International Food and Agribusiness Management Review
Volume 11, Issue 2, 2008

Structural Change in a Food Supply Chain[1]

Desmond W. Ng[①]

Department of Agricultural Economics,Texas A&M University,
349B Blocker Building, College Station, TX 77843-2124, U.S.A.

Abstract

As changes in modern agribusiness markets have placed increasing emphasis to the study of structural change processes, this research advances an agent based model to examine transitions from a spot market exchange to a vertically coordinated arrangement in a supply chain system. This agent base simulation model draws from the subjective theme of Austrian entrepreneurship, behavioral theories of the firm and social networks. The results of this agent based simulation model indicate that structural change occurs with market structures that facilitate information transmission rather than from incentive based contractual arrangements.

Keywords: Agent based models, structural change, Austrian economics, and social networks

[①]Corresponding author: Tel: + 979-845-1192
Email: dng@ag.tamu.edu

* I would like to thank the four anonymous reviewers of IFAMR. The ideas of this paper have been significantly sharpened by their challenging comments and queries. In addition, I would also like to thank the Managing Editors, and Editor, Peter Goldsmith, for their Editorial contributions.

Structural Change in a Food Supply Chain

Advances in genomic development and the increasing sensitivities of consumer choices to the social, ethical and health aspects of food production have prompted a rising interest to understanding and predicting the changing face of agriculture (Boehlje 1996, 1999; Just 2001). Such change has often been termed the "industrialization" or "structural change" of agriculture (Boehlje 1995, 1996, 1999; Cook and Chaddad, 2000; Just 2001). Although there are numerous dimensions that characterize structural change, the transition towards vertically coordinated relationships has been a prominent feature of the U.S. food market system (Boehlje 1995, 1999; Lazzarini et al. 2001; Omta et al. 2001; Poray et al. 2003; Purcell and Hudson, 2004).

Traditionally, agricultural markets have been coordinated by open / spot market exchanges, whereby market prices coordinate the supply and demand of commodity industries, such as grain. However, in recent history, the broiler, beef, and hog industries have witnessed periods of structural change towards tighter vertical coordination (Barkema and Cook, 1993; Boehlje, 1995, 1996, 1999; Cook and Chaddad, 2000; Drabenstott, 1994; Hurt, 1994; Purcell and Hudson, 2004; Sporleder, 1992). For instance, in the broiler industry, production contracts had risen from 10% in 1950 to 90% in 1955 and remained fairly constant at 80% (Martinez, 1999). Similarly, in the hog industry, contracts and related vertical integrated arrangements had increased from 2% in 1970 to 59% in 1999 (Martinez, 1999).

According to principal-agent reasoning, such transitions toward vertical coordination is a response to improving the "efficiency" of buyer and supplier relationships (e.g. Cook and Barry, 2004; Cook and Chaddad, 2000; Halldorsson et al., 2007; Hornibrook and Fearne, 2001; Purcell and Hudson, 2004; Sporleder, 1992). A central tenet of principal agent reasoning is that an agent, such as a supplier, can act in ways that are contrary to the interests of its principal, its buyer. The primary concern is, therefore, to design an "efficient" contract to influence the agent to act in ways that serve the interests of the principal (Cook and Chaddad, 2000). To align such interests, outcome based incentives are often employed. For instance, in beef supply chains, price premiums are used to align the economic interests of the feedlot producers with the beef packers to develop specific product quality traits, such as beef tenderness (e.g. Purcell and Hudson, 2004). By "getting the contract right", the design of an "efficient" contract tightens the coordination of agricultural supply chain activities to which increase the overall efficiency of the supply chain (e.g. Cook and Chaddad, 2000; Halldorsson et al., 2007; Hornibrook and Fearne, 2001; Purcell and Hudson, 2004).

However, structural change can also arise from the discovery and innovative efforts of entrepreneurs. Most notably, the Austrian economist, J. Schumpeter (1934) contends the innovative efforts of the subjective "entrepreneur" can be instrumental to the "creation" of new markets to which can lead to the "destruction" of existing market arrangements (Kirzner, 2000). With subjectivity, entrepreneurs possess heterogeneous knowledge to which requires leveraging the experiences of others to exploit new found opportunities in the market (Kirzner, 1979, 2000). By leveraging such social or collective knowledge experiences, these social interactions can lead to revolutionary market processes that yields the "creative destruction" (Schumpeter, 1934) of existing market arrangements (Kirzner, 2000).

For instance, in the biotechnology industry, the subjective entrepreneur can be viewed as a biotech start up that has unique experiences and perceptions in their development and commercialization of specific genomic technologies. As subjectivity suggests that individuals have incomplete knowledge, individuals can benefit from learning the experiences of others. As a result, start-up companies are often involved in many joint ventures, R&D collaborations and other related cross-licensing arrangements (e.g. Rothaermel and Deeds, 2004). By learning from such social arrangements, biotech start-ups build upon the collective achievements of other biotech startups. This can lead to the "creation" of new "agriceutical" products whose traits can displace or "destroy" the conventional traits of commodity based agricultural products (e.g. Goldberg, 1999).

Yet, despite a recent revival of Austrian economics in management research (Shane, 2000), empirical methods to examine such complex market processes remain limited (see O'Driscoll and Rizzo, 1985). Some researchers (e.g. Vriend, 1999), however, have suggested the Austrian market process can be modeled by agent-based simulation methods. This is because like Austrian economics, agent based simulations attribute complex macro processes to the interactions of heterogeneous (i.e. subjective) behaving agents (see Vriend, 1999). These agents are governed by simple rules or heuristics that enable the agent to interact and adapt to the decisions of other agents (Lane, 1993; Fagiolo et al. 2006; Windrum et al., 2007). Through such interactions, complex adaptive systems can yield revolutionary system behaviors (Lane 1993; McKelvey 1998, 1999; Vriend 1999; Windrum et al., 2007).

The objective of this study is, therefore, to draw on agent based simulations to introduce an Austrian economic explanation of the structural change of agricultural markets. Specifically, as the transition towards vertical coordinated markets – hogs, broiler, cattle - have been attributed to increased price premiums, an agent based model that is based on the discovery processes of the Austrian entrepreneur is developed to examine the impact of price premiums to the structural change of an agricultural supply chain.

This Austrian economic / agent based approach offers three contributions / implications to the management of food supply chains. First, unlike the "efficiency" explanations of principal-agent reasoning, structural change can also be explained by the Austrian entrepreneurial discovery process. Second and subsequently, our simulation results show supply chain entrepreneurs do not favor markets that offer higher price premiums. Rather, entrepreneurs favor markets with greater information transparency. This suggests that the dissemination of end user or customer data to upstream suppliers may be more "effective" in improving the performance of an entire supply chain than through contractual arrangements. Third, since greater information transparency is favored over contractual exchanges, fewer supplier contracts are needed to which can reduce costs in drafting, monitoring and enforcing contractual obligations.

To develop this agent based approach, this research is organized into four sections. First, a brief discussion of agent based models is presented. Then in drawing from the subjective theme of Austrian entrepreneurship (Kirzner 1979, 1997, 2000) and related behavioral theories of the firm (Cyert and March 1963; Simon 1976), a behavioral model of rent seeking entrepreneurial agents is developed within an agent based simulation setting. This analytical model is then used to examine the structural change of a generic food supply chain. Its results are discussed. The conclusions and managerial implications of this agent-based model follow.

Conceptual Foundations

Origination from Complexity science, agent based models challenges the reductionist tenet of the modern scientific method (Jantsch 1980; Prigogine and Stengers 1984; Stacey 1992; Windrum et al., 2007). Reductionism is '…defined as the view that all aspects of a complex phenomenon must be explained in terms of one level, or type or unit' (Hodgson 1997, 401). That is, in accordance to economics, market level behaviors are deduced by the aggregation of 'representative' firm behaviors (Hodgson 1997; Windrum et al., 2007). Reductionism requires that 'representative' firms are homogeneous and atomistic; firm heterogeneity and social relationships are often regarded as a nuisance to economic analysis (Kirzner 1979, 1997; Shane 2000; Windrum et al., 2007).

Agent based simulations depart from this reductionist tenet in which macro system behaviors are the result of the interactions of heterogeneous and adaptive agents (Axelrod 1997; Goldspink 2002; Lane 1993[1]; Windrum et al., 2007). In particular, although there are various representations of agent based simulations, such as cellular automata (used in traffic models) and neural networks, the most basic element of an agent based approach is the decentralized nature of the system in which it focuses on the interactions of heterogeneous and rule based behaviors of agent (Lane, 1993[2]). Furthermore, an agent's adaptive behavior is unlike the

[1] For readers interested in a general introduction to the method of agent based models, please refer to Lane (1993).
[2] For a broader introduction to agent based methodology, interested readers are directed to Lane (1993).

unlimited cognitive powers of economic agents (Windrum et al., 2007). Rather, an agent's knowledge is heterogeneous in which agents are subjected to cognitive limits commonly associated with 'bounded rationality' (Simon 1976; Windrum et al., 2007). With limits on rationality, an agent draws on heuristics or "rules of thumb" that enable the agent to adapt to other boundedly rational agents (Kirzner, 2000; O'Driscoll and Rizzo, 1985; Windrum et al., 2007).

Austrian Entrepreneur: Subjectivity

Such a view of agent behavior closely follows the Austrian economic characterization of the 'subjective entrepreneur' (Kirzner, 2000; O'Driscoll and Rizzo, 1985; Vriend, 1999). According to the subjective theme of Austrian economics, entrepreneurs are heterogeneous in their perceptions of rents (Kirzner, 1979). With subjectivity, entrepreneurs hold different perceptions on the productivity of their assets or inputs (Lachmann, 1977). To operationalize this subjectivity, an agent / entrepreneur's subjectivity is reflected by a vector, $A_{t,i}$, that denotes an agent, i's, subjective perceptions of the marginal productivity for a vector of eight inputs, $X_{t,i}$, at a given time, t. Since subjective perceptions has been commonly modeled as a uniform probability distribution (e.g. Fox and Clemen, 2005), this subjectivity, $A_{t,i}$, is determined by a random number generating process which depicts an agent's stochastic perceptions of the marginal productivities for this vector of inputs, $X_{t,i}$. This subjective marginal productivity is then used within a Cobb-Douglas production function shown by equation 1[3]. As a result, given each agent's subjective marginal productivities, $A_{t,i}$, equation 1 shows that each agent has a unique perception of the productive contributions for any given set of inputs, $X_{t,i}$. These inputs subsequently constitute a given plan or technological choice, $\Gamma_{t,i}$ (Lachmann, 1977).

$$(1) \quad F_{t,i}(X_{t,i} \mid A_{t,i}) = A_{t,i} \cdot X_{t,i}^{\overline{\alpha}}$$

Behavioral Rules

Yet, since an entrepreneur's subjective knowledge is incomplete, an entrepreneur does not have complete knowledge of all possible input combinations[4] and thus plan / technological choices. This provides opportunities for entrepreneurs to develop new plan / technological choices. Entrepreneurs discover new plans by drawing on heuristics or rules, $R_{t,i}$, that draw upon the subjective input / plan choices of others

[3] As production functions are commonly depicted by diminishing returns, this Cobb-Douglas function also exhibits diminishing return behaviors, $\overline{\alpha} < 1$.

[4] Technically, speaking, for any given product-market (three in total), and given eight inputs, there are 2^8=256 possible binary combinations of inputs.

(Kirzner, 1997, 2000; Lachmann, 1977). Namely, by drawing on the collective input/plan choices of others, an agent's interaction with its social network serves to improve upon the agent's own subjective knowledge of its input choices. As a result of such heuristics or rules, these interactions, therefore, lead to the discovery of new inputs plans / technologies. These behaviors are described by behavioral and interaction rules shown in table 1.

Specifically, from table 1, each of these behavioral and corresponding interaction rules enable an agent to learn from the successes of its neighbors so as to develop an agent's choice of inputs, $X_{t,i}$, and subsequent plan, $\Gamma_{t,i}$. For instance, the competitive imitation rule (rule 1) is a common heuristic found in organizational research (see Scott, 1995) in which firms replicate the successful practices of leading rivals. For instance, in the retail sector, K-mart adopted the EDI (electronic data interchange) practices of Wal-mart in the early 1980's (Bradley and Ghemawat, 2002). In addition, as plans are subjective and thus are inherently imperfect, entrepreneurs can build or revise upon the plans of others (Hayek, 1967; Kirzner, 1997; Lachmann, 1977) (see rule 2). For instance, Starbuck's success of the premium coffee market has led to the adoption of other forms of "premium" coffee by food service companies, such as Burger King, Dunkin Donuts, McDonalds. However, unlike Starbucks, food service companies do not compete on the "service" dimensions of Starbuck's "coffee experience". These rules are termed as rule following.

An important feature of these rule following behaviors is they can generate negative feedback effects. According to complexity science, negative feedback is a non-linear process that "dampens" fluctuations in a system (i.e. heterogeneous behaviors of agents) toward a system's equilibrium state (Jantsch, 1980). Such negative feedback occurs when social interactions occur among agents with similar input / plan experiences. For instance, Feigenbaum and Thomas' (1995) study of the insurance industry finds insurance firms tend to compare and adjust their behaviors to firms within the same strategic group. This social comparison yields a "dampening" tendency towards increasingly homogenous behaviors (Feigenbaum and Thomas, 1995; Ng 2004). This is consistent with findings in strategic group research that find firms have an overall tendency to imitate firms that possess "similar" competitive traits (Porac and Thomas, 1990; Reger and Huff, 1993). Therefore, since this negative feedback process requires interactions with "similar" agents, each of the rule following heuristics is associated with a corresponding interaction rule that only permits the agent to interact with others that possess similar technologies.

To distinguish interactions with "similar" agents, three distinct product-markets, designated by M_t where =1, 2, or 3, were created. Each product market, M_t, is distinct in the use of a specific combination of inputs to reflect the technologies of that product-market. For instance, beef quality assurance programs tend to require specialized assets in the monitoring of beef attributes and superior genetics in the herd (51% Angus) that are specialized for improving beef tenderness (Purcell and Hudson, 2004). Hence, given differences in the production technologies of these product markets, interactions with agents in the same product market are associated with the rule-following heuristics.

Table 1: An Agent's Behavioral Rule Choices, $R_{t,i}$

Rule-following: Behavioral Rules	Corresponding: Interaction Rule
1) Imitate the most profitable plan among one's product-market group.	Interact only with those agents in the same product-market yielding negative feedback.
2) Copy and revise upon the most profitable agent among one's product-market group.	Interact only with those agents in the same product-market yielding negative feedback.
Rule-generating: Behavioral Rules	**Corresponding: Interaction Rules**
3) An agent adopts one innovative input from the most profitable agent in one's social network.	Interact with agents in any product-market yielding positive feedback.
4) Choose the first innovative input that one has not used before.	No social interactions
5) Recombine an agent's existing input combinations with the most profitable agent in one's social network.	Interact with agents in any product-market yielding positive feedback.

However, in the technology diffusion studies of Abrahamson and Rosenkopf (1997), Leblebici et al., (1991), and Tushman and Romanelli (1985) find that in conditions of crisis, firms broaden their search so as to adopt innovations from peripheral regions of their socio-technological domain (Leblebici et al., 1991). To capture such innovative and explorative behaviors, table 1, also includes "rule generating" heuristics.

Unlike rule following, rule generation emphasizes the innovation of new inputs through broadening an agent's interactions to agents in other product-markets. Specifically, as innovations stem from expanding an agent's search, an agent's rule generating heuristic has a corresponding interaction rule that involves interactions with agents in any of the three product markets. This is because by broadening an agent's social interactions, it exposes the agent to a greater diversity of input and plan choices. This exposure promotes greater possibilities to recombine new inputs to which facilitate the creation of new innovations (e.g. Schumpeter, 1934). These innovations can lead to a positive feedback process in which the innovative efforts of an entrepreneur can be self-amplified to cause a large scale change event (Jantsch 1980; McKelvey 1998, 1999). This is because as new innovations are created, this increases the overall diversity of inputs / plans in the market to which provide further possibilities to recombine new inputs and thus creating further innovations. Through this positive feedback, an agent's rule generation can, thus, lead to a "creative destructive" process (Schumpeter, 1934) that displaces the technologies of an incumbent product-market.

As a result, through both of these rule following and rule generating heuristics, they emphasize market processes are driven by a social / sectoral learning process. In particular, Chattoe (1998) contends that an issue of agent based modeling research is the choice of agent heuristics should reflect social learning processes rather than that of an optimization of the model. For instance, although a classifier system has been suggested to be reflective of human decision processes, the application of classifier systems has been used for optimization purposes (e.g. Holland, 1995). Thus, by using a classifier system, structural change could be viewed as an optimization of the model rather than a result of an agent's social learning. In this study, the agent's heuristics are argued to reflect more closely a process of social learning rather than an optimization of the model. This is because agent heuristics are based on social learning behaviors described by the Austrian tradition (see Hayek, 1978; Kirzner, 1997; Schumpeter, 1934), behavioral school (Cyert and March, 1963) and Institutional arguments (e.g. DiMaggio and Powell, 1983; see Scott, 1995).

For instance, rule 1 stems from institutional arguments whereby individuals are subject to pressures to conform to institutional practices (Scott, 1995). Rule 2 captures Hayek (1978) and Kirzners' (1997) characterizations of alert entrepreneurship in which entrepreneurs build upon the experiences of others. While, rules 3, 4, and 5 are variations to Schumpeter's (1934) definition of innovation which involves the development of new resource combinations. In addition, in drawing on a well accepted heuristic in management decision research (Argote and Greve, 2007), the behavioral concept of "aspirations" is also used (e.g. Cyert and March, 1963).

Agent's Adaptive Behavior

To elaborate, an agent's selection of rules is dependent on its aspirations. The concept of aspirations refers to the notion that changes in behavior arises in conditions of adversity or crisis. This is supported in various studies that have shown rent seeking behaviors tend to increase in conditions of adversity (Greve, 2003; March and Shapira, 1987). In particular, these studies have found when a firm's performance, such as its profits, falls below its' "aspirations" - reflecting a threshold level of performance-, firms tend to seek new rent opportunities.

To capture such rent seeking behaviors, equation 2 is used in which an agent selects a rule (table 1) when its profits, $\Pi_{t,i}(\Gamma_{t,i})$, from a current plan choice, $\Gamma_{t,i}$, falls below its aspiration, λ_τ.

(2) $\Pi_{t,i}(\Gamma_{t,i}) < \lambda_\tau$

An agent's aspiration, λ_τ, is subsequently modeled by equation 2a, which measures the cumulative average profits for all plans chosen within a given product market, M_t (see also Greve, 2003).

$$(2a)\quad \lambda_\tau = \frac{\sum_{t=1}^{T-1}\sum_{i=1}^{\Gamma_t}\Pi_{t,i}(\Gamma_{t,i})}{\sum_{t=1}^{T-1}\sum_{i=1}^{\Gamma_t}\Gamma_{t,i}^{f}}$$

With equations 2 and 2a, an agent selects one of the five rules shown in table 1, when its historical plan profits, $\Pi_{t,i}\left(\Gamma_{t,i}\right)$, falls below its aspirations, λ_τ. As the choice of rule determines an agent's social interactions, such interactions influence the onset of the aforementioned non-linear system behaviors.

Product-Market Choice: M_t

Furthermore, as rents can be earned from entering different product-markets, M_t, an agent's rent seeking behavior is also influenced by its perception of opportunities in these product-markets. As agents are more likely to enter a product-market that exhibits the greatest profits, equation 3 shows an agent's propensity to change to a given product market or its optimal product-market choice, M_t^*, is determined by the ratio of the cumulative profits of a given product-market to the cumulative profits earned for all product-markets (first term). The optimal product market choice (i.e. most profitable market) is, therefore, determined by product-markets that exhibit the greatest ratio. Furthermore, in Mitchell's (1989) study of the U.S. ethical drug industry, he finds entry into a new field increases with the presence of specialized assets in that field. As a result, an agent with specialized resources is more likely to enter product-markets that require the use of those specialized resources. The second term in equation 3 captures this input specific requirement which is defined by the ratio of the volume of a product-market's specific input, $\hat{X}_{t,i}$, to all product-market specific inputs. With the aggregation of both terms, equation 3 shows agents are more likely to enter those product-markets that are most profitable vis. a vis. other markets and / or enter those product-markets in which an agent has a large share of that product-market's specific inputs.

$$(3)\quad M_t^* = \underset{M_t^s}{Max}\left[\frac{\sum_{t=1}^{T-1}\sum_{i=1}^{\Gamma_{i,t}}\Pi_{t,i}(\Gamma_{t,i})}{\sum_{M_t=1}^{3}\sum_{t=1}^{T-1}\sum_{i=1}^{\Gamma_{i,t}}\Pi_{t,i}(\Gamma_{t,i})} + \frac{\hat{X}_{t,i}}{\sum_{\hat{X}}^{X}\hat{X}_{t,i}}\right]$$

Agent Trade-off Function.

To integrate all the elements discussed so far, an agent's trade-off function (equation 4) is presented. The purpose of this trade-off function is to evaluate an agent's perception of profits for each rule, $R_{t,i}$, shown in table 1. The optimal choice of rule – one that yields the greatest subjective profits – subsequently determines an entrepreneur's input, $X_{t,i}$, and plan, $\Gamma_{t,i}$, choice.

$$(4)\quad \Pi_{t,i}^{s,*}\left(\Gamma_{t,i}^{s,*}\left(R_{t,i}^{s,*}\right) \mid M_t^{s,*}\right) = \underset{R_{t,i}^s}{Max}\left\{P_t^s(\eta_t^s)\, F_{t,i}^s(X_{t,i}^s(R_{t,i}^s)) - C^s \Delta X_{t,i}^s \quad + \Pi_{\tau,i}^s(\Gamma_{\tau,i}^s\ )\right\}$$

$$(1)\quad F_{t,i}^s(X_{t,i}^s(R_{t,i}^s) \mid A_{t,i}^s) = A_{t,i}^s \cdot X_{t,i}^s(R_{t,i}^s)^{\bar{\alpha}}$$

$$(2)\quad \lambda_\tau^s \ = \frac{\sum_{t=1}^{T-1}\sum_{i=1}^{\Gamma_t}\Pi_{t,i}^s(\Gamma_{t,i}^s)}{\sum_{t=1}^{T-1}\sum_{i=1}^{\Gamma_t}\Gamma_{t,i}^{s,f}}$$

$$(2a)\quad \Pi_{t,i}^s(\Gamma_{t,i}^s) < \lambda_\tau^s$$

$$(6)\quad \Pi_{\tau,i}^s(\Gamma_{\tau,i}^s) = \frac{\sum_{t=1}^{T-1}\Pi_{t,i}^s(\Gamma_{t,i}^s)}{\sum_{t=1}^{T-1}\Gamma_{t,i}^{s,f}} \bullet \frac{\sum_{t=1}^{T-1}\Gamma_{t,i}^{s,f}}{\sum_{t=1}^{T-1}\sum_{i=1}^{\Gamma_t^s}\Gamma_{t,i}^{s,f}}$$

Specifically, for an agent *i* in a supply stage, *s*, an agent's selection of an optimal rule, $R_{t,i}^*$, arises from maximizing equation 4 with respect to the five rules (table 1) subject to constraints 1, 2, 2a and 6. For each rule, profits are calculated by the product of output prices, $P_t^s(\eta_t^s)$ and the entrepreneur's subjective production function, $F_{t,i}^s(X_{t,i}^s(R_{t,i}^s) \mid A_{t,i}^s)$ (equation 1)[5]. Output product-market prices, $P_t^s(\eta_t^s)$, are a function of η_t^s which is based on a linear difference of demand and the aggregate outputs produced by all agents for a supply stage, *s*, for a given product market. The plan costs are derived as the sum of the product of a vector of input prices, C^s, and changes in a vector of inputs between adjacent time periods *t* and *t*-1, $\Delta X_{t,i}^s$. The input price vector, C^s, contains fixed input prices for non product market specific resources, $X_{t,i}^s$. While for product-market specific resources, $\hat{X}_{t,i}^s$, the input price vector, C^s, contains prices that are determined by the aggregate supply of its adjacent upstream stage, *s'*, and the aggregate input demands of its own supply stage, *s*. Stated differently, the input prices for an agent in supply stage,

[5] Readers are reminded that the inputs are now a function of the behavioral rule.

s, is set to the output prices received by its adjacent upstream supply stage, *s'*. This is defined by equation 5.

$$(5) \quad P_t^{s'}(\eta_t^{s'}) = C^s$$

More over, agents also exhibit adaptive expectations (Windrum et al., 2007). Such adaptive expectations have been found in management research whereby managers can be constrained by a "dominant logic" in which beliefs of past successes can constrain future behavior (e.g. Audia et al., 2000; Prahalad and Bettis, 1986). For instance, in Audia et al.'s (2000) study, they found that a firm's cumulative successes increase managerial confidence in their past experiences which reduce efforts to seek information contrary to their past experiences. Furthermore, cognitive studies find managers tend to repeat frequent activities because repeated activities are more ingrained in managers' memory and therefore are more likely to be repeated in use (e.g. Russo and Shoemaker, 1992).

To capture this path dependent behavior, the profitability of an agent's previous plan choices are used to develop an agent's expectations on the profitability of a currently evaluated plan. Specifically, for a given plan, $\Gamma_{\tau,i}$, equation 6 shows that this expectation is based on a plan's historical average profits, $\Pi_{\tau,i}(\Gamma_{\tau,i})$, which is calculated as the ratio of the sum of profits, $\Pi_{t,i}(\Gamma_{t,i})$ over the frequency, $\Gamma_{t,i}^f$, at which this plan has been used for the elapsed time period, τ, , where $\tau = T\text{-}1$ periods of entrepreneurial experience. This historical average profit is also adjusted by the ratio of the frequency of this chosen plan to the frequency of all plans –the sum of the frequency of plans, $\Gamma_{t,i}^f$ -chosen by the entrepreneur for the elapsed time period, τ. By substituting equation 6 into an agent's trade-off function, equation 4, the agent favors rules that reinforce previously successful plan choices.

$$(6) \quad \Pi_{\tau,i}(\Gamma_{\tau,i}) = \frac{\sum_{t=1}^{T-1} \Pi_{t,i}(\Gamma_{t,i})}{\sum_{t=1}^{T-1} \Gamma_{t,i}^f} \cdot \frac{\sum_{t=1}^{T-1} \Gamma_{t,i}^f}{\sum_{t=1}^{T-1} \sum_{i=1}^{\Gamma_t} \Gamma_{t,i}^f}$$

Given an agent's optimal rule, $R_{t,i}^*$, plan, $\Gamma_{\tau,i}^{s,*}$, and product-market, $M_t^{s,*}$, choice, an agent's realized rents are then computed. These realized rents are calculated by a profit function that is based on 'real' or objective marginal productivities which exclude an agent's heterogeneous knowledge constraints. The computation of these realized rents, then, becomes market feedback that 'updates' an agent's profit experiences with its plan and product-market choices. This market feedback is then iterated for t periods to which shape the heterogeneous knowledge of the agent over time.

Overview of an Agent's Adaptive Behavior

Figure 1 summarizes the agent's adaptive behavior. For a given supply stage, *s*, an entrepreneur's rent-seeking behavior arises from its choice of a rule, $R_{t,i}^{s,*}$ (table 1). This rule corresponds to a specific social network involving either local (i.e. within the agent's product-market) or non-local (i.e. all product-markets) social interactions. These social interactions draw upon the input, $X_{t,j}^{s,*}$, and plan, $\Gamma_{t,j}^{s,*}$, choices of its network members to which determine an agent's optimal inputs, , and thus optimal plan, $X_{t,i}^{s,*}$. Each rule in table 1 and their associated inputs are then evaluated by the agent's trade-off function (equation 4). This trade-off function, then selects the rule that maximizes its perceived profits. As this optimal rule choice, $R_{t,i}^{s,*}$, determines the agent's optimal input, $X_{t,i}^{s,*}$, it also impacts an agent's optimal product market choice, $M_{t}^{s,*}$.

However, as these decisions are based on an entrepreneur's subjectivity, the realized profits of these decision choices are then calculated. These realized profits n agent's plan choices. This process is then repeated iteratively for t periods. In this iterative fashion, the agent continually acquires new and idiosyncratic knowledge experiences. These serve as market feedback that 'update' the profitability of a profit experiences are also utilized to assess the profitability of other product markets to which aid in the agent's discovery of rents in these product-markets.

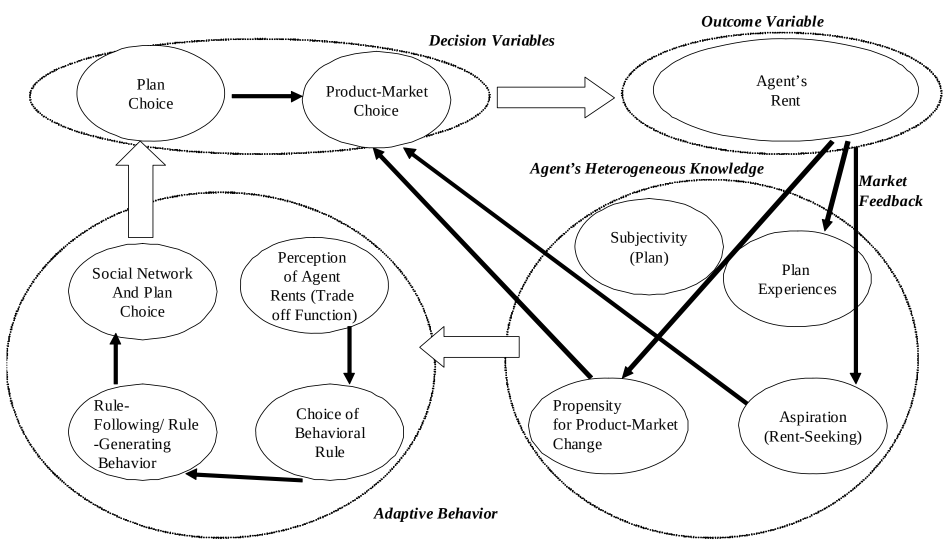

Figure 1: Adaptive and Heterogeneous Agent Behavior

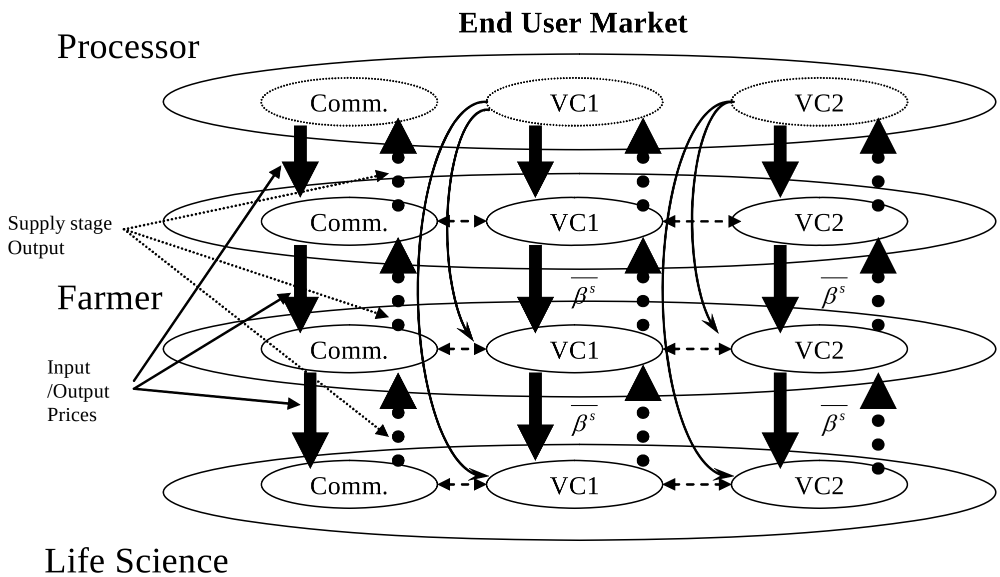

Figure 2: Information Structure of Supply Chain

Agricultural Supply Chain Market

The adaptive behavior of agents described in figure 1 was programmed in the Mathematica software package (version, 5.1). To simulate these agents, the agents are populated within one of three supply chains shown in figure 2. Each supply chain consists of an exogenous end-user market connected to three supply stages - processor, farmer / producer and life science. In particular, agribusiness is traditionally defined by a system consisting of farmer producers that are interconnected to downstream members of the food and fiber system (e.g. Boehlje, 1996; Cook and Chaddad, 2000; see also Davis and Goldberg, 1957). However, more recently, Goldberg (1999) contends the agribusiness system should be viewed as an "agriceutical" system that includes the upstream members of the life science industry. This is because advances in genomic research provide important agri-food innovations that can impact the changing face of modern agribusiness systems. To reflect this "agriceutical" distinction, a supply chain that includes members of the life science sector was, thus, included. In addition, three supply chains are created in which each supply chain differed in the manner to which they transmit end-user values (i.e. prices) to the different stages of the supply chain. Such differences in supply chain structures are reflected by three different product-market arrangements –commodity (Comm.), Vertical Coordination 1 (VC1), and Vertical Coordination 2 (VC2). These three product-markets highlight the potential structural changes that food markets can undertake.

In particular, a key distinction of the commodity product-market (Comm.) is that, market prices for any given supply stage, s, coordinate the demand and supply conditions of that supply stage. In such a commodity market, the market prices for each upstream supply stage is based on a linear difference in the input demands of the adjacent downstream stage and the aggregate supply of outputs of that supplying sector. As a result, upstream agents are only responsive to prices determined by the supply and demands conditions of their supply stage and not to the market conditions of their end user market (i.e. customer). This spot / commodity market therefore leads to a lack of information transparency because upstream supply chain agents can choose plans that are not in the direct interests of its end-users. Furthermore, since upstream agents respond to the input demands of their adjacent downstream market, the subjective input choices of their downstream market can distort the price signals sent by the end-user market. As a result, in a spot / commodity market arrangement, the price signals from the end-user market are not transparent to upstream agents. This leads to a basic misalignment in the production activities of the upstream agents with that of the interests of the end user. This is consistent with Ottesen's (2006) study of the Norwegian Salmon farming industry in which they found upstream managers had poor perceptions of their customers' quality preferences.

However, unlike the spot/commodity market arrangement, the VC1 product market provides a greater transmission of end-user market information to "all" supply chain members and thus face fewer of the above agency problems. Specifically, end-user market information is transmitted through a contractual exchange that specifies a price premium to all upstream agents. These price premiums provide financial incentives for supply chain members to develop plans that are desired by the end user. For instance, quality assurance beef programs (e.g. Certified Angus Beef) typically offer price premiums to develop specific beef quality attributes that are desired by the end consumer (e.g. consistent tenderness) (Purcell and Hudson, 2004). This is supported by Lusk et al.'s (2001) study where they found customers are willing to pay premiums of $1.84 for guaranteed tender beef (see also Purcell and Hudson, 2004).

Price premiums are determined by the end user market (i.e. the processor and end-user price interface) because agricultural market systems are typically driven by the valuations of its end user (i.e. customers) (Boehlje, 1999; Taylor and Fearne, 2006). Each input purchasing stage is, then, responsible for payment of these premiums to the adjacent upstream supplying stage. Specifically, price premiums, PP_t^s, are calculated by equation 7 where the premium allocation, $\overline{\beta}^s$, determines the proportion of rent sharing for the supplying stage, s. For instance, larger values of this premium allocation, , indicate a large portion of the price premium is received by that supplying stage. For the VC1 arrangement, the farmer and life science agents, respectively, receive a 25% and 15% premium.

$$(7) \quad PP_t^s = \overline{\beta}^s \cdot P_t^{End\ user}(\eta_t^{End\ user})$$

Although the VC1 product-market can overcome the agency problems of the spot / commodity market, opportunities to improve a supply chain's "effectiveness" can also be another factor impacting the structural change of agricultural markets. Namely, increases in a supply chain's "effectiveness" can arise through greater information transmission because it stimulates greater exploration and innovation of new products. This is also expressed by supply chain researchers (Li et al., 2006; Ottesen, 2006; Zhang et al., 2006). They find greater information transmission of consumer preferences to upstream supply chain members increases value chain flexibility which allows firms to more quickly adapt to changing customer needs and stimulate greater product innovation.

To examine this "informational" argument of structural change, a VC2 product market was created. Since information on consumer preferences is transmitted through price signals, the VC2 product market retains the use of price premiums to transmit end user information to all supply stage participants. However, unlike the VC1 product-market, the financial incentives associated with "price premiums" are either absent or reduced. To explain, in the VC2 product-market, the farmer and life science agents, receive a premium of 10%. Yet, since premiums are paid by the adjacent downstream stage, the farmer of a VC2 product market effectively does not earn a price premium, but still receives information on its end-user market. The life science agent, however, does receive a 10% price premium, but albeit a smaller rate than the VC1 product market. This is because studies suggest that increasing concentrations in the input sectors can lead to greater market power (King, 2001; IFAP, 2002; Malloy, 1999; Persidis, 1999). As a result, to provide a more realistic depiction of the competitive structure of this input sector, the life science agents receive a 10% premium. However, as this premium is lower than the VC1 product market, it emphasizes the informational features of the VC2 product market.

Results and Discussions

Assumptions and Simulation Setup

With the following simulations, a number of assumptions were first made. First, structural change is defined by the radical transition in the population of product-market agents. Since such a change in product market population requires fundamental alterations to an entrepreneur input, plan and network relations, this captures the revolutionary features of structural change. Radical changes in population (i.e. changes exceeding 50% of population) have also been used by other simulation studies to explain revolutionary changes in markets (e.g. Sastry, 1997; Tushman and Romanelli, 1985). Each simulation assumes a fixed time horizon of

300 time steps. Further increases in time steps did not change simulation findings. Furthermore, 40 agents populate each supply stage with a total of 120 agents occupying all three supply stages. More over, within each supply stage, the population is initially distributed with 80% (32 agents), 10% (4 agents) and 10% (4 agents) of Commodity (Comm.), VC1 and VC2 agents, respectively. Specifically, an 80% share in the commodity market was chosen to provide a more stringent test for structural change. Namely, given the path dependencies associated with this study's model, an 80% share can render the system to be highly resilient to structural change. In that, by using lower shares (e.g. 10%), it would be relatively easy for the system to experience structural change because it is not subject to the inertial tendencies of the 80% share scenario. As result, simulating a lower share scenario would not provide a sufficient or strong enough test for structural change. In addition, each product-market is confronted by a constant end-user demand of 2000 units and each product market does not have any particular advantages in production technology nor cost over others. These assumptions were made to avoid incidences where structural change were caused by market and / or technological level biases. This enables us to more directly examine the impact of price premiums and the role of information dissemination on the structural change of markets. These assumptions, however, can be relaxed in future studies.

Figures 3, 4, and 5 show the population trajectories of agents in each of the three product-markets for each stage of the supply chain for a single simulation run. The radical changes in population trajectories for these product-markets are used to denote the structural change of agricultural markets. All figures are presented in stacked bar format.

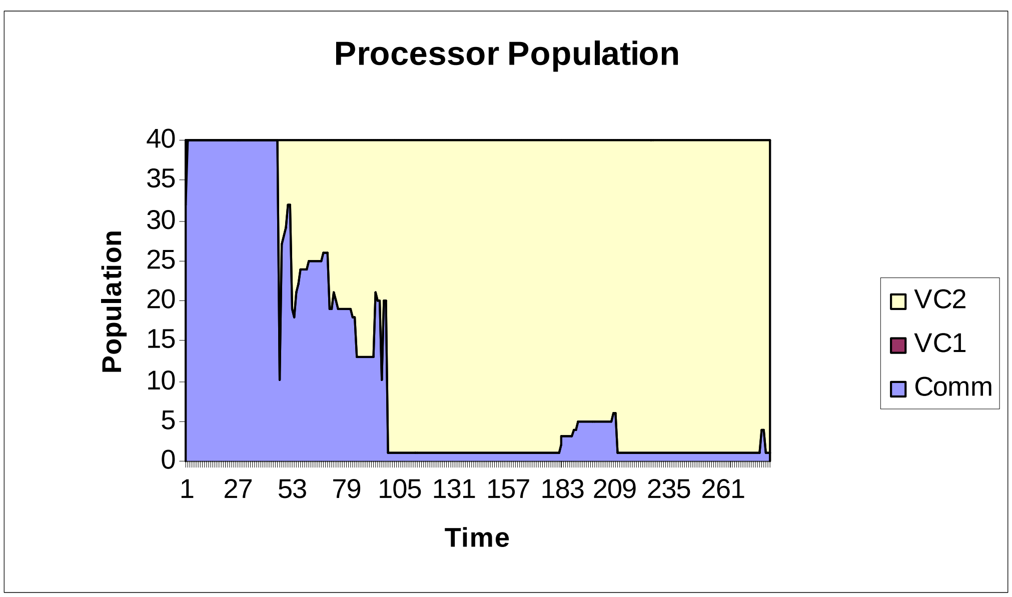

Figure 3: Processor Population

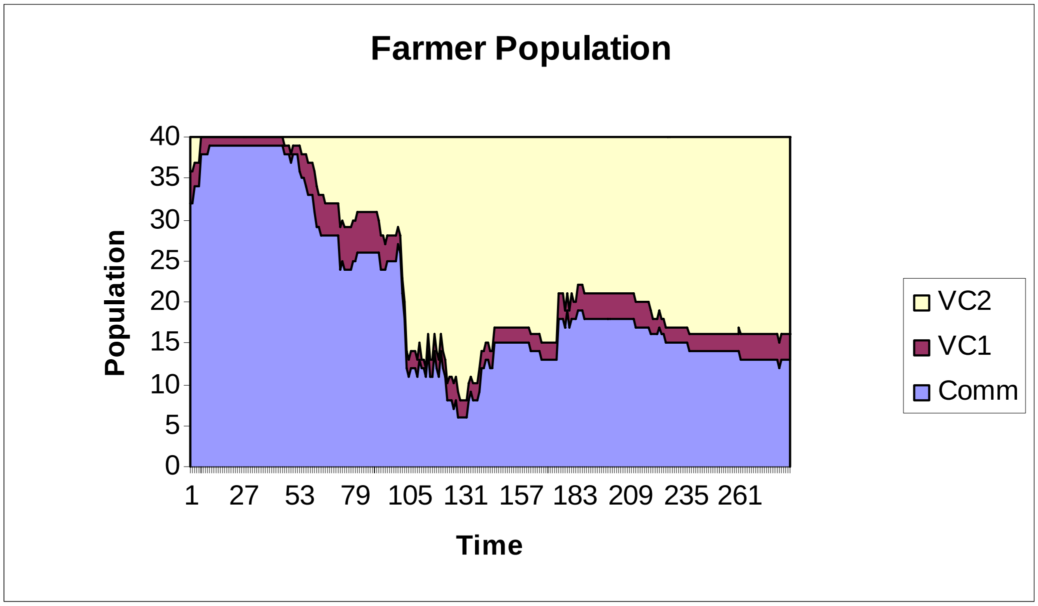

Figure 4: Farmer Population

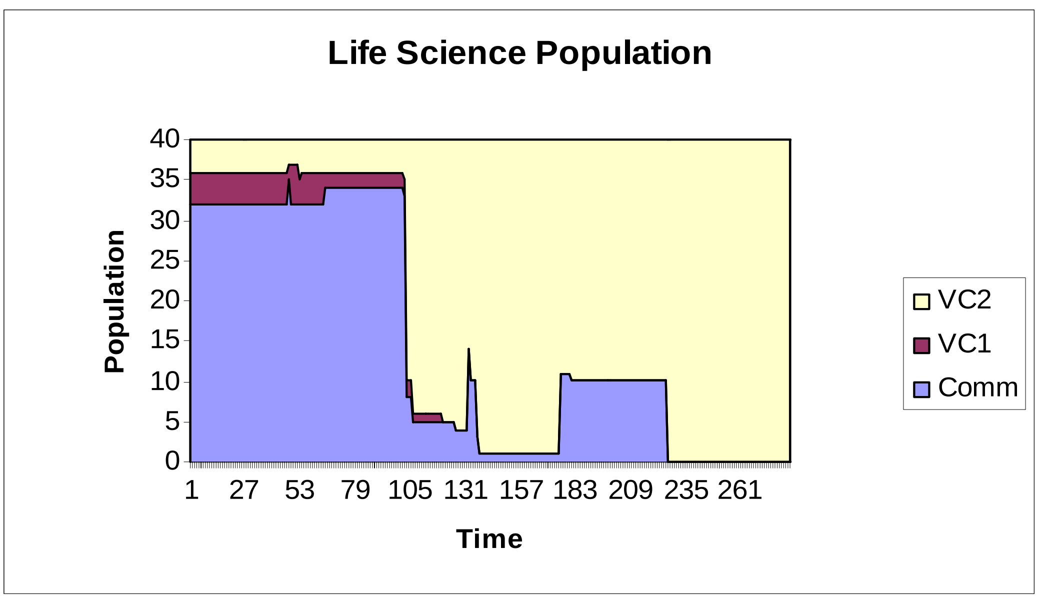

Figure 5: Life Science Population

Complex population behavior, as shown in figures 3 (processor stage), 4 (farmer stage), and 5 (input/life science stage), all supply stages displayed an initial stability in the population of the commodity product-market. At least 80% of the population (32 out of a total 40 entrepreneurs) in each supply stage remained in this commodity product-market. This stability is attributed to the dominant expression of rule-following behaviors. Specifically, for the respective processor, farmer and life science stages, an average of 98%, 85.4% and 96% of these agents chose rule following behaviors. As rule following largely consists of imitating plans from other agents in the same product market (i.e. commodity agents), this generated negative feedback tendencies that resulted in this initial stability of the commodity population.

A result of this rule following behavior is the formation of increasingly homogenous plans. This renders increasingly competitive conditions in the commodity market because agents can no longer derive competitive advantages from asymmetric knowledge differences. Entrepreneurs therefore have a strong incentive to differentiate (Jacobson, 1992; Lachmann, 1977). This appears to be borne out in this simulation. In that, the average profits prior to the structural change in markets was highly negative (results not shown but are available). This stimulated rent-seeking behavior to experiment and seek out alternative plans and product markets. This change in behavior resulted in a structural change in the commodity population that occurred in simulation periods 61,117 and 118 (approx.) for the processor, farmer and life science stages respectively. Table 2 shows this transition towards differentiated behavior is observed by the marked increases in rule generation during the structural change period.

Table 2: Proportion of Rule-Generation (Following) [6]

Supply Stage (Commodity)	Pre-Structural Change	Structural Change
Processor	7.01% (92.9%) [t=1-61]	32.6% (67.3%) [t=62-115]
Farmer / Producer	11% (88.9%) [t=1-61]	28.5% (71.5%) [t=62-180]
Life science	5.6% (94.4) [t=1-115]	21.8% (78.2%) [t=116-200]

In explaining the onset of this structural change, this product-market structural change is likely to have originated by a few processor agents in the commodity product-market. From table 2, rule generation in the processor group during the pre-structural change period is 7%. Roughly 2 agents among the 32 agents in the commodity product market actively conducted experimentation of alternative plans

[6] The time frame used to calculate these proportions are specified in the [brackets]. The time frames were chosen where the population started to exhibit stable behaviors.

and product markets. Due to the utmost downstream position of the processor agents, these processor agents have the most accurate information of demand conditions than upstream players. As a result, despite being few in number, these agents are likely to have been successful in revealing innovative plans. These innovative plans subsequently become exposed through social interactions to other processors in the commodity product market to which stimulate further rule generating behaviors. This leads to further experimentations causing a positive feedback of further rule generating behaviors. Such positive feedback is consistent with the marked increase in rule generation / experimentation behaviors (20-33%) that was observed in the structural change period (table 2). Furthermore, such rule generating behaviors subsequently impacted the experimental behaviors of upstream agents. This is consistent with the dynamic behaviors shown in figures 3, 4, 5, in which structural change in the processor stage preceded the structural changes of the upstream supplying stages. This “ripple” effect has a significant managerial implication because it suggests that despite a dominant commodity market structure, a few entrepreneurs in the down stream stage of a supply chain can radically alter the technology or plan choices of the entire supply chain.
More over to further demonstrate that the structural change dynamics of figures 3, 4, and 5 are attributed to agents’ rule behaviors, table 3 shows the proportion of rule following and rule generating behaviors across all product markets. The aggregation of all product-markets was used because rule generating behaviors involve interactions to all product markets.

In table 3, three periods are shown: pre-structural change, structural change and post structural change. In comparison to the population dynamics of figures 3, 4, and 5, table 3 shows an overall pattern in which rule following behaviors tend to result in a stable population behavior, while rule generating behaviors result in radical changes in populations. Table 3, therefore, indicates supply chain processes, in particular, structural change processes are influenced by the underlying rule behaviors of agents.

Table 3: Proportion of Rule (Following) Generation and Analysis of Bifurcation

Supply Stage (All Product Markets)	Pre-Structural Change (Stable population)	Structural Change (Unstable population)	Post Structural Change (Stable population)
Processor	7.1% (92.9%) [t=1-61]	29.7% (70.3%) [t=62-115]	6.6% (93.4%) [t=116-300]
Farmer / Producer	14.5% (85.4%) [t=1-61]	51.1% (48.9%) [t=62-180]	31.7% (68.3%) [t=181-300]
Life science	11.8% (88.2%) [t=1-115]	36.3% (63.7%) [t=116-200]	24.7% (75.2%) [t=201-300]

Post-Structural Change

During the post-structural change period, figures 3, 4 and 5 show agents transitioned to the VC2 product-market arrangement. This structural change was attributed to the greater profitability of this VC2 product-market. For instance, figure 6 shows the sum of the mean profits[7] of each supply stage for the three different product markets. The mean profits over the 300 periods are $525,129 (VC2), $86,801 (VC1), and $99,563 (Commodity). Structural change, therefore, appears to favor the information based VC2 product market over that of the higher premiums of the VC1 product-market.

However, since agent based model results are sensitive to the subjective (i.e. stochastic and idiosyncratic) behaviors of agents, the above simulation trial could have arisen as a matter of chance. Windrum et al. (2007), therefore, suggest the validity of agent based simulation results can be strengthened by examining the outcomes of repeated trials. 40 independent simulations with different subjective marginal probabilities were run and the mean profits for each product-market were computed. The mean profits from these repeated trials were $43,717 (VC2), $8011 (VC1), and $39,985 (Commodity). Similar to the single trial results, the repeated trial results show the information based VC2 product market had greater profits than all other markets. Structural change, therefore, appears to favor market arrangements that emphasize information transmission.

These result stand in contrast to Purcell and Hudson (2004) and Poray et al.s' (2003) respective studies on the cattle and pork industries where they contend price premiums can be an important factor impacting the transition to vertically coordinated market arrangements. Nevertheless, these results are consistent with others, such as Boehlje (1996) who predicts modern food systems are transitioning towards systems that promote greater information transmission. This is also consistent with Taylor and Fearnes' (2006) case analysis of food supply chains in which they point out a greater transparency of consumer information to all supply chain members is needed to increase the overall effectiveness of the supply chain. Our profit results for the VC2 product market appear to be consistent with these arguments. The implications of our results suggest that the adoption of information technologies such as "point of sale" scanner technology and customer loyalty cards, as used in the grocery retail sector, can be a source of competitive advantage for the entire supply chain. However, this is contingent on the condition that information is shared to all participants (e.g. Boehlje, 1999; Salin, 1998).

---

[7] Mean profits are based on the sum of the mean profits for agents in each supply stage.

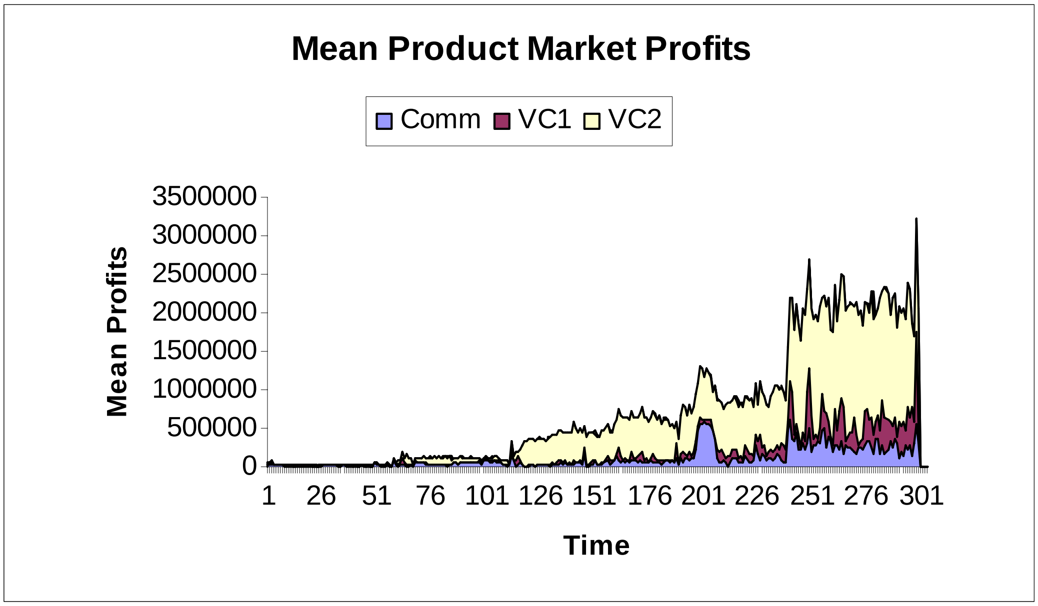

Figure 6: Mean Product Market Profits

Multiple Simulations: Premium Responsiveness and Structural Change

However, one could argue that structural changes to the informational VC2 product market may be attributed to lack of sufficient premiums in the VC1 product market. To examine this argument, a sensitivity analysis on the effect of increasing price premiums on the VC1 population was conducted. In following the sensitivity analysis described by Windrum et al. (2007), multiple simulation trials were aggregated to examine the effect of increasing price premiums on the VC1 population. Figure 7 shows the VC1 population over various percentage increases in the VC1 product market's premium. The mean population of 35 different simulation trials – each with different subjective marginal productivities – was reported for each 10% increase in the VC1 price premiums[8]. As a result, a total of 350 different simulation trials were conducted to examine the effects of increases in VC1 price premiums on the population of the VC1 product market.

Figure 7 shows when premiums in the VC1 product group increased from 0% to 100% [9], the mean population was relatively constant. Therefore, in both the

[8] An analysis of higher moments would be preferred but was technically infeasible. There may be benefits for future research to analyzing higher moments because such structural change processes may have implications for power regimes in the supply chain structure.

[9] As a point of note, the 0% point reflects the base case (i.e. VC1 yields a 25% premium to the farmer and 15% to the input sector), while 100% denotes 100% increase from this base case in which the VC1 farmer faces a 50% premium and 30% for the input sector.

individual and multiple simulations, product-market change is largely unresponsive to increases in price premiums. This finding suggests that the structural change to the information based VC2 product market is not likely attributed to a lack of financial incentives in the VC1 product markets. More over, this finding suggests that there may be limits in a supply chain manager's ability to control the activities of a supply chain system. In that, principal-agent explanations are based on a logic of control in which an efficient supply chain can be "designed" through outcome based incentives, such as price premiums. However, the repeated simulation trial results suggest efforts for a supply chain manager to influence the interests of supply chain agents through greater price incentives do not appear to impact changes towards this supply chain structure. As a result, these results suggest they may be limits on a manager's control of a supply chain system.

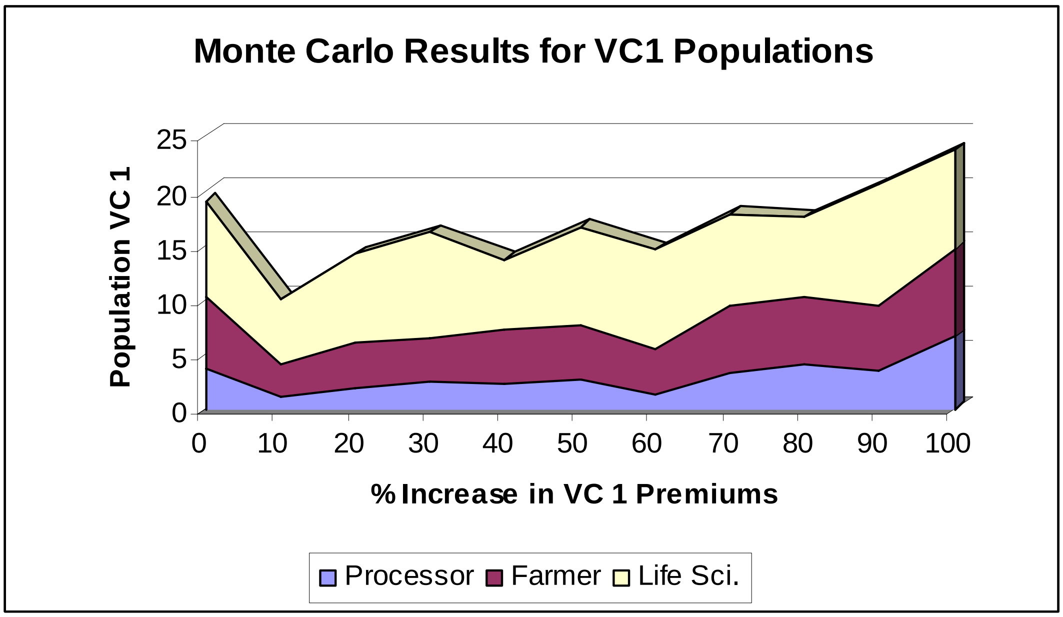

Figure 7: Premiums and Structural Change Tendencies

Discussion and Conclusion

In drawing on Austrian economics, this research advances an agent based model to examine the structural change of a food marketing system. A central premise of this agent based model is that subjective entrepreneurs are instrumental to the structural change of agricultural supply chains. Subjective entrepreneurship introduces non-linear interactions that impact both the stability and structural change of a supply chain system. As a result, this Austrian approach offers an examination of market change processes that are absent in the static orientation of principal agent models. This is because Austrian economics explicitly deals with change processes under Knightian uncertain conditions (see Lachmann, 1977; Mises, 1949; O'Driscoll and Rizzo, 1985). In that, with subjectivity, entrepreneurs have incomplete knowledge of all possible technological choices and thus entrepreneurs engage in an open ended search to uncover new technological opportunities. Through their social interactions, this open ended search endogenously introduces genuine novelty to a system whereby new plans are not only introduced to a supply chain system but as consequence endogenously alter the payoffs and structure of the system (see O'Driscoll and Rizzo, 1985; Windrum, et al., 2007). Thus, as subjectivity introduces new system behaviors, it introduces genuine novelty and thus Knightian uncertainty to the market discovery process (see Mises, 1949; O'Driscoll and Rizzo, 1985). Such novelty yields the emergence of new behaviors that can revolutionize existing market arrangements. A principal agent framework does not distinctly recognize this subjective nature of human action and thus does not accommodate for such Knightian uncertain change processes. Furthermore, this Austrian approach also contributes to the study of structural change in three ways.

First, in spite of the recent revival of the Austrian economic tradition (Jacobson, 1992; Shane, 2000), advances in Austrian economics have been limited by the lack of a methodological approach that embraces the subjective and interdependent nature of the Austrian entrepreneur. The proposed agent-based model illustrates the non-equilibrium market processes described by Austrian economics. This study shows the behavioral and social mechanisms (i.e. rules) that can lead to the onset of Schumpeterian creative destruction processes in a food supply chain. Such a non-equilibrium framework offers an alternative to "efficiency" explanations of structural change. "Efficiency" based explanations, such as principal-agent reasoning, contend that the structural change of agricultural markets is a response to improving the relationships between buyers and suppliers. However, as this study shows, structural change is influenced by the innovative (i.e. rule generating) efforts of the subjective entrepreneur. This has implications to agribusiness managers because it suggests that predicting the changing face of modern agriculture may involve more than "getting contracts right" (Cook and Chaddad, 2000), such as setting the right price premiums for its suppliers. But, prediction of market change may also require monitoring the innovative behaviors of downstream participants, especially during times of their crisis. During times of crisis (i.e. food safety recalls), the innovative behaviors of only a few processors or downstream agents can cause a "ripple effect" to the activities of an entire supply chain (see figures 3, 4, and 5). As a result, upstream agribusinesses may be better able to understand the changing face of agriculture by not only paying attention to the changing needs of its consumers but also by paying closer attention to the innovative activities of its retailers, especially during times of their crisis.

Second and subsequently, this Austrian approach has distinct implications to the management of supply chains. Simulation results show supply chain entrepreneurs do not favor markets with higher price premiums, but rather favor markets with more information transparency. This suggests that the dissemination of end user or customer data to their upstream suppliers may be more "effective" in improving the performance of an entire supply chain than by setting higher price premiums. This follows arguments made by Boehlje (1999) and Salin (1998) in which they argue greater information transmission can lead to competitive advantages that enhance the performance of the entire supply chain. This study provides a preliminary confirmation of this argument. The managerial implications of this finding suggests supply chain systems with IT systems that promote the sharing of consumer data - such as Quick Response (QR), Efficient Consumer Response (ECR), Vendor Managed Inventory (VMI) and Continuous Replacement Program (CRP) not only contribute to gains in inventory optimizations (Li et al., 2006), but can also lead to competitive advantages in innovation.

Third, since information transparency (VC2) is favored over contractual exchanges (VC1), fewer supplier contracts are needed to which economize on transactions costs. This has obvious implications to management because it would reduce the need for managers to draft, monitor, and enforce contractual obligations and thereby reducing transaction costs. Furthermore, information transparency also reduces principal agent problems. As principal agent problems fundamentally arise from a problem of asymmetric information – one party knows more than the other. Information transparency reduces such asymmetric information problems to which suppliers can produce products that are aligned with the exacting needs of its consumers. Therefore, information transparency can significantly reduce agency costs, especially in a supply chain with lengthy vertical interdependencies. However, managers are reminded that although information transparency reduces transaction and agency costs, information transparency also alters the basis of power in modern food market systems. Boehlje (1999) and others (Li et al.; 2006; Salin, 1998; Zhang et al.; 2006) argue food retailers, being closest to the consumer, possess the greatest power and control in a supply chain system. With greater information transparency, such power and control is no longer centralized to downstream supply agents, but rather distributed across all supply chain members. Therefore, from a managerial stand point, especially for downstream retailers, information transmission strategies underlie a basic trade-off between reductions in transaction and agency costs and the loss of supply chain power and control.

There are however limitations to this study. Although agent based modeling offers a distinct advantage over neoclassical economics in understanding complex market phenomena, agent based models, however, face several key methodological issues (Fagiolo et al., 2006; Windrum et al, 2007). Empirical validation of agents based models remains a key research issue (Fagiolo et al, 2006; Windrum et al.; 2007). Various approaches have been proposed (see Fagiolo et al.; 2006; Goldspink, 2000; Windrum et al., 2007), yet, each has distinctive limitations. For instance, a "historical friendly" has been suggested that involves comparing the trace outputs of the simulation with a detailed trace history of an economic system (Windrum et al.; 2007). Yet, such a "historical" approach faces some deep seated methodological problems. A historical approach only shows that the underlying model is "capable" of producing the observed empirical phenomena because multiple combinations of parameter settings, initial conditions, and structural assumptions can lead to the same simulated trace output (Windrum et al., 2007). Although there have been some efforts to confine this search space of parameters and initial conditions, these efforts are largely preliminary in nature and are yet to be established in agent based research (Windrum et al., 2007). Furthermore, Windrum et al. (2007) suggests the validity of a model's findings can be increased through comparison of model results with comparable studies. Yet, as also argued by Windrum et al. (2007), there has been considerable heterogeneity in agent base models in which models have been built upon different theoretical contexts to which renders comparisons inappropriate. As agent based models are rather limited in Agribusiness research, validation of this model's finding through such comparisons are difficult. As a result, although an agent based modeling approach offers a novel approach to modeling agribusiness system behaviors, the further advancement of such modeling efforts requires not only the development of a methodological basis of empirical validation, but also a method that reflects the specific features of an Agribusiness food systems. This is called for in future research.

References

Abrahamson, E., L. Rosenkopf. 1997. Social network effects on the extent of innovation diffusion: a computer simulation. *Organization Science,* 8(3), 289-309.

Audia, P.G., Locke, E.A & Smith, K.S. 2000. The paradox of success: an archival and laboratory study of strategic persistence following radical environmental change. *Academy of Management Journal*, 43 (5), 837-853.

Argote, Linda & Greve, R. Henrich. 2007. A Behavioral Theory of the Firm-40 Years and Counting: Introduction and Impact. *Organization Science*, 18(3) 337-349.

Axelrod, R. 1997. *The Complexity of Cooperation: Agent-Based Model of Competition and Collaboration.* New Jersey: Princeton University Press.

Barkema, A. and Cook, M. 1993. The Changing U.S. Pork Industry: A Dilemma for Public Policy, *Federal Reserve Bank of Kansas City Economic Review*, 78 (2), 49-65.

Boehlje, Michael. 1995. Vertical Coordination and Structural Change in the Pork Industry: Discussion, *American Journal of Agricultural Economics*, 77 (5), 1225-1228.

Boehlje, M. 1996. Industrialization of Agriculture, *Choices*, First Quarter, 30-33.

Boehlje, M. 1999. Structural Change in the Agricultural Industries: How do we measure, analyze and understand them?, *American Journal of Agricultural Economics*, 81, 5, 1028-41.

Bradley, S.P. and Ghemawat, P. 2002. Wal-mart Stores, Inc. *Harvard Business School Case* 9-794-024.

Chattoe, E. 1998. Just How (Un) realistic are Evolutionary Algorithms as Representations of Social Processes? Journal of Artificial Societies and Social Simulation 1, 3. http://www.soc.surrey.ac.uk/JASSS/1/3/2.html

Cook, M. and Barry, P. 2004. Organizational Economics in the Food, Agribusiness and Agricultural Sectors. *American Journal of Agricultural Economics*, 88, 740-743.

Cook, M. and Chaddad, F. 2000. Agro industrialization of the Global Agrifood Economy: Bridging Development Economics and Agribusiness Research. *Agricultural Economics*, 23, 207-218.

Cyert, R.M. and J.G. March. 1963. *Behavioral Theory of the Firm*, Englewoods Cliffs: Prentice-Hall.

Davis, J.H. and Goldberg, R.A. 1957. A concept of Agribusiness, Harvard University, Boston.

DiMaggio, P.J., and W.W. Powell. 1983. The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. *American Sociological Review.* 48, 2, 147-160.

Drabenstott, M. 1994. Industrialization: Steady Current or Tidal Wave, *Choices*. 4, 4-8.

Fagiolo, G., Windrum, P., and Moneta, A. 2006. Empirical validation of Agent Based models: A critical survey. *LEM (Laboratory of Economics and Management, Saint Anna School of Advanced Studies)*. Working Paper Series: 1-44.

Feigenbaum, A. & Thomas, H. 1995. Strategic groups as reference groups: theory, modeling and empirical examination of industry and competitive strategy. *Strategic Management Journal*, 16, 6, 461-476.

Fox, C.R. and Clemen, R.T. 2005. Subjective Probability Assessment in Decision Analysis: Partition Dependence and Bias toward the ignorance prior. *Management Science*, 51, 9, 1417-1432.

Goldberg, R. 1999. The business of Agriceuticals, Nature Biotechnology, 17, 5-6.

Goldspink, C. 2000. Modeling Social Systems as Complex: Towards a Social Simulation Meta-Model, *Journal of Artificial Societies and Social Simulation*, 3, 2, 1-23 <http://jass.soc.surrey.ac.uk/JASSS/3/2/1.html>

Goldspink, C. 2002. Methodological Implications of Complex Systems Approaches to Sociality: Simulation as a Foundation for Knowledge, *Journal of Artificial Societies and Social Simulation*, 5, 1, 1,1-19 <http://jass.soc.surrey.ac.uk/5/1/3.html>

Greve, H.R. 2003. A behavioral theory of R&D expenditures and innovation: evidence from shipbuilding. *Academy of Management Journal,* 16 (6), 685-703.

Hayek, F.A. 1967. *Studies in Philosophy, Politics, and Economics,* Chicago: University of Chicago Press.

Hayek, F.A. 1978. *New Studies in Philosophy, Politics, Economics and the History of Ideas*, Chicago: University of Chicago Press.

Halldorsson, A., Kotzab, H., Mikkola, J. H., Skjott-Larsen, T. 2007. Complementary theories to supply chain management. *Supply Chain Management: An International Journal*, 12, 4, 284-296.

Hodgson, G.M. 1997. Economics and the return to Mecca: the recognition of novelty and emergence, *Structural Change and Economic Dynamics,* 8, 399-412.

Holland, J. 1995. Hidden Order: How Adaptation Builds Complexity. Reading, MA: Addison-Wesley.

Hornibrook, S., and Fearne, A. 2001. Managing perceived risk: a multi-tier case study of UK retail beef supply chain. *Journal of Chain and Network Science*, 1, 2, 87-101.

Hurt, Chris. 1994. Industrialization in the Pork Industry, *Choices*, 4, 9-13.

IFAP (International Federation of Agricultural Producers). May 2002. Industrial concentration in the agri-food sector.
http://www.ifap.org/en/publications/documents/Concentration6thdraftrevE.pdf)

Jacobson, R. 1992. The Austrian School of Strategy, *Academy of Management Review,* 17, 4, 782-807.

Jantsch, E. 1980. *The Self-Organizing Universe: Scientific and Human Implications of the Emerging Paradigm of Evolution,* New York: Pergamon Press.

Just, R. 2001. Addressing the Changing Nature of Uncertainty in Agriculture, *American Journal of Agricultural Economics (proceedings),* 83, 5, 1131-54.

King, J.L. 2001. Concentration and technology in Agricultural input industries. *USDA / ERS, Agriculture Information Bulletin* no. 763, 1-13.

Kirzner, I. M. 1979. *Perception, Opportunity and Profit: Studies in the theory of Entrepreneurship*. Chicago: University of Chicago Press.

Kirzner, I. M. 1997. Entrepreneurial discovery and the competitive market process: an Austrian approach, *Journal of Economic Literature*, 35, 1, 60-85.

Kirzner, I.M. 2000. *The Driving Force of the Market: Essays in Austrian Economics*. Routledge, London.

Lachmann, L. M. 1977. *Capital, Expectations, and the Market Process: Essays on the Theory of the Market Economy,* Kansas City, Kansas: Sheed Andrews and McMeel.

Lane, D.A. 1993. Artificial Worlds and Economics, Part I, *Journal of Evolutionary Economics*, 3, 89-107.

Lazzarini, S. G., F.R. Chaddad and M. L. Cook. 2001. Integrating Supply Chain and Network Analyses: The Study of Netchains, *Journal on Chain and Network Science*, 1, 1, 7-23.

Leblebici, H., Salancik, G.R., Copay, Anne. & King, Tom. 1991. Institutional Change the Transformation of Inter-Organizational Fields: An Organizational History of the U.S. Radio Broadcasting Industry, *Administrative Science Quarterly.* 36, 333-363.

Li, G., Lin, Y., Wang, S., Yan, H. 2006. Enhancing agility by timely sharing of supply information. *Supply Chain Management: An international journal*, 11, 5, 425-435.

Lusk, J., Fox, J.A., Schroeder, T.C., Mintert, J and Koohmaraie, M. 2001. In store valuation of steak tenderness, *American Journal of Agricultural Economics*, 83 (3), 539-550.

Malloy, M. 1999. Merger and Acquisitions in biotechnology. *Nature Biotechnology* 17, 11-12.

March, J.G., Shapira, Z. 1987. Management perspectives on risk and risk taking. *Management Science,* 33 (11), 1404-1418.

Martinez, S. W. 1999. Vertical Coordination in the Pork and Broiler Industries: Implications for Pork and Chicken Products, *ERS, U.S. Department of Agriculture. Agricultural Economic Report* No.777.

McKelvey, B. 1998. Self-organization, complexity catastrophe and microstate models at the edge of chaos,. In J. Baum and W. McKelvey (Eds.), *Variations in Organizational Science: In Honor of Donald T. Campbell*, 279-310. CA: Sage Thousand Oaks.

McKelvey, B. 1999. Complexity Theory in Organization Science: Seizing the Promise or Becoming a Fad?, *Emergence*, 1, 1, 5-32.

Mises, L. 1949. *Human Action: 4th Edition (1996)*. (translated by Greaves, B.).Auburn, Alabama: Ludwig Von Mises Institute.

Mitchell, W. 1989. Whether and when probability and timing of incumbents' entry into
emerging industrial subfields. *Administrative Science Quarterly*, 34, 208-230.

Ng, D. 2004. The Social Dynamics of Diverse and Closed Networks, *Human Systems Management*, 23, 111-22.

O'Driscoll, G. P. and M. J. Rizzo. 1985. *The Economics of Time and Ignorance*. Basil Blackwell.

Omta, S.W.F, J. Trienekens, and G. Beers. 2001. The Knowledge Domain of Chain and Network Science, *Journal on Chain and Network Science*, 1, 2, 77-87.

Ottesen, G.G. 2006. Do upstream actors in the food chain know end-users quality perceptions? Findings from the Norwegian Salmon farming industry. *Supply Chain Management: An International Journal*, 11, 5, 456-463.

Persidis, A. 1999. Consolidations in biotechnology. *Nature Biotechnology* 17, 3-4.

Poray, M., A. Gray, M. Boehlje, and P. Preckel. 2003. Evaluation of Alternative Coordination Systems between Producers and Packers in the Pork Value chain, *International Food and Agribusiness Management Review*, 6, 2,1-28.

Porac, J. & Thomas, H. 1990. Taxonomic Mental Models in Competitor Definition. *Academy of Management Review*, 15 (2), 224-240.

Prahalad, C.K. & Bettis, R.A. 1986. The Dominant Logic: a New Linkage Between Diversity and Performance. *Strategic Management Journal*, 7, 485-501.

Prigogine, I. and I. Stengers. 1984. *Order Out of Chaos: Man's New Dialogue with Nature*. New York: Bantam.

Purcell, W., and Hudson, W.T. 2004. Risk sharing and compensation guides for managers and members of vertical beef alliances. *Review of Agricultural Economics*, 25, 1, 44-65.

Reger, R. K. & Huff A. 1993. Strategic Groups: A Cognitive Perspective. *Strategic Management Journal,* 14, 103-124.

Rothaermel, F.T. and Deeds, D.L. 2004. Exploration and exploitation alliances in biotechnology: a system of new product development, *Strategic Management Journal*, 25, 201-221

Russo, J.E &, Shoemaker, P.J.H. 1992. Managing Overconfidence. *Sloan Management Review*, 33 (2), 7-17.

Salin, V. 1998. Information technology in Agri-food Supply Chains. *International Food and Agribusiness Review*, 1 (3), 329-334.

Sastry, M.A. 1997. Problems and paradoxes in a model of punctuated organizational change. *Administrative Science Quarterly* 42 (2), 237-275.

Schumpeter, J. A. 1934. *The Theory of Economic Development* (R. Opic, Trans.). Cambridge, MA, Harvard University Press (original work published in 1912)

Scott, R.W. 1995. *Institutions and Organizations*. CA: Sage Thousand Oaks.

Shane, S. 2000. Prior Knowledge and the Discovery of Entrepreneurial Opportunities, *Organization Science*, 11, 4, 448-69.

Simon, H. 1976. *Administrative Behavior: A Study of Decision-Making Processes in Administrative Organization. 3rd Edition*. New York: Free Press.

Sporleder, T. 1992. Managerial economics of vertically coordinated agricultural firms. *American Journal of Agricultural Economics*, 74, 5, 1226-1231.

Stacey, R.D. 1992. *Managing the Unknowable: Strategic Boundaries Between Order and Chaos in Organizations*. San Francisco: Jossey-Bass Publishers.

Taylor, D.H. and Fearne, A. 2006. Towards a framework for improvement in the management of demand in agri-food supply chains. *Supply Chain Management: An International Journal*, 11, 5, 379-384.

Tushman, M.L., E. Romanelli. 1985. Organizational evolution: a metamorphosis model of convegence and reorientation. L.L. Cummings, B. Staw eds. *Research in Organizational Behavior*. JAI Press, Greenwich, CT, 171-222.

Zhang, Q., Vonderembse, M.A., and Lim, J. 2006. Spanning flexibility: supply chain information dissemination drives strategy development and customer satisfaction. *Supply Chain Management: An International Journal*, 11, 5, 390-399.

Vriend, N. J. 1999. "Was Hayek an ACE?", London: Queen Mary and Westfield College, University of London, Dept. of Economics, Mile End Road. <http://www.qmw.ac.uk/~ugte173/>.

Windrum, P., Fagiolo, G., and Moneta, A. 2007. Empirical validation of Agent-based models: Alternatives and Prospects. *Journal of Artificial Societies and Social Simulation*, 10, 2, 8. <http://jasss.soc.surrey. ac.uk/10/2/8.html: 1-35.

