and R&D feedbacks at work (as well as external increasing returns); finally, there are spillover effects between the technologies. Competition effects pressure established technologies' installed base through the balancing feedback of reallocation of vehicle discards according to platforms' relative attractiveness. Those that receive a larger market share than their installed base share, will grow until they match. Attractiveness depends on each platform's technology potential, the current relative state of their technology. Learning-by-doing and -R&D, allow improving the technology performance through internal processes that further build attractiveness which can drive up sales, feeding back to investment in those processes. Generally these are subject to diminishing returns, and therefore, when presented in isolation, they will allow laggards to catch up (see Struben 2006a). Finally, the spillover effects derive from interaction between competitors' relative performance that borrow ideas from each other. The net spillover effect involves a flow towards the entrant, and the magnitude depends on their amount of internally produced knowledge.

Equilibrium is established when the forces from these three interactions offset each other, balancing market share, relative resources, relative flows of internal and spillover flows. We saw that with for two platforms an increase in spillovers benefits the entrant. However, for differences in technology potential, for multiple technologies, or when other scale effects are included, one can see the existence of different conditions for equilibrium, or multiple equilibria and strong path-dependency, based on the specific interdependencies between platforms. This is will be analyzed next.

Analysis of AFV competition: spillovers, scale effects and multiple entrants

Having an increased understanding of the general dynamics generated by the model, I now analyze how different technologies fare in a multi-platform race, focusing on the role of spillovers and learning, on their interaction with scale effects and with the effect of differences in the technology potential of the platforms. I specify an incumbent, I_1, with a large and saturated installed base, analogous to ICE in 2000. I first analyze the dynamics when entrance is limited to one platform only.

The model captures internal economies of scale that represent, for instance, reduced production cost when production plants are scaled up or economies of scope. However, platforms are also subject to increasing returns to adoption related to external factors, such as complementarities or other (network) externalities that affect the perceived consumer utility in one way or the other. In particular, the co-evolution of demand for alternative fuel vehicles and infrastructure is an important feedback for many technologies, especially hydrogen, but also to some extend CNG, flex-fuels, EVs, and plug-in hybrids. Further, as is discussed in Struben (2006a), the requirement of building up familiarity greatly. Other increasing returns result from economies of scope such as increased sales and experience, the number of models offered (which will greatly enhance demand, as vehicles have limited substitutability). Expanding the product portfolio also results in a wider experience, both in using (users will drive the vehicles in different climates, or environments), and in production (the variety of trials available for innovation is wider). These increasing returns to adoption can be a function of cumulative adoption, the current installed base, or the current sales rate. To test how the learning and spillover effects I have analyzed so far interact with such external scale effects. I introduce as the third attribute, one aggregate scale effect as a function of installed base share $\sigma_j^v = V_j \big/ V^T$:

$$a_{j3} \equiv \varepsilon_j^s = f\left(\sigma_j^v\right); f' \geq 0; f\left(\infty\right) = 1; f\left(\sigma_{ref}^v\right) = \varepsilon_{ref}^s \tag{17}$$

Appendix 2f discusses the functional form used, but Figure 8 shows the shape of the function and the parameters. At the reference installed base share σ_{ref}^v , the scale effect on attractiveness relative to the case of full penetration equals ε_{ref}^s . The scale factor, defined as the inverse of the relative scale effect, $f_j^s \equiv 1 \big/ \varepsilon_j^s$, serves as a measure of the strength of the scale. The scale factor gives the relative attractiveness of an entrant when its installed base share equals the reference installed base share, compared to when it is fully penetrated. At full penetration all scale effects work maximally to its advantage. For the reference I use an installed base 5% of the fleet and sensitivity parameter $\beta^s = 1$, which measures the slope at the reference installed base share.

Figure 9 a) shows the sensitivity of the entrant's equilibrium installed base share to scale effects (technology potential is equal that of the incumbent, $T_\Delta^0 = 1$; the same holds true for other parameters). **Table** 3 lists parameter manipulations for all the following analyses. The equilibrium installed base is very sensitive to scale effects. For any scale factor f^s larger than 4, equilibrium penetration remains below 0.1 (that is, all results fall below the iso-installed base line of 0.1). Increasing the spillover effectiveness improves the range of scale factors that result in take off. However, the entrant, otherwise equivalent to the incumbent, approaches 50% of the market only in absence of scale factors. Thus, while the scale effects have no effects when learning is ignore, and limited effects when spillover potential is large, the interaction of this feedback with those from learning lead to strong strong barriers to entry, when spillover effects become smaller.

The installed base for different values of technology potential ($T_{\Delta}^0 \equiv T_{21}^0 / T_{11}^0$, see equation(13)), and spillover potential κ_{Δ} is illustrated in Figure 9b. Absent any spillover and learning, the predicted share of the entrant is equal to:

$$\sigma_2^s = \frac{\varepsilon^s\left(\sigma_2^v\right)u_{21}^{\Delta}}{\left(\varepsilon^s\left(\sigma_2^v\right)u_{21}^{\Delta} + \varepsilon^s\left(1-\sigma_2^v\right)\right)}$$

with $u_{21}^{\Delta} = \exp\left[-\beta^{\theta}\theta^{I}T_{\Delta}^{0}\right]$, where β^T is the aggregate sensitivity of adoption to technological advance and θ^I is the status of the incumbent technology, relative to the reference.[9] In our case, $\beta^T \approx 0.9$ and $\theta^I = 1$. Equilibrium requires that the sales share equals the installed base share, $\sigma_2^s = \sigma_2^v$. This equilibrium is indicated Figure 9b. We see here that, when learning dynamics are included, a superior entrant technology reaches a larger share in equilibrium, provided presence of limited spillovers (above the dotted

[9] The technology state parameter of the incumbent makes explicit that MNL models predict that, holding the relative difference between two technologies constant, the gap between the relative shares that technologies receive increases with the advancement of the technology (as the effect of the unobserved characteristics remains constant).

line). An entrant with technology potential that is equivalent to the incumbent (T_{Δ}^{0} close to 1) achieves equal shares only when spillover effects are very strong. A weak technology never approximates its potential.

Under what conditions can superior or equivalent entrant technologies catch up with incumbents? The process of learning and spillover determine the technology trajectory. This, however, is very much a function of the mix, diversity, and quantity of alternative technologies available in the market. The analysis illustrates that scale effects create a barrier to entry, as can be seen in the low spillover case. Beyond that, they allow for spillovers to flow to the incumbent, before the entrant catches up. This was the situation for example in the case for EVs in the early 20th century. They diffused slowly with limited progress in critical aspects such as battery life, recharging speed, and availability of recharging points, due to limited penetration and limited standardization of electricity systems at that time. Gradually, the batteries and dynamo system improved and around 1910 they experienced a second wind. However, this also provided spillovers to the more established ICE platform, and led in particular to the commercialization of the electric self-starter by Kettering, a critical device that was implemented in ICE vehicles as of 1911 (Schiffer et al. 1994). Ultimately, more and more ICE vehicles were able to gain market share in areas that were previously considered EV niches. This supports the notion that neither learning and spillover dynamics, nor scale effects must be explored in isolation. They interact tightly with each other and also with others such as vehicle placement and consumer choice dynamics. Together they determine the transition trajectories and potential for different technologies. It is for this reason that we need to explore dynamics of multiple platforms in depth.

In reality competition plays out not between one incumbent and one entrant, but between a mix of platforms, as was illustrated by Figure 1. Further, such platforms are different from each other across different attributes. For instance, where ICE and HEVs share an engine, HEVs and HFCFs share an electric motor system. Advances in ICE experience, with respect to the engine, are thus relevant to great extent to HEVs, but not so to General Motors' HyWire HFCV, which radically alters most design elements (Burns et al. 2002). On the other hand advances in some elements, such as body weight, are relevant to great extent across all platforms. Many more of such cases can be found considering the enormous set of combinations of mono-, bi-, flex-fuel vehicles, or the consideration of gaseous versus liquid fuels. This context of multiple, heterogeneous platforms greatly limit our ability to intuitively grasp the dynamic implications of the basic interactions discussed above.

I study the fundamental dynamics of such a situation, by analyzing the case in which one hybrid platform (E_2) that has reasonably large overlap with the incumbent (I_1), and a radically different platform (E_3), with technology that has little in common with the incumbent, but significant overlap with the hybrid. To do so I define the spillover effectiveness between the i^{th} and the $i+1^{th}$ as $\kappa_{i,i\pm1} \equiv \kappa_{\Delta}$, representing the spillover effectiveness between the incumbent and the hybrid, but also between the hybrid and the radical. In addition I also define the spillover effectiveness between the i^{th} and $i+2^{nd}$

platform as $\kappa_{i\pm2} \equiv \kappa_{\Delta 2} \leq \kappa_{\Delta}$, setting spillover effectiveness between two platform pairs equal. Thus, $\kappa_{\Delta 2}$ represents the spillover effectiveness between the incumbent and the radical. Figure 10a) shows the simulated trajectories of the installed base shares of both entrant technologies, for four different spillover configurations: symmetric and asymmetric situations between $\{S,A\}$, for which respectively $\kappa_{2\Delta} = \{\kappa_{\Delta}, 0.4\kappa_{\Delta}\}$ and high and low spillover effectiveness $\{H,L\}$, for which respectively $\kappa_{\Delta} = \{0.75, 0.25\}$. See also **Table** 3.

Technology potential and scale factors are equal to one. The dotted line along the 45-degree line show the trajectory for the symmetric, high spillover effectiveness scenario $\{S,H\}$. Dots represent samples with a 2.5 year interval. The three other trajectories with dots show trajectories of the asymmetric, high spillover effectiveness scenario, in which the hybrid and radical technology are introduced, simultaneously $\left(\tau_2^i = \tau_3^i\right)$ and with 15 years between them. Both trajectories appear to yield the same equilibrium. In fact, the case where the radical technology is introduced later, results in the highest market share. This is because the hybrid technology matures before being able to capture some benefits from the HFCV. Along the axes we can observe the trajectories where only one entrant is introduced ($\tau_{-i}^I \to \infty$).The equilibrium installed base shares for these cases are equal to those with corresponding parameters in Figure 9a, where the scale factor 1, and spillover potential is 0.25 (E3 in this analysis) and 0.75 (E2 in this analysis).

While the combined market share is considerably higher than for the individual introductions, the individual shares of the entrant platforms are lower than in the case when they are introduced individually. That is, under current assumptions, the competition effects limit market share and dominate the spillover effects. For instance, the hybrid technology learns much from the incumbent. This, however, is of limited value to the radical technology. Further, the incumbent also learns and, while attractiveness of the platforms is higher than is the case with individual introductions, this is also the case for the incumbent. Also shown is the equilibrium installed base share for the symmetric and asymmetric, low spillover effect case {S,L}, {A,L}. Figure 10b) shows the evolution of installed base share for the {A,H} trajectory with late introduction of the radical technology against time.

This simulation reveals that the radical technology does not reach as much of its potential as the hybrid does. In equilibrium, all market shares remain constant while for each platform internal knowledge as well as spillover knowledge can be different. However, the growth rate of total knowledge must be identical across each. Three competing effects are at work to contribute to knowledge. First, there are competition effects that distribute the instantaneous market shares based on platforms' relative attractiveness. Second, there are internal learning and innovation feedbacks at work as production and sales proceed, allowing for improved attractiveness and that further build production and sales. Finally, there are spillover effects between the technologies. Initially the radical can catch up with the hybrid, through spillover. However, it will also build up knowledge itself, through learning-by-doing and R&D investment. However, that is partly available to the hybrid.

The net spillover effect to the radical captures the flow towards the radical (from mainly the hybrid), less those towards the incumbent (from the mainly the hybrid), and the hybrid (from both other players), each closing the gap with the other's learning. However at the same time there is also intensive interaction between the hybrid and the incumbent. This additional feedback, results in a steady state advantage for the hybrid.

Generally the technology potential is not identical across platforms. For example, hybrid vehicles will have to sacrifice space and weight to offer multiple propulsion technologies. Vehicles that propel on gaseous fuels have lower energy density, in volume, compared to those that drive on liquid fuels and thus generally lower tank ranges. Radically different designs, such as HFCVs could offer more space, and more features than others due to their inherently electric system, which also requires few moving parts. Figure11 adds this dimension to the analysis, showing scenarios as before, for varying technology potential, while we explore with it the role of scale effects. Figure 11a) shows the equilibrium penetration levels for the high, symmetric spillover effectiveness scenario, in the absence of scale effects. I show the equilibrium installed base share for E2 and E3, as a function of the technology potential of E3, relative to the incumbent, keeping the product of the hybrid and the radical identical to that of the incumbent: $T_{\Delta}^{0} = T_{3}^{0} / T_{1}^{0} = T_{1}^{0} / T_{2}^{0}$ (thus values $T_{\Delta}^{0} > 1$, corresponds with the technology potential for the radical being larger than that of the incumbent, while that of the incumbent is larger than that of the hybrid). The hatched line shows the analytically derived equilibrium for when all technologies are equal to their potential value. We see that including dynamic effects of learning and spillover reinforces the effects of a difference in technology potential on the installed base shares. Figure 11b) shows the same scenarios, except that now we also apply a weak scale factor of value 3. This scale effect is considered weak as for this value no effect can be detected for the equilibrium value in the static case (dotted lines are identical to those in Figure 11a). In the dynamic case, we now see a tipping point: only one entrant will survive – the most superior.

Figure 11c) and d) show the same scenarios as in Figure 11a) and b), but for asymmetric spillover effectiveness, representing the true situation of a hybrid and a radical entrant. In absence of scale effects, the point where the hybrid and radical have identical market share is shifted to the right - the situation where the radical is superior and the hybrid is inferior to the incumbent. The case where all technologies are identical corresponds with the equilibrium of simulation (1) in **Figure** 10b, which was identical to the case of simultaneous introduction). Figure 11d shows again the weak scale effect scenario, now under asymmetrical spillover effects. In this case there is again a tipping point, allowing for only one entrant to succeed. This graph reveals how the superior technology can fail dramatically. In fact, successful penetration occurs for the radical only under extreme conditions. The weak scale effect imposed was sufficient to greatly reinforce the effect already apparent without any such effects. The radical succeeds only when it is significantly superior to the incumbent and the hybrid. For asymmetric spillover potential, the hybrid can accumulate its technology much faster than the radical, diffuses and sustains successfully for intermediate scale factors as well, while the radical fails for a larger range of scale factors. Under these conditions, hybrids can benefit enough from the spillover dynamics, improve their technology, and offset limitations from scale effects. The more radical technology does not improve its technology fast enough to overcome the initial barriers. The hybrid survives under more adverse conditions, in the presence of a weaker alternative.

The mechanisms that were discussed to be at work in **Figure** 10, are drastically reinforced under the scale effects: while initially the system might get close to equilibrium, the scale advantage of hybrids widens the gap between the hybrid and the radical. Importantly: as the hybrid benefits, by definition, much more from the mature technology, the incumbent will generally lag, which makes the relevance of a installed base gap larger.

While the scale effects have little impact in isolation and the asymmetric spillover effects alone do not lead to the dramatic tipping, their interaction results in the real dramatic failure. With understanding from the preceding analyses it may seem likely that there are a large number of combinations of contexts that can generate conditions that result in failed diffusion of superior radical technologies. However, these conditions, when examined in isolation, do not have any significant impact. For instance, alternative fuels are introduced in the market at different times, after much of the competitive landscape has changed, they rely upon different fueling, distribution, and production infrastructures, parts of which may be compatible with those of other AFVs. I address this in the concluding analysis with three scenarios that capture different, small dissimilarities. Figure 12, left columns (a-c 1), show successful transitions towards the radical entrant. The right columns (a-c 2) show the failed transitions for the radical platform, achieved by one parameter departure from the corresponding scenario on the left. Detailed parameter settings are provided in **Table** . The scenarios show for the failed cases: a) a further reduced spillover effectiveness between the incumbent and the radical, in absence of scale effects; b) less scale effects for the hybrid compared to the radical, in the case of more superior radical. This may be the case, for instance because the hybrid depends on an infrastructure that is compatible with that of the incumbent, which is the case for gasoline ICE-HEVs; and c) a lagged introduction of the radical with respect to the hybrid, which is a natural situation. In this case the combination of an (already improved) incumbent and maturing hybrid, the performance gap is too big to be overcome through spillovers.

Discussion and conclusion

The early decades of the transition to the horseless carriage in the late 19th and early 20th century constituted a period of excitement, but also a period of great uncertainty about which technology would prevail. The technology of steamers, EVs and the eventually prevailing ICE vehicles all changed dramatically during those periods. Technological change was particularly large when the industry became more organized and sales increased. Also, there were large spillovers between the various technologies within and outside the infustry. As Flink (1988) argues, critical to further development of the automobile was the development of the bicycle around 1890. Key elements of the automotive technology that were first employed in the bicycle industry included product innovations such as steel-tube framing, pneumatics, ball bearings, chain drive, and differential gearing, as well as process innovations, such as quantity production, utilizing special machine tools and electric resistance welding. Importantly, not all vehicles benefited in the same way from this. For instance the differential gears contributed to those of ICE and steamers, while steel-tube frames were particularly beneficial to EVs, making them significantly lighter, providing a larger action radius (McShane 1994; Schiffer 1994).

Another types of interaction involved induced research intensity in response to upcoming threats. For instance, the light two cylinder cycle car stormed the market in the 1910s, responding to increasing congestion in the urban streets. But it did not take long before genuine vehicles became smaller in response to this threat, soon after which the cycle cars disappeared from the landscape, not being able to keep up with their limited experience. The prospective transition in the automobile industry, this time away from the fossil fuel burning ICE vehicles with many alternatives enter the market is subject to similar complex dynamics.

In this paper I emphasized the dynamics of and interaction between technology trajectories. This analysis was supported by a dynamic model that included explicit and endogenous consideration product innovation, learning-by-doing, investment decisions, and spillovers between the technologies. In contrast to other treatments of technology spillovers (e.g. Cohen and Levinthal 1989; Jovanovic and Macdonald 1994; Klepper 1996), spillovers, in this paper, are a function of the relative similarity between heterogeneous technologies. Further, in this setting, leading technologies may also learn from laggards, capturing various forms of sailing-ship effects.

To provide sufficient but controlled variation of relevant interactions, the analysis focused on the competitive dynamics of up to three players, one incumbent, one hybrid, and one radical platform. The competitive landscape under which the alternatives are introduced matters enormously for their likelihood of success. I analyzed in detail the dynamics resulting from three competing effects at work: competition effects that distribute the market shares, internal learning and R&D feedbacks, and spillover effects between the technologies. I found plausible conditions under which a superior technology may fail, competing against inferior entrants.

As expected, an entrant with a radically different technology, say the HFCV, may benefit from the existence of a hybrid technology, such as HEVs, when its technology potential is significantly higher than that of the hybrid. Alternatively, various alternative technologies may co-exist in equilibrium. The net spillover effect to the radical captures the flow towards the radical (from mainly the hybrid), less those towards the incumbent (from the mainly the hybrid), and the hybrid (from both other players). However, to illustrate the dynamic complexity, at the same time there is also intensive interaction between the hybrid and the incumbent. This is why a radical platform, occupying the margin within the space of spillover can be suppressed, even when equivalent or even superior to its competitors in terms of technology potential.

The automobile industry is subject to various forms of scale effects. The challenges for policy and strategy makers become apparent in when these are included in the analysis.

Successful diffusion and sustenance of AFVs are dramatically affected when spillover dynamics are allowed to interact with scale effects. Scale effects are important in the automotive industry. New platforms, consumer and investor familiarity needs to build up before they are considered on equal par (see Struben 2006a). Similarly, complementarities, such as fueling infrastructure need to build up with the vehicle fleet (see Struben 2006b). The analysis in this paper illustrates how such scale effects, modeled in reduced form, can have drastic effects on the technology trajectory and adoption dynamics, even when the effects in isolation are moderate. In particular technologies that develop slower, for instance those on the outside of a spillover landscape, are negatively affected.

On top of that, HFCVs will be introduced later and their scale effects are much stronger. Such a situation was the case with the transition towards the horseless carriage, with EVs having the burden of a slow developing support infrastructure, and steamers experiencing a liability of public acceptance from earlier times. This allowed ICE vehicles to gain market share, build experience and innovate more, and keep learning from its slower developing competitors. Similarly, in the modern transition, the various hybrid technologies might be well positioned. However, for a full policy analysis, an integrated model is needed that explicitly captures the various feedbacks of infrastructure, consumer acceptance, and fuel production and distribution dynamics, that all act differently for the various alternatives. The model must be subjected to more empirical cases and in more depth analyzed. A particular enrichment will be to study introductions that had variations of success.

With respect to the model structure, for the purpose of analytical clarity, I have allowed several simplifications. For instance individual firms were not modeled explicitly. Doing so will allow for a more elaborate capturing of industry level effects from the bottom up, such as learning-curves. Further, some firms will produce multiple platforms, thus yielding a richer distribution of spillover rates. Facing the transition challenges, several consortia emerge, but also partial collaborations across them. For instance GM, BMW and Toyota collaborate on hybrid technology, but not on their HFCV related R&D. Capturing such firm detail will also allow exploration of firm specific strategies. However, I do not expect that the central conclusions of this paper will be affected.

Another potential area of expansion is the consumer choice structure. While the technology heterogeneity was captured carefully, from the demand side substitutability among platforms differs as well. For instance the total portfolio of gaseous fuel vehicles might be treated by consumers as one "nest" of partially substitutable choices. Advances and increased demand for one platform of such a nest can have a positive effect on market shares of others that are also considered part of that nest. For instance, once familiarity of one type of gaseous fuels grows, others also benefit from this. Beyond our research focus, transition dynamics in the automobile industry, the PLC model can find a broader application in various new and mature markets, especially those that involve more complex products, with large diversity and large volumes, such as the upstream-high tech sector (e.g. semiconductor), as well as downstream high-tech sector (computers, PDA, cameras, mobile phones), energy (wind-energy), and aircrafts.

Besides opportunities for further work, the findings illustrate already the enormous challenges for policy and strategy makers. There are a wide range of patterns of behavior possible, including early success and failure, even of superior technologies. Small differences that have limited significance in isolation may have dramatic impact. Strategy and policy makers that support technology neutral incentives, such as fuel taxes, to stimulate AFVs may see unexpected side-effects through the co-development of the various other AFVs and incumbents that compete at the same time. On the other hand focused support of a single technology such as E85 or HFCVs is likely to stall when interdependencies between the technologies are not well understood. Further many other non-technology related dynamics, including those related to consumer acceptance and learning (as discussed in Struben 2006a), to infrastructure complementarities (Struben 2006b), or to product portfolios will dramatically alter strategies and policies of preference. However the research also suggests that there are opportunities for management at the level of technology portfolios. With the tools that are geared to support analysis of the dynamic complexity, the challenges to the transition can be understood, allowing for high leverage policies to be identified.

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Figures

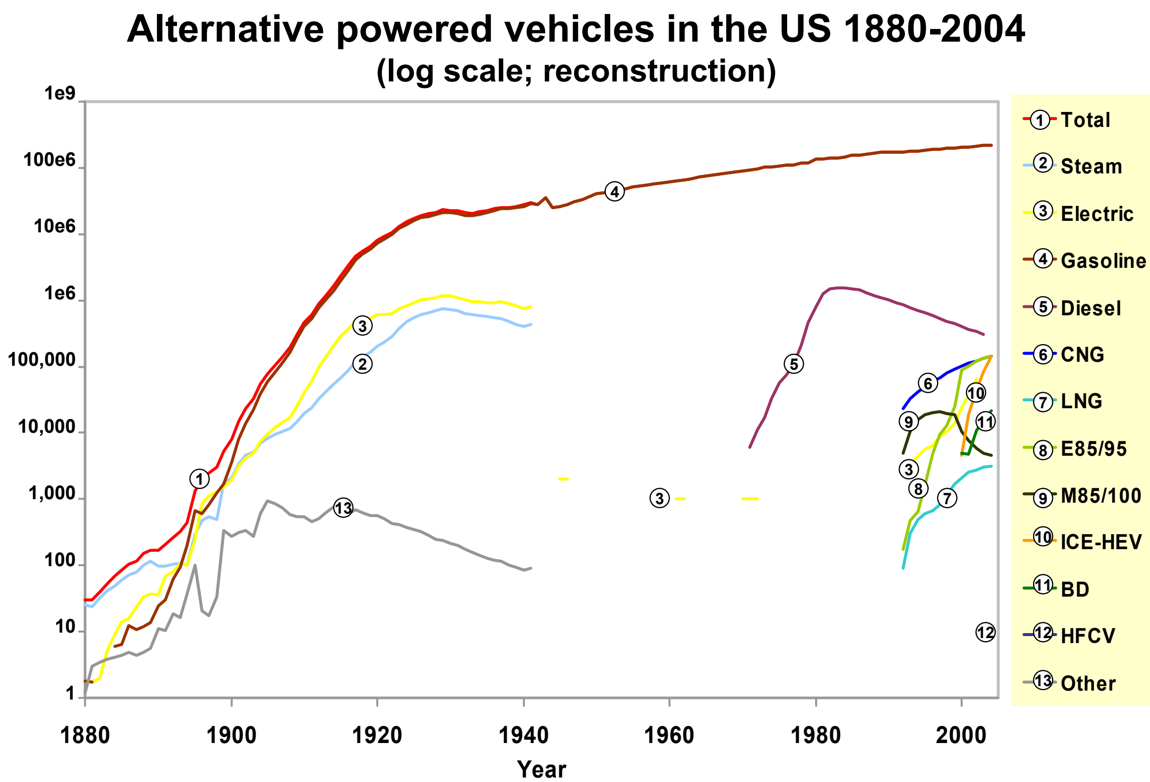

Figure 1 Early diffusion and preparation for substitution; reconstructed by author for qualitative illustrative purposes. Abbreviations of: LNG - liquid natural gas; M85 - Blend of 85% Methanol and 15% gasoline; BD - Biodiesel. Main sources: Energy Information Administration 2005, Kimes and Clark 1996).

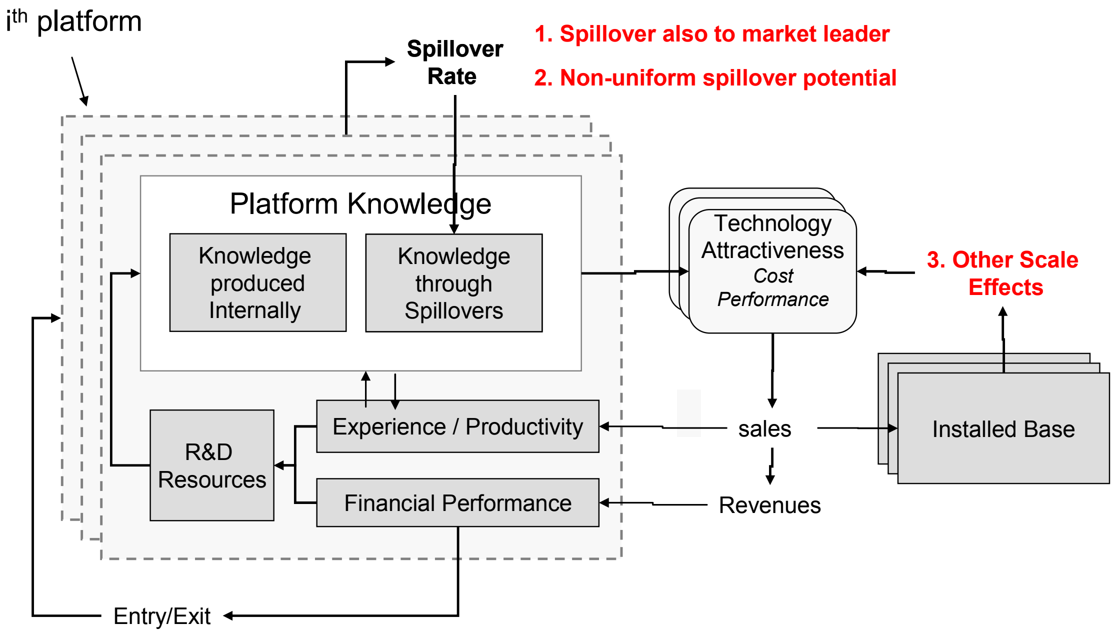

Figure 2 Model boundary. The model corresponds in many ways with the mainstream PLC models. Differences are: the unit of information and resource collection and allocation is the platform; spillovers flow between heterogeneous technologies; dynamics are explored in combination with non-technology related scale effects.

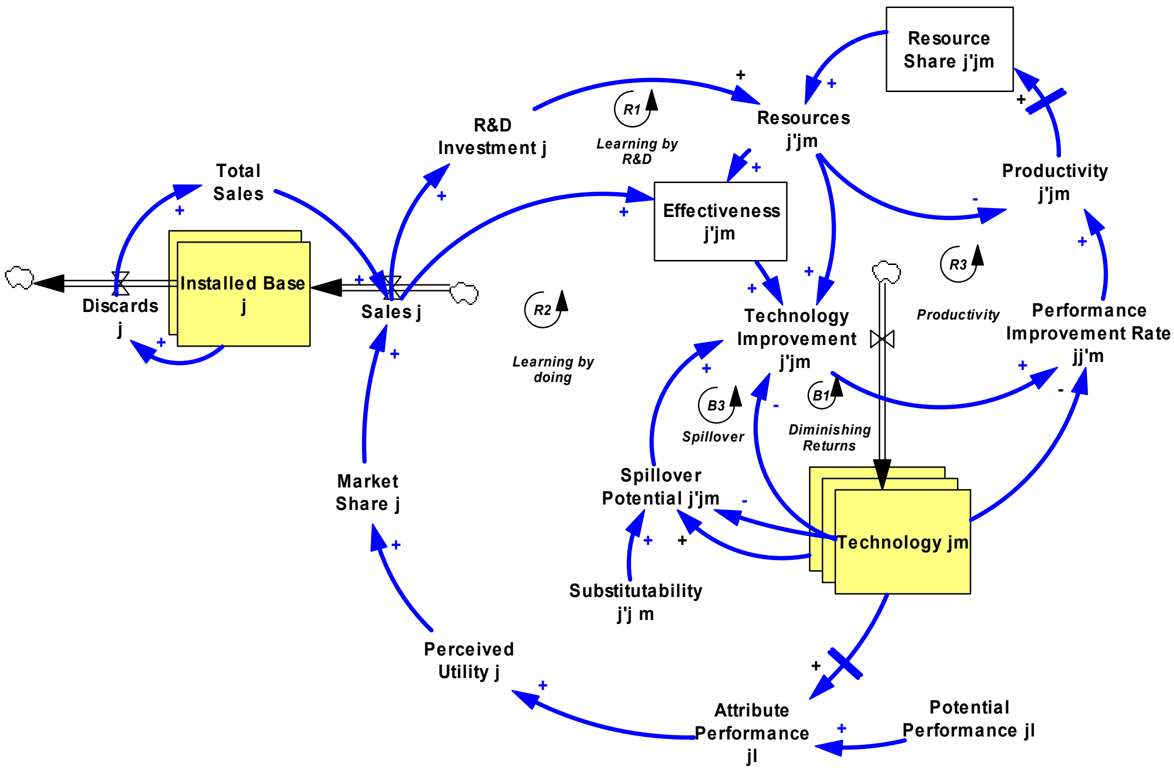

Figure 3 Principal feedbacks in the model.

segment	variable	indices	operation
Consumer choice	σ_j Market share	Platform j Attribute l	Multinomial Logit Model
	u_j Utility	Platform j	
	a_{jl} Attribute	Platform j Attribute l	Mapping of technology on Attributes: {w} → {l}
Technological Performance	θ_{jw} Relative technology	Platform j Activity type w	Normalization of technology
	T_{jw} Technology	Platform j Activity type w	Diminishing returns
Knowledge Accumulation	K^e_{jw} Effective knowledge	Platform j Activity type w	CES function
	K_{ijw} Knowledge Input	Source platform i Target platform j Activity type w	Learning-by-doing, R&D, and spillovers;
Resource Allocation	R_{ijw} Resources	Source platform i Target platform j Activity type w	Improve marginal return on effort

Figure 4 Diagramed representation of chain of operations from between resource allocation by producers to market share to vehicle consumer choice by consumers.

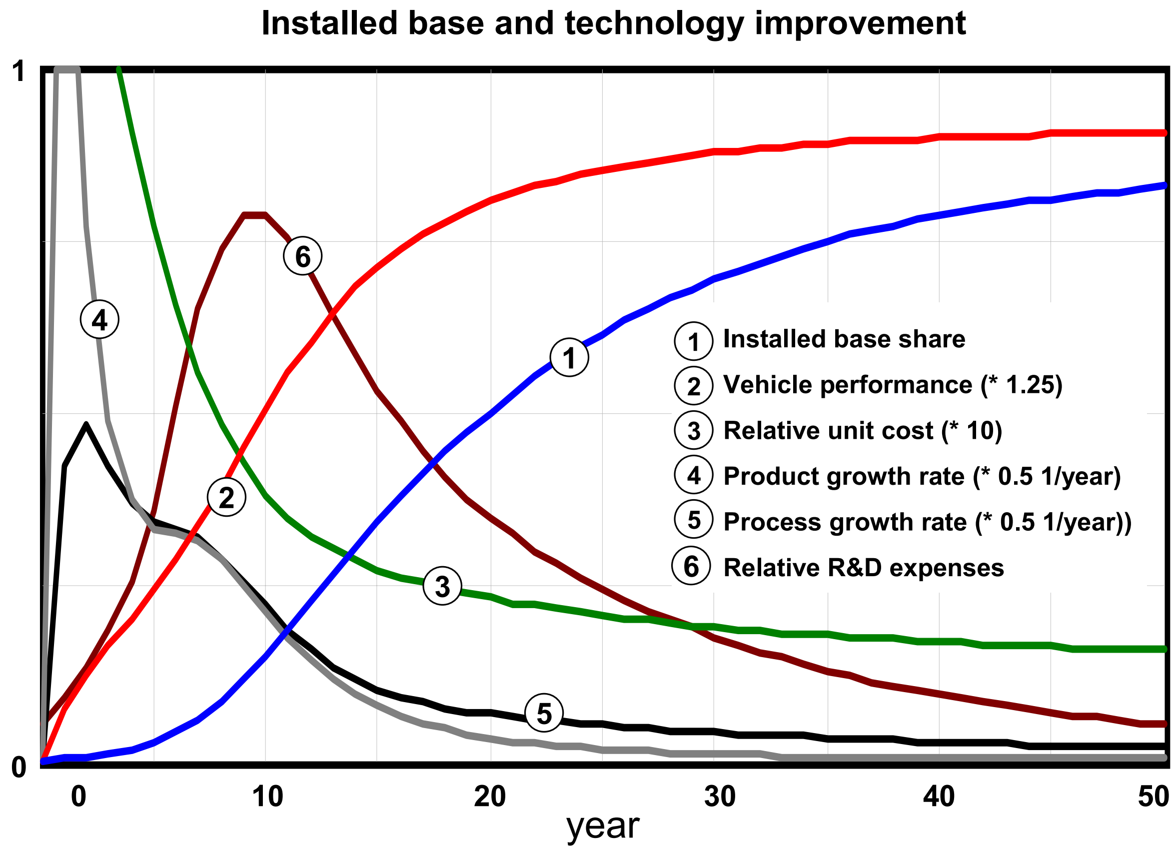

Figure 5 Simulation of PLC trajectory for single platform.

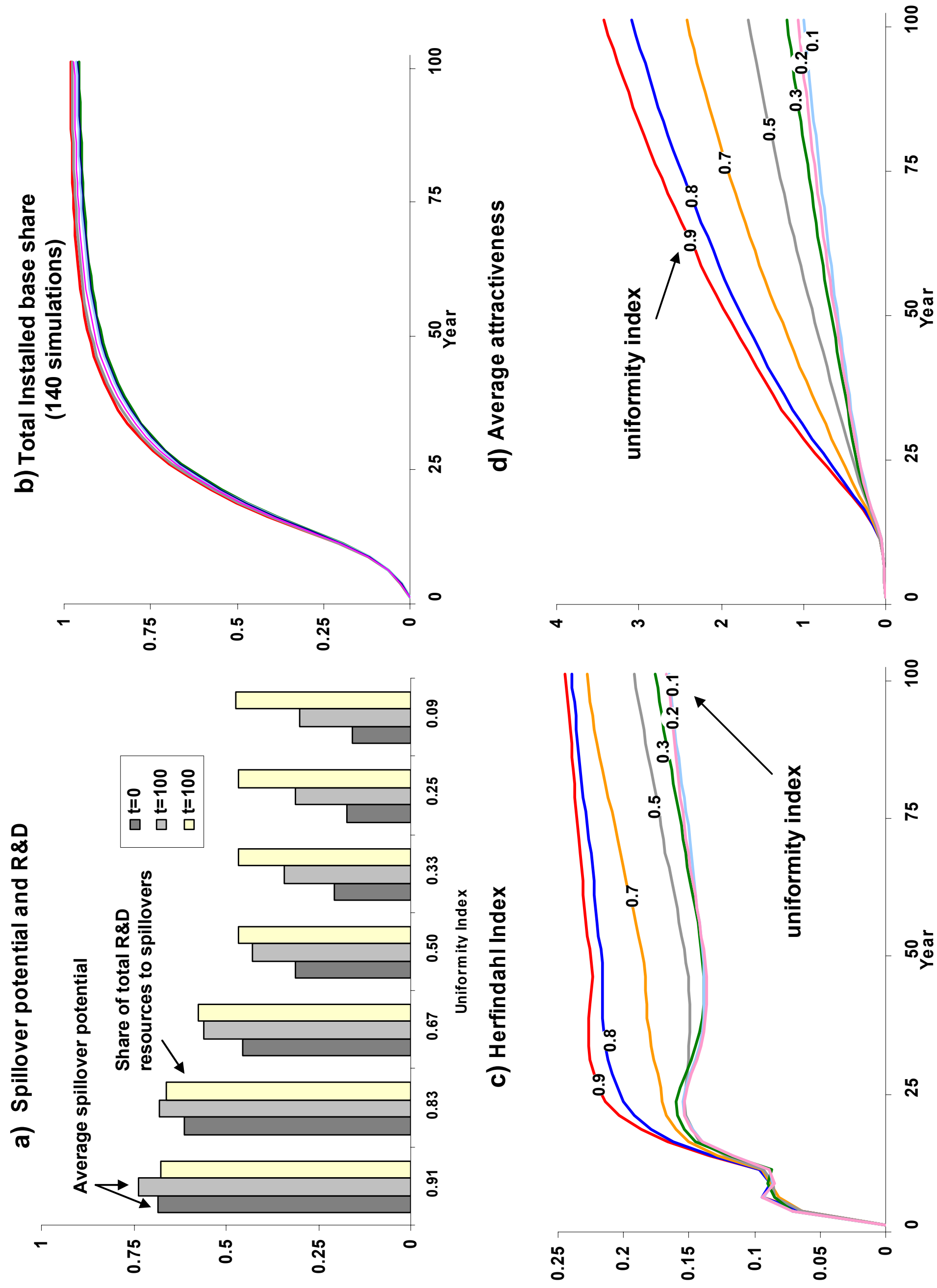

Figure 6 Endogenous platform entry. a) spillover potential, and R&D; b) total installed base for all simulations; c) Herfindahl over time for different levels of technology uniformity; c) share of total R&D resources allocated to internal R&D; b) Attractiveness of technologies in the market for different levels of technology uniformity.

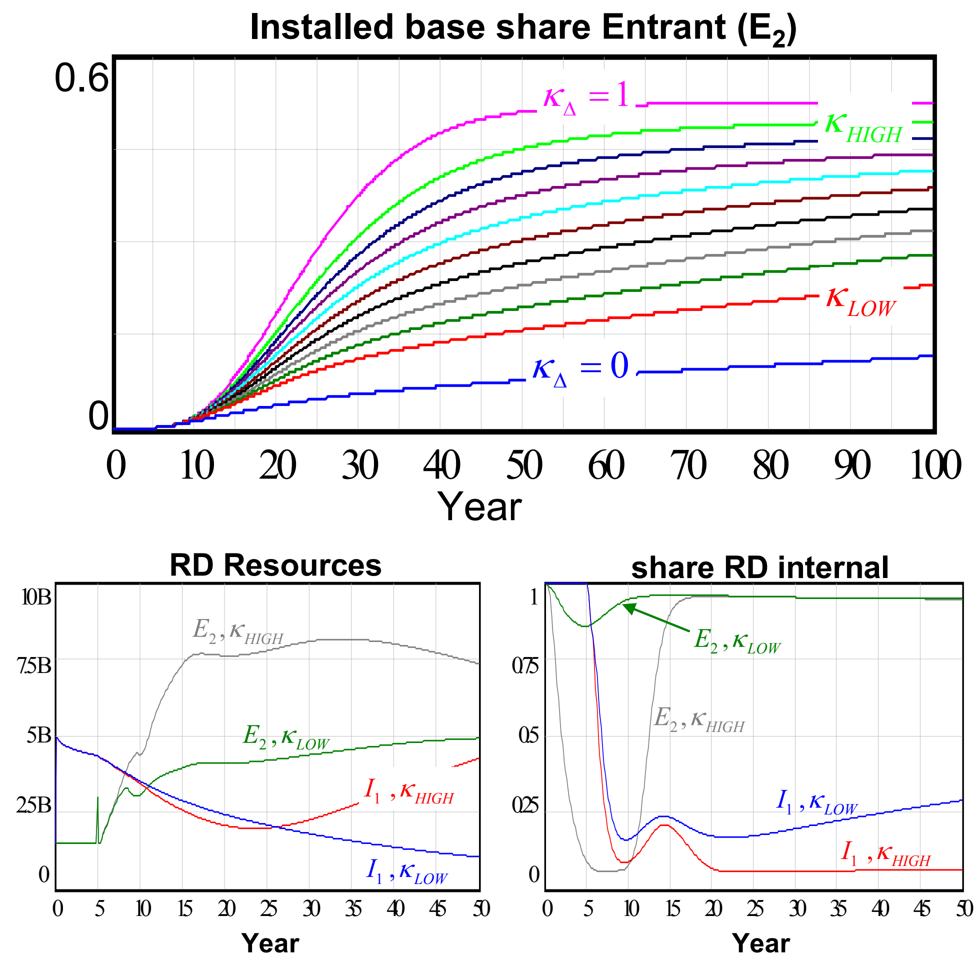

Figure 7 Base run dynamics for one incumbent and one entrant: a) entrant installed base share for various spillover potential factors; b) RD resource allocated over time for the low and high case of spillover potential factor. The low/high spillover potential case correspond each with one simulation for which both entrant and incumbent resources allocation are traced; c) share of resources allocated to internal R&D, further as in b).

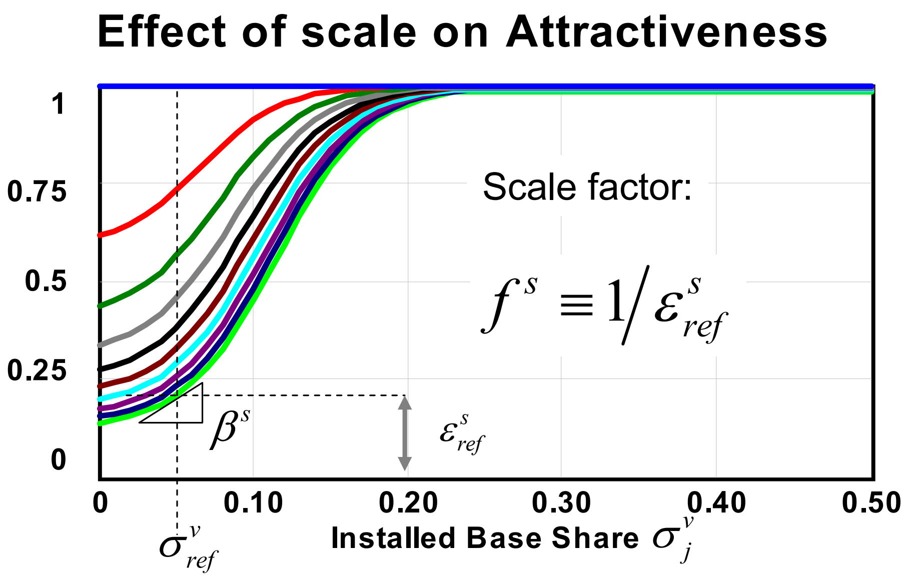

Figure 8 Incorporating complementarities and other scale effects. We vary the scale factor f^s in later analysis.

Equilibrium installed base share of the entrant

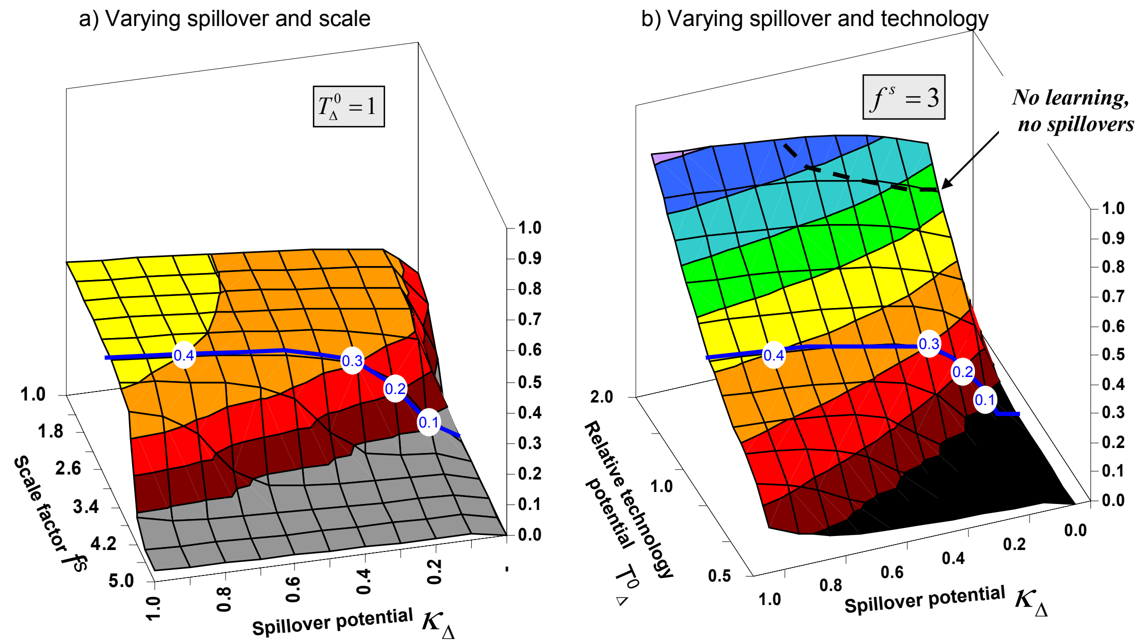

Figure 9 Entrant equilibrium adoption fraction as a function of spillover potential between the entrant and the incumbent and a) scale factor, b) relative technology potential. Thick lines correspond with identical.

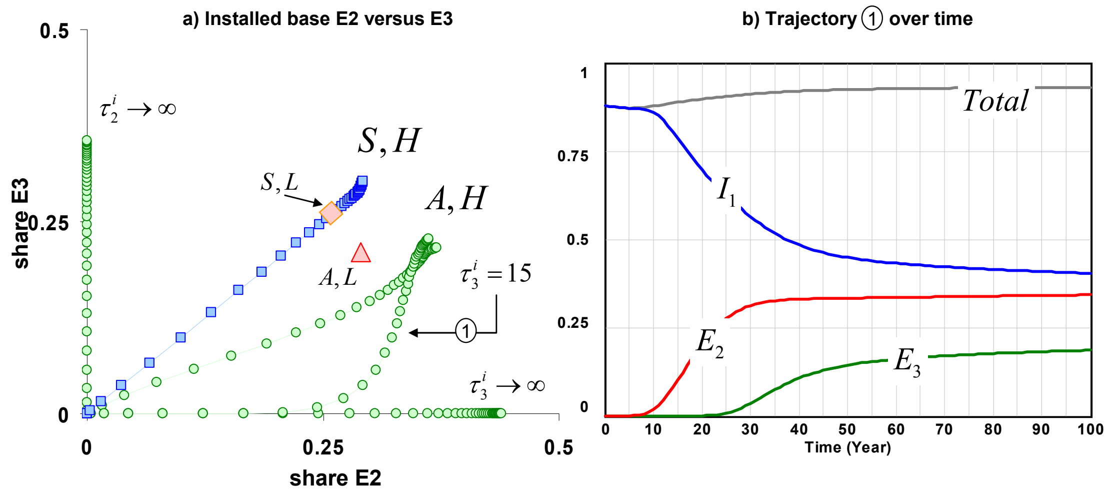

Figure 10 Technology trajectories, for incumbent and 2 entrant competition – base runs including spillovers.

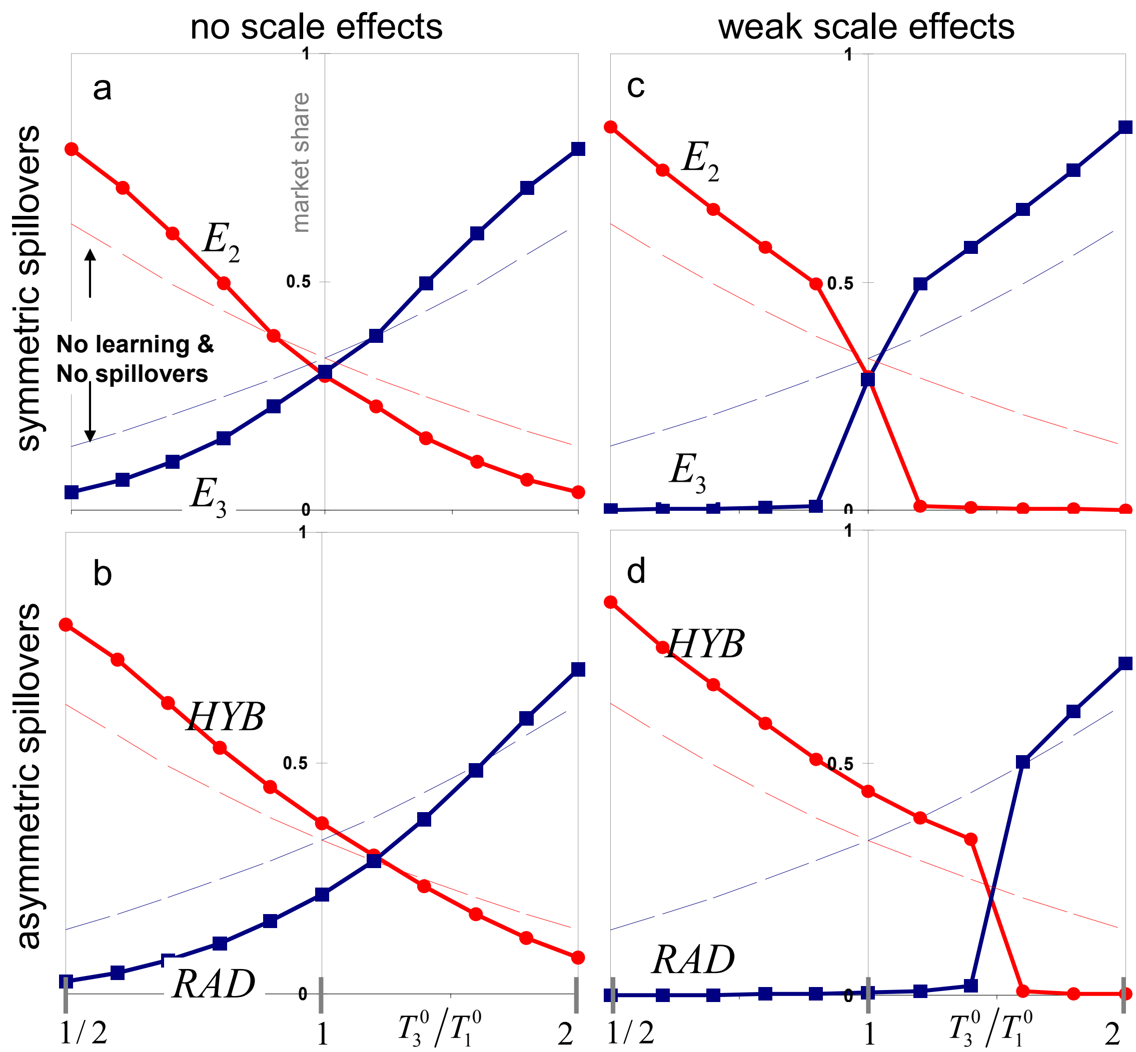

Figure 11 Scale effects and technology potential interacting with spillovers.

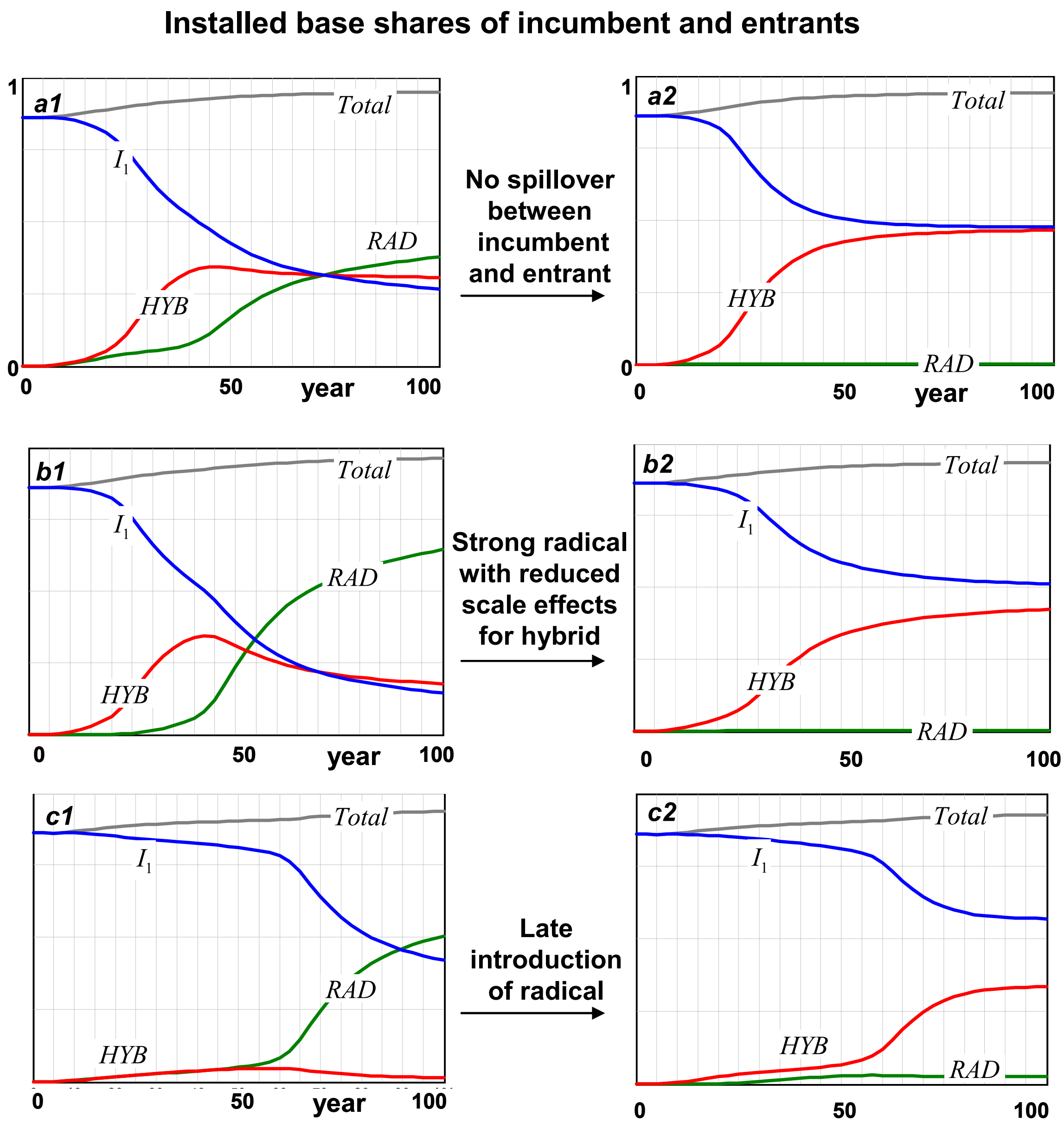

Figure 12 Transition trajectories for hybrids and radical platforms under asymmetrical configurations. The top row shows successful transitions to the radical, the bottom shows failures, as a function of: a) varying spillover potential; b) varying scale effects; c) varying introduction timing.

Tables

Table 1 Evolution of the automobile industry: users, technology, firms. Source: compiled by author.

Area	ICE 1890	ICE 1910	ICE 1960
Users	almost none	few	millions
User familiarity	almost none	moderate	high
User experience	almost none	small	large
Firms/entrepreneurs of main product	many	many	few
Firms across value chain	few	moderate	many
Performance of technology	low, growing rapidly	medium, growing	high, stable
Variety of technology	large	moderate	small
Cost of production	high, stable	medium, fluctuating	stable
Experience (cumulative vehicles)	~hundreds	~million	~billion
Diversity of Experience	large	moderate	small
Sources of innovation	many	moderate	few
Complementarities developed	few	rising	many

Table 2 Parameter settings for simulations, unless otherwise stated. All reference parameters that are not mentioned are set equal to 1.

Short	Description	Value	Units	
General				
H	Total households	100e6	people	
Firm Structure				
m_j	Markup	0.2	dmnl	
C_j^k	Capital cost	0	$/year	
c^f	Unit production cost not subject to learning	3,000	$/vehicle	
c^v	Unit production cost variable at normal technology	12,000	$/vehicle	
Technology and Knowledge				
τ^t	Time to realize technology frontier	2	years	
η_w^k	Technology learning curve exponent to knowledge accumulation	0.3	dmnl	
K_w^0	Reference Knowledge	50	Knowledge units	
ς_{jw}^k	Elasticity of Substitution Parameter	1.5	Dmnl	
Γ_w	Normal knowledge growth rate	1	Knowledge units/year	
$\eta_1^i, \eta_2^i, \eta^s$	returns to resource allocation	1,0.2,0.8	Dmnl	
s_0	Reference sales for normal production	4e6	Vehicles/ year	
η_w^o	returns to resource allocation spillover	0.3	Dmnl	
g_w^o	Normal spillover knowledge growth fraction	10	Dmnl/year	
R^0	reference resources for total R&D	1.5e9	$/year	
τ^r	Time to adjust resources	1	year	
τ^p	Planning horizon for resource allocation	5	Years	
Consumer Choice				
τ^d	Time to discard a vehicle	10	Years	
τ^a	Time between adoption decisions for non-drivers	10	Years	
β_1	Sensitivity of utility to vehicle performance	0.6	Dmnl	
β_2	Sensitivity of utility to vehicle price	-0.3	Dmnl	
K_{11w}^0	Knowledge of incumbent at introduction	1	Knowledge units	
$K_{jjw}^0 \ j \neq 1$	Knowledge of entrant at introduction	0.1	Knowledge units	
K_{ijw}^0	Spillover knowledge at introduction	0	Knowledge units	

Table 3 Parameters manipulated for graphs 8-11

Graph	Scenario	$\frac{T_2^0}{T_1^0}$	$\frac{T_3^0}{T_1^0}$	κ_Δ	$\frac{\kappa_{2\Delta}}{\kappa_\Delta}$	f_2^s	f_3^s	$\tau_3^i - \tau_2^i$
9a	Variable spillover potential & scale factor	VAR	-	VAR	-	1	-	-
9b	Variable spillover & technology potential	1	-	VAR	-	VAR	-	-
10a	Symmetric/Strong spillover (SS)	1	1	0.75	1	1	1	{0,15}
10a	Symmetric/Weak spillover (SW)	1	1	0.25	1	1	1	0
10a	Asymmetric/Strong spillover (AS)	1	1	0.75	0.25	1	1	0
10a	Asymmetric/Weak spillover (AW)	1	1	0.25	0.25	1	1	0
11a	Symmetric spillover, No Scale	T_1^0/T_3^0	VAR	0.75	1	1	1	0
11b	Asymmetric spillover, No Scale	T_1^0/T_3^0	VAR	0.75	0.25	1	1	0
11c	Symmetric spillover, Weak Scale	T_1^0/T_3^0	VAR	0.75	1	3	3	0
11d	Asymmetric spillover, Weak Scale	T_1^0/T_3^0	VAR	0.75	0.25	3	3	0
12a1	Base	0.75	1.33	0.75	0.25	2	2	0
12a2	RAD Fail	0.75	1.33	0.75	0	2	2	0
12b1	Base	1	2	0.75	0.25	3	3	15
12b2	RAD Fail	1	2	0.75	0.25	2	3	15
12c1	Base	0.75	1.33	0.75	0.25	3	3	0
12c2	RAD Fail	0.75	1.33	0.75	0.25	3	3	15

Technical Appendix

The technical Appendix can be downloaded from:

http://web.mit.edu/jjrs/www/ThesisDocumentation/Struben3Appendix.pdf