An Agent-Based Computational Economics Approach To Technology Adoption Timing And The Emergence Of Dominant Designs

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ABSTRACT

Dominant technology designs emerge as the sum of adoption decisions across many firms. We take the position that if certain factors drive adoption by an individual firm, then in the aggregate, they may also illuminate the conditions under which a particular dominant design might emerge. In order to show this, we develop an agent-based computational model to explore linkages between firm specific, industry, and environmental factors, such as knowledge overlap, firm size, environmental uncertainty, and the scope of returns to adoption. We show that the significance of these factors varies with the stage of the technology contest. Early in the process, firms that have a compelling reason to adopt (such as to avoid obsolescence of key resources) choose to enter to create momentum for a particular approach. Other firms, due to indifference, inability or uncertainty, may defer until outcomes are clearer or choose not to adopt at all. More importantly, what constitutes a compelling reason for adoption varies with the nature of the firms that lead as innovators and the external environmental factors. On a broad scale, strong regularities in adoption timing and characteristics of technology winners emerge from the analysis.

Keywords: Innovation adoption; dominant design; increasing returns

INTRODUCTION

Radical or discontinuous innovations can change industry structure by making the knowledge and competencies of incumbents obsolete. Successful variants of such innovations become dominant designs when the majority (and sometimes all) of industry sales or production reflect the new approach. This can elevate new industry leaders, drive out firms that cannot adapt, and facilitate the entry of former unknowns to the industry. While the mechanics of which firms choose to adopt and when they do so, as well as some of the factors that drive adoption, have been widely studied (e.g., Wernerfelt & Karnani, 1987; Mitchell, 1989, 1991; Teece, 1996; Christensen, Suarez & Utterback, 1998), an integrated inquiry into the emergence of dominant designs has been less analyzed. This may be due, in part, to the observation that technology winners emerge more as a result of social or political interactions and negotiations rather than the straightforward merits of the technology and as such, cannot be determined in advance (Tushman & Murmann, 1998).

A dominant design emerges as the sum of a sequence of decisions across many firms and is analogous to a political election - no single vote likely creates a victor, but the sum of votes does. We take the position that if certain factors drive adoption by an individual firm, then in the aggregate they may also illuminate the conditions under which a dominant design might emerge, and which technology it may be. In order to show this, we develop an agent-based computational model that helps us explore the linkages between firm specific, industry, and environmental factors, such as knowledge overlap, firm size, environmental uncertainty, and the scope of returns to adoption.

In general, we show that the significance of these factors varies with the stage of the technology contest. Early in the process, firms that have a compelling reason to adopt (such as to avoid obsolescence of key resources) choose to enter to create momentum for a particular approach. Other firms, due to indifference, inability or uncertainty, may defer until outcomes are clearer or choose not to adopt at all. More importantly, what constitutes a compelling reason for adoption varies with the nature of the firms that lead as innovators and the external environmental factors. On a broad scale, strong regularities in adoption timing and characteristics of technology winners emerge from the analysis.

The innovation and diffusion literatures are rich in theoretical and empirical work describing the role of knowledge and learning firms' size in the technology adoption decision and, in the case of increasing returns to adoption economies, the importance of critical mass or bandwagoning. Our paper contributes to the research by integrating and interrelating these factors and illustrating their dynamic nature.

THEORY AND HYPOTHESES

Most technological change in an industry tends to be close to what has been developed in the past. Dosi (1988) describes this as a result of the technological paradigm for the industry or the commonly held knowledge about how to solve the fundamental economic problem the industry addresses. Techniques and approaches that work are preserved and failures discarded. These approaches disseminate through the interested community and add to the core of inquiry and answer. Thus, because the general search and development processes draw upon existing knowledge and competencies, innovations within the industry – or the paradigm - are generally incremental (Anderson & Tushman, 1990) or regular (Abernathy & Clark, 1985) additions to the knowledge base. Conversely, significant technological change in what industry firms produce (or how they produce it) can radically affect and even destroy industry structures and positions because they make the industry paradigm and associated firm knowledge obsolete.

The emergence of such innovations typically stimulates an "era of ferment" as firms seek to understand the new solution, judge own abilities to adopt or emulate, and when to do so if at all. Competition emerges between the old technology and the innovation(s) and between alternative innovations. Even within a new technology, competition emerges because the initial innovation is typically crude and experimental: alternative versions are introduced as firms seek to not only implement the new technology but differentiate themselves in doing so. This period ends when a dominant design emerges. An innovation becomes a dominant design when a sufficiently large number of firms – a technology coalition - in an industry have adopted it through decisions to produce (Anderson & Tushman, 1990). It is the single product architecture that establishes market superiority and has been described as a best compromise among differing buyer needs and preferences (Suarez & Utterback, 1995). Still, the introduction of an innovation need not necessarily lead to a new dominant design. One innovation may be superseded by another, thus ending one cycle of development. Further, when market demand is low or governments become involved in the process, true domain designs may not have the chance to emerge (Teece, 1996; Tushman & Murmann, 1998).

Another perspective on the process is that in some cases, social and political forces (rather than market forces) can affect the formation of coalitions that set the standard or dominant design. Such forces include particularly powerful firms, industry committees, and coalitions of firms acting as de facto committees (Tushman & Murmann, 1998; Warner, 2003; Warner & Fairbank, 2008). During the era of ferment, firms group themselves by their technology choices and the competition can be reconsidered as that between coalitions. Coalitions in this sense are not necessarily sets of firms that intentionally act together (though, as in the case of block alliances, they can be (Warner, 2003)). The minimum level of organization is that of members who gain value from their own actions and from the coalition itself. These have been described as hedonic coalitions (Dreze & Greenberg, 1980). Competition thus shifts to coalition-based because members derive value from their own actions and that of the coalition as a whole.

The literature on innovation diffusion and adoption from a managerial perspective has focused on when adoption occurs and the factors that drive that decision. The theoretical underpinning is one of rational expectations: firms adopt when and if they have a compelling reason to do so. That is, the expectation of utility is higher with the selected technology than with any of the alternatives (Farrell & Saloner, 1986; Katz & Shapiro, 1986, 1992; Choi 1997). The factors that enter the calculation include firm level (ability to enter through possession of relevant knowledge and firm size), industry level (coalition size), and environmental (uncertainty and scope of returns to adoption). Prior empirical and theoretical analyses have addressed one or some of these but little if any larger scale work has been done. In this paper, we integrate the factors to demonstrate how they affect the entry timing decision.

Knowledge and the Ability to Enter

The ability of firms to imitate an innovation is heterogeneous. The best positioned are firms that can quickly unravel the information implicit in the innovation and reapply it in a new organizational context (Jensen, 1988). Knowledge transfers occur through spillover, worker transfer, reverse engineering, and the public nature of patents and other property rights measures. However, even these require a foundation of relevant knowledge on the part of the learning firm (Schewe, 1996). Cohen and Levinthal (1990) describe this as absorptive capacity or the ability to recognize and value new knowledge, incorporate it into the organization, and apply it to commercial ends. This requires prior related knowledge because learning is cumulative and path dependent. Thus, lack of the right knowledge resources means firms are handicapped in the ability to respond to innovative new knowledge because the absence of the right prior learning investments means firms are unprepared to assess and assimilate new knowledge when it becomes available. Further, because learning requires time and investment, such gaps are costly to overcome.

Relevant knowledge affects the timing of entry. If competing firms are already in the process of developing similar products or if important capabilities are accessible, the less lead time innovators will have (Mitchell, 1989; Zander & Kogut, 1995). For example, the ability of some Japanese firms to quickly imitate or offer "improved" innovation is not just a function of investment in research but also in competitive information acquisition and management (Bolton, 1993). Thus, high knowledge overlap is argued to be a condition for early entry or imitation. However, it is not a sufficient condition.

Suppose two competing innovations have been introduced into an industry. If a firm has high overlap with both innovators then, all else equal, it should be indifferent to which one succeeds because it can respond effectively in either direction. This is particularly true if choosing either requires a commitment of resources in a specific learning direction. If the firm chooses the losing technology, it will be disadvantaged relative to winners in sales and in costs. On the other hand, firms that have a much higher overlap with one firm than the other should be highly motivated to enter early if that choice influences the decisions of later entrants (as often happens in coalition formation) (Wernerfelt & Karnani, 1987; Warner, 2003). Deferring entry could permit the less desirable technology to prevail and place the firm in a long learning cycle position, again with adverse effects on sales, profits, and costs. We hypothesize:

H1: As a firm's knowledge overlap difference between two innovators increases, the firm will enter earlier.

Adopter Size

In a general sense, the findings on the effect of firm size in the entry process are contradictory. Larger firms are argued to be more specialized in processes and thus possess deeper knowledge bases, which should enhance innovation and imitation (Dewar & Dutton, 1986; Damanpour, 1996). Conversely, inertia and bureaucracy increase with size and are argued to have a negative effect on innovation and adoption (Damanpour, 1996; Schoenecker & Cooper, 1998).

From our perspective, the size of potential adopters is interesting because of two opposing tendencies with regard to adoption under uncertainty. In the general discussion of increasing returns markets, adoption is argued to send a signal to the undecided about the desirability or prospects for success of a particular technology. Large firms send a strong signal because the coalitions they join become more likely to win the technology battle. Firms that can choose a technology but have not yet done so should be influenced to join as they do not want to be caught on the losing side (Katz & Shapiro, 1986; Choi, 1997). Therefore, large firms should choose early to stimulate the adoption of the technology of their choice. Conversely, Wernerfelt and Karnani (1987) argue that large firms can wait until there is less uncertainty and enter so as to maximize their impact on deciding the technology race. In short, there are two conflicting theories of entry timing. We argue that since firms should rationally want to be associated with wining coalitions and because large firms by virtue of their size can exert power in that direction, we hypothesize:

H2a: Larger firms will enter earlier.

H2b: As the difference in coalition size increases, undecided firms will be less likely to enter.

Uncertainty

The role of uncertainty in innovation adoption has been extensively examined on several levels and has been decomposed into several elements. The first is "technical" uncertainty or the uncertainty as to whether particular innovative approach actually works. This is resolved at the firm level by investment (McGrath, 1997). We are more concerned with the subsequent uncertainty that is resolved through competition: Market uncertainty. Under "market" uncertainty, firms may not be certain about which, if any, of several competing technologies will win (for example, VHS versus Betamax videotape technologies (Cusumano, Mylonadis, & Rosenbloom, 1992), Fast Ethernet versus AnyLAN (Didio, 1993; Didio & Caron, 1993), or competing DVD formats (Holyoke & Armstrong, 1995). On a larger scale, there may be uncertainty as to whether any form of the innovation will succeed. The failed history of stereo AM introduction in the United States is an example of how several competing and exclusive technologies can each fail to gain sufficient adoption to become dominant design (Besen & Farrell, 1994; Farrell & Saloner, 1988; Katz & Shapiro, 1994).

Because market uncertainty entails actually going to market with products, McGrath (1997) and Miller and Folta (2002) have noted and discussed strategic workarounds managers in some industries have developed to circumvent competitive loss. In these circumstances, managers seek to shape how the uncertainty is resolved by attempting to influence how dominant designs or standards emerge. The Fast Ethernet and DVD examples cited above were characterized by coalitions or alliances of firms that formed prior to actual introduction to avoid actual market competition. This approach is not a complete solution, however: the competition between US Robotics and Rockwell over 56K modem technologies featured alliances of users and producers on both sides in an attempt to sway the market winning design. The relative parity of the coalitions did not resolve the uncertainty potential adopters had about the outcomes which led some observers to claim that growth in modem sales were damaged (Korzeniowski, 1998).

The inability to forecast winners in a technology race means that early entrants are exposed to a higher risk of failure (Audretsch, 1995; Christensen, et al, 1998) or at least additional costs to switch to the winning technology (Tegarden, Hatfield, & Echols, 1999). On the other hand, moving early and picking the right technology can improve subsequent competitive positions, especially if there are learning or lead time effects (Lieberman & Montgomery, 1988, 1998). All else equal, lower levels of uncertainty should drive earlier adoption but the opportunity costs of a poor choice may deter entry under high uncertainty – at least until there are clearer signals from the market. These effects lead to the following hypothesis:

H3*:* As market uncertainty increases, firms are less likely to enter.

Returns to Adoption

Increasing returns (IR) markets differ from the more common decreasing or constant returns markets because they tip to one technology only. Incompatible competing technologies will not reach an equilibrium where they share the market so competition between technologies will result in dichotomous, winner-take-all outcomes. The complete success of VHS over Betamax is a frequently used example (Cusumano, et al, 1992), as is the QWERTY keyboard (David, 1985), AC power generation (David & Bunn, 1988), and nuclear power generation (Cowan, 1990).

Increasing returns to adoption arise from learning by doing, coordination by technical groups and through the presence of network externalities (Cowan, 1991; Islas, 1997). Network externalities imply that users of a technology receive increasing benefits as the user network expands. For example, users of telephone service or email benefit as others adopt the technology because the reach or usability of the investment has increased at no cost to them. Similarly, support services for a product (such as the availability of mechanics for certain types of automobiles) or complementary goods (such as software) can constitute an externality. Other examples include experience and learning because important knowledge is portable and thus more available to prospective new users the more widely the technology is adopted (Katz & Shapiro, 1986, 1992).

These markets have been characterized as path-dependent and self-reinforcing. Path dependency implies that even if a variety of outcomes is initially feasible, the one that actually occurs is a function of small events that occur early in the adoption history (Arthur, 1989). Self-reinforcement occurs when adoption by one increases the likelihood of adoption by others. This can lead to several issues. First, such markets may display excess inertia: the apprehension that an early choice could lead to being stranded with a losing technology reduces the willingness of firms to adopt. The opposite problem – excess market momentum - occurs as expectations about technology competition outcomes leads adopters to choose based on beliefs about the ultimate winner rather than real preferences (Katz & Shapiro, 1986; Arthur, 1989; Choi 1994, 1997).

However, there is evidence that ostensibly IR markets do not always proceed to the single solution outcome. Arthur's (1989) foundational work implies that if the number of adopters is small, the market may halt with two technologies still in play. Lamberson (2008) demonstrates that small pockets or locales of competing technologies can persist even in IR markets (citing the growth of Firefox and Safari web browsers as an example). Other examples might include the persistence (and recent growth of) the Macintosh operating system or the resurgence of double-edged razors in a market dominated by cartridge razor styles. Lamberson argues that localized rather than global increasing returns can cause these outcomes.

This has implications for the timing of adoption choice. As returns to the coalition size increase, firms should anticipate that payoffs will be increasingly skewed (toward the dichotomous outcome). As discussed above, varying conditions of IR localness should motivate entry timing. Specifically, we argue that as the returns to adoption increase, the estimated risk to early entry and stranding increases. Thus:

H4: As the adoption returns shift parameter increases, firms will enter later.

DATA AND METHODS

Data

For this paper, we develop data through an agent-based computational economic (ACE) model. ACE's have been developed as an alternative exploratory mechanism for quasi-empirical investigations and are particularly suited to problems of choice, motivation for choice, and in modeling how large scale social effects emerge from self-motivated micro behavior (Tesfatsion, 2000). For example, Schelling uses such an approach to demonstrate how simple rules governing choices about where to live illustrate how segregation or partitioning naturally emerges on a larger scale (Schelling, 1978).

Agent-based models provide the flexibility to test the hypotheses in this paper. We argue, for instance, that when a firm joins a coalition is influenced by which firms lead in innovation. Standard cross sectional analysis of real adoption decisions is historical so discussion of alternative outcomes is strictly speculative. More testing over a range of conditions can eliminate some speculation but at the cost of the ability to hold the firm or industry constraints we are interested in constant. In contrast, an ACE model can test many combinations of innovation leaders and state variables in an industry and how coalition formation is affected. To examine how firm specific attributes of knowledge overlap and coalition size affect choice and timing of technology adoption, we construct an industry of ten firms endowed with randomly generated firm and environmental attributes.

Knowledge overlap (that is, how much technical knowledge a firm has in common with an innovation leader) is based on a random draw from a normal distribution [0.2, 0.8], reflecting the intuition that while firms in an industry share a certain level of knowledge (Dosi, 1988), knowing very much or very little is less likely than knowing an intermediate amount. The normal curve captures this effect. Market share is based on a draw from a uniform distribution where the share of firm i is proportional to the sum of all ten draws.

Environmental or state variables include uncertainty about adoption and the increasing returns parameter. Uncertainty is a random draw from a uniform distribution over the range [.5,1]. The lower bound is based on the idea that firms would not introduce an innovation if they perceived a less than even chance of success. The AR parameter is based on a logistic function with an expectation that firm *i*'s ultimate or post-dominant design share in a technology coalition is

$$\frac{\text{share}_i}{\text{share}_J} * \frac{1}{1 + e^{-\gamma x}}$$

where share $_i$ is the firm pre-innovation market share, share $_J$ is the sum of shares of the technology coalition participants, x= share $_J$ -.5, and γ is the AR parameter (Arthur, 1989). Higher values of γ correlate to outcomes that skew toward complete dominance by one technology. To analyze how expectations of dominance affect choice, four values of γ are selected to reflect particular post-choice coalition shares. For example, based on a pre-innovation coalition share of 40%, the γ values return a post-dominant design share of 80%, 50%, 20%, and 5% of initial state (i.e., a final share of 32%, 20%, 8% and 2% respectively). These correspond to γ values of 7.5, 14, 24.5 and 39, respectively. Figure 1 illustrates the sharp effects of a change in γ on final coalition market share. Note that relative to the base case for existing market share, as the AR increases, the market looks more and more like the dichotomous result Arthur (1989) describes.

The data for this study are event histories or records of the decision firms made at each stage of the simulation. The data were generated by first randomly drawing two firms to be competing lead innovators and then capturing the event histories of the remaining eight firms in the industry with respect to when or if they introduced compatible products. We generated and ran 100 distinct scenarios of knowledge overlap/share/ uncertainty values and ran each scenario through each of the four AR values. Each scenario was run until all firms in an industry had joined a coalition or through 25 decision cycles if not all firms joined. This generated a data set of approximately 30,000 events.

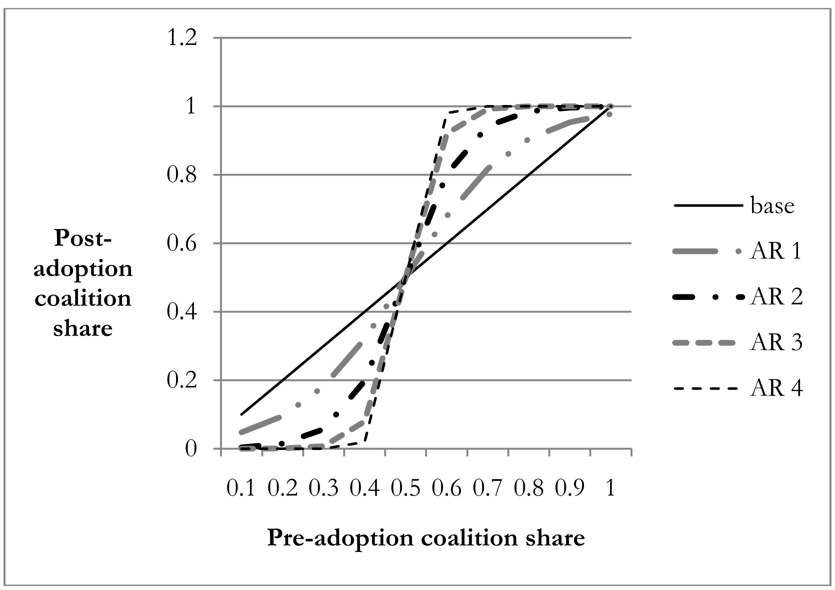

Figure 1: Returns to Adoption (Gamma) Effects on Post-dominant Design Market Share

The dependent variable *join* is an indicator of when a firm joined a coalition through product introduction. This is a dichotomous variable as in any given cycle a firm has or has not joined. The ability to enter is based on knowledge overlap and learning. Under the assumption that a certain level of equivalent knowledge is required to produce a compatible product, we set a standard of achieving 90% knowledge overlap with an innovator. As described above, each firm is endowed with knowledge overlap relative to the innovators and further with a learning capacity that varies between 5% and 10% of the overlap base. Thus, at each cycle, a firm assesses overlap and generates a prospective entry time based on overlap and learning rate. The decision to join is based on a utility function incorporating an estimate of final coalition sizes, the benefit of early entry (Wernerfelt & Karnani, 1987; Christensen, Suarez & Utterback, 1998), and the cost of switching coalitions if the first decision appears to be a costly error. The actual join occurs when a firm has reached the 90% threshold in knowledge overlap.

The independent variables include *uncertainty*, *share,* and *AR* as described above as well as several transformations of the knowledge overlap variable. First, we determined the absolute difference (*abs overlap*) between overlap scores for a firm relative to the two innovators. This captures knowledge asymmetry. However, simple asymmetry may not illuminate completely. For instance, a firm might have overlap scores of 0.2 and 0.4 or .6 and 0.8 and have the same absolute overlap of 0.2. However, the much higher level of relevant knowledge in the second case should make a difference in entry timing. Thus, our second knowledge variable is *max overlap*, which is the highest overlap score for a firm relative to the two innovating lead firms. To test H2b, we introduce a variable called *coalition diff,* which captures the contemporaneous difference between technology coalition sizes as of the prior cycle. We also include dummy versions of the AR variable for further testing.

Methods

Our inquiry is about when an event occurs with the characteristics that the data are reported in discrete duration form and exhibit clumping in particular periods. This is common to many econometric studies in that the event occurs in continuous time but reporting constraints show only a larger, discrete period in which it occurred (Beck, Katz & Tucker, 1998). The most popular method for analyzing continuous time event data is the semi-parametric Cox proportional hazards model and has been extended to treat grouped duration data. Beck, et al, (1998) demonstrate that the complementary log-log model (cloglog) can be derived from the continuous Cox base model. The data are modified from the standard reporting of the period in which an event occurred to a dichotomous event did or did not occur in a given period. The cloglog transformation generates the model:

$$P\left(y_{i,t}=1 \middle| x_{i,t}\right)=h\left(t \middle| x_{i,t}\right)=1-\exp\left(-e^{x_{i,t}\beta+k_{t-t0}}\right)$$

This approach works well with grouped data but the derivation from the Cox model implies that the underlying assumption of proportional hazards still applies, which may not be reasonable for some economic data (Jenkins, 1995). Given the same data structure as that imposed on the cloglog model, the logit model has been adapted to the problem (Jenkins, 1995; Beck, et al, 1998; Shumway, 2001).

The logit form of the hazard model is an alternative to the cloglog version:

$$P\left(y_{i,t}=1 \middle| x_{i,t}\right)=h\left(t \middle| x_{i,t}\right)=\frac{1}{1+e^{-(x_{i,t}\beta+k_{t-t0})}}$$

where $y_{i,t}$ implies an adoption. Shumway (2001) has demonstrated this is a consistent and efficient maximum likelihood estimator. Beck, et al, (1998) show that the cloglog and logit models are virtually identical in their estimations over a broad range of event probabilities. Given that the logit model is well understood and easily estimated, we use it to test the hypotheses. The models are:

A) p(join = 1) = f (cycle) (this establishes the baseline hazard)
B) p(join = 1) = f (cycle, uncertainty, AR, share, coalition difference, abs overlap, max overlap)
C) p(join = 1) = f (cycle, uncertainty, AR (dummy version), share, coalition difference, abs overlap, max overlap)
D) p(join =1) = Model B plus interactions

RESULTS AND DISCUSSION

As noted above, the simulation was run 100 times with random draws for the share and overlap independent variables. Events were recorded as a “join” when a firm had developed enough knowledge overlap (i.e., 90% relative to one innovator or the other) to introduce a product in a specific technology line. Each simulation was run until all firms had joined a coalition or for 25 cycles, whichever came first. This generated a data set of approximately 30, 000 event history records. Summary statistics and correlations are presented in Table 1.

Table 1: Summary Statistics and Correlations

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1	Cycle	7.89	5.03	1.00									
2	Uncertainty	0.11	0.08	-0.04	1.00								
3	Adoption Returns (AR)	21.33	13.11	0.01	-0.24	1.00							
4	AR1	0.33	0.47	-0.01	0.26	-0.74	1.00						
5	AR3	0.16	0.37	0.01	-0.01	0.11	-0.31	1.00					
6	AR4	0.31	0.46	-0.01	-0.20	0.90	-0.47	-0.30	1.00				
7	Share	0.09	0.04	-0.14	0.01	0.02	-0.01	-0.05	0.04	1.00			
8	Coalition diff	0.18	0.19	0.55	-0.05	0.12	-0.15	0.05	0.09	-0.20	1.00		
9	Absolute overlap	0.16	0.12	-0.05	-0.03	-0.02	0.00	0.01	-0.02	-0.02	-0.07	1.00	
10	Max overlap	0.55	0.12	-0.15	-0.02	0.03	-0.06	0.06	-0.01	-0.13	-0.04	0.54	1.00

The results of the grouped duration logit model are presented in Table 2. Model A is a baseline model suggested by Beck, Katz, and Tucker (1998) to test for duration dependence. If the effect of the time variable is not significant, then the data are duration independent. In this case, the likelihood ratio test rejects the null of no significance as the LR $\chi 2$ is 227.46 with related probability of 0.000. Therefore, we conclude time effects are present and this is an appropriate model for analysis of this data. The results also indicate that in general, firms that adopt are more likely to do so earlier.

Model B is the primary specification, model C distinguishes between the levels of AR γ, and model D adds time-effect interactions. Following Hosmer and Lemeshow (1989), we report significant interactions and groups of interactions where at least one proved significant.

In Hypothesis 1, we argued that as knowledge overlap asymmetries increased, firms would enter earlier. In other words, if firms had equivalent knowledge about both technologies, they would be little motivated to choose. All else equal, a knowledge bias in one direction would lead to earlier adoption as firms seek to secure the value of their knowledge investments. We captured the knowledge overlap measures two ways: first, as a straightforward measure of the absolute difference between knowledge bases (*Absolute overlap*) and second as the highest value of overlap *vis a vis* an innovator (*Max overlap*). The Model B results about the likelihood of entry at all are somewhat surprising in that *Absolute overlap* is negatively signed and significant. We attribute this to some correlation between *Absolute* and *Max* variables in this way. *Absolute overlap* will have its highest values when the overlap with one firm is near complete and near zero with the other. However, the introduction of *Max overlap* also captures higher values so *Absolute overlap* tends to reflect more the effect of mid and lower level maximum overlap scores. In this case, firms may have a comparatively high overlap but lack sufficient knowledge to enter quickly. In fact, unless the technology they know most about wins without their contribution, they may never enter at all.

Table 2: Results

	Model A Baseline	Model B Main effects	Model C With dummies	Model D Time Interactions
Cycle	-0.109 (0.007)***	0.030 (0.009)***	0.030 (0.009)***	-0.032 (0.015)**
Uncertainty		-0.570 (0.475)	-0.295 (0.480)	-0.750 (0.614)
Adoption Returns		-0.005 (0.003)*		0.002 (0.003)
AR (1)			0.314 (0.101)***	
AR (3)			0.078 (0.119)	
AR (4)			-0.079 (0.102)	
Share		17.884 (0.863)***	18.804 (0.870)***	21.225 (1.049)***
Coalition diff		-3.679 (0.224)***	-3.673 (0.225)***	-3.605 (0.236)***
Absolute overlap		-1.942 (0.285)***	-1.954 (0.286)***	-2.856 (0.379)***
Max overlap		11.751 (0.468)***	11.879 (0.472)***	11.779 (0.465)***
Unc x cycle				-0.171 (0.122)
AR x cycle				0.003 (0.001)***
Share x cycle				1.096 (0.212)***
Coalition x cycle				-0.709 (0.062)***
Abs x cycle				-0.176 (0.075)**
Max x cycle				-0.501 (0.095)***
Constant	-2.682	-11.861	-12.197	-11.609
LR χ^2	227.46	1963.36	1971.81	2208.39
P> χ^2	0.000	0.000	0.000	0.000
Pseudo R^2	0.026	0.227	0.228	0.256
n	30,523	30,523	30,523	30,523

*significant at p< .10
**significant at p< .05
*** significant at p< .01

Both the *Abs x cycle* and *Max x cycle* interactions clarify this. Both are negatively signed and significant, so we conclude that both do contribute to early entry. Alternatively, the results could be interpreted to suggest that firms with high *Absolute* and *Max overlap* scores that have not entered before cycle *t* should be less likely to do so in cycle *t* than firms with lower scores. If a firm with a high overlap score has not entered, it should imply that the likelihood of a winning technology has shifted toward the technology the firm knows less about. The knowledge stocks of such firms are increasingly marginalized and they will not find it easy to enter. While noting the ambiguity of the main effects, we conclude for H1. We further infer that these outcomes make clear that if adoption is limited to incumbents, the more the new technology varies from industry knowledge stocks, the more the adoption decision is deferred.

The role of *Share*, with a coefficient that is positive and significant, indicates that larger firms are at any point more likely to adopt than are smaller firms. However, the interaction term with time (*Share x cycle*) is positive and significant also, indicating that firms that have not adopted up to cycle *t* are more likely to do so in cycle *t* as size increases. That is, they are more likely to adopt relatively late. There is, as noted earlier, an implicit conflict in the theory of large firm adoption. Wernerfelt and Karnani (1988) suggest that large firms are more likely to wait to adopt so as to utilize their size most effectively and resolve uncertainty about winning technologies with their entry. The limit to this argument is that in order for size to be an important factor in the outcome, the firms should adopt early enough to have impact. Still, the results of this analysis indicate that large firms are deliberate in entry. We reject H2a.

The change in the size of the adopting coalitions (*coalition diff*) was hypothesized to decrease the likelihood of adoption. The results from models B and D strongly support this. The results from Model B indicate that firms that are going to adopt do so earlier, which affects the balance of power between coalitions. In terms of the firm specific variables or attributes tested above, asymmetries in knowledge overlap can become irrelevant if the outcome favors the "wrong" innovation (that is, the technology the firm knows less about). Similarly, after a point, the value of size in forcing a decision becomes mot as outcomes shape up and no late adoption can change the outcome. Therefore, any firms that do not choose relatively early and shape coalition sizes are more likely to make no adoption decision at all. If the new technology coalition reaches dominant design, non-adopting firms can be forced out of the market. We conclude for H2b.

The results of the Hypothesis 3 tests are ambivalent. *Uncertainty* is signed as we expect but does not turn out to be a significant factor in the decision of when to adopt a technology in any model as a main or interaction effect. We reject H3 and conclude that uncertainty *per se* about the likelihood of success in the market is not a drive of the adoption decision.

The results for the *AR* market shift variable are at least initially consistent with Hypothesis 4. As the AR γ factor increases (i.e. the asymmetry of returns to adoption increases), adoption tends to occur later. In the main effect of Model B, this is significant at a 0.1 level. When we assessed the effect of the specific levels of AR 2, using $\gamma = 14$ as our base, we find that AR 1 (our lowest specified level of increasing returns to adoption) is significantly associated with early entry while ARs 3 and 4 are not significantly different from AR 2. Two observations come to mind. First, there is little internal difference among higher levels of AR. All are significant with respect to AR 1. This suggests that to the extent a simulation models behavior effectively, we would expect that firms need not face the absolute dichotomous outcomes Arthur (1989) argues for (and as AR 4 approaches) but only fairly highly skewed outcomes to evoke a particular adoption pattern. Second, given these results, neither the excess momentum nor excess inertia theories of adoption (Katz & Shapiro, 1986; Choi, 1997) really capture what happens. By including the interactions between *Cycle* and *AR*, we conclude that high AR values lead to a temporary waiting game until outcomes begin to clarify, at which point adoption is accelerated.

CONCLUSION

In this paper, we have explored linkages between and effect of various factors affecting the adoption decision in the wake of innovation introduction and the subsequent emergence of dominant designs. The use of the agent-based computational simulation approach permitted the assessment of a large number of firm, industry, and environmental factors in varying combinations, which is difficult to accomplish with actual innovation and adoption events.

We have several findings. First, the effects of Adoption Returns are not uniform. Arguments for either excess inertia or momentum in adoption under high AR conditions do not capture the complexity of what happens. When returns are high, shifting post-dominant design shares significantly toward the winner, firms appear to play a waiting game rather than be wrong-footed early. Once a signal about a likely winner emerges, however, adoption proceeds rapidly. All else equal, a signal should never emerge as firms would all prefer to wait (Katz & Shapiro, 1986). That one does emerge is more often due to asymmetries in firm specific characteristics of knowledge stocks and size.

Second, what firms know matters in interesting ways. Neither strict asymmetries nor absolute knowledge stocks individually capture the complexity of the entry decision but the two together do matter. All else equal, symmetry in knowledge stocks with both innovators will retard adoption until a clear signal about likely winners is received. Asymmetries in knowledge stocks, but low absolute levels of overlap will also delay entry as firms need to not only choose a technology, but also invest in learning to reach competence.

Finally, the effect of coalition size on the decision is useful. Early entry can shift the value of one technology *vis a vis* another in the view of the undecided firms because value is not implicit in the technology, but in market control. Our findings suggest that to the extent firms can affect coalition size or membership through own decisions, the more influence over ultimate outcomes they can exercise. While this research does not explicitly capture the social and political elements alluded to earlier, it does parallel the effect of how the actions of major firms in an industry can signal the value of a particular coalition and subsequently influence the dominant design or standard (Warner & Fairbank, 2008).

Wernerfelt and Karnani (1998) proposed that innovation adoption by firms be predicated on preference for or the ability to influence particular outcomes. This paper has explored an integrated set of conditions under which such decision might actually generate the desired outcome.

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