International Food and Agribusiness Management Review
Volume 11, Issue 3, 2008

Innovation in Food Products: First-mover Strategy and Entropy Metrics

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Abstract

The objective of this research is to investigate food product innovation in the context of the first-mover strategy among food manufacturers within agrifood supply chains. The emphasis of the analysis is on developing a useful metric for tracking new product development in the context of first-mover strategy. Entropy is introduced as a novel and useful means of examining first-mover strategy and new product development (NPD) in general. Understanding the complexities of the first-mover strategy and tracking NPD with entropy metrics holds promise for enhancing the analysis of agrifood supply chains and assisting firms in deciphering broad strategies of their rivals.

Keywords: first-mover strategy, food product innovation, entropy, organic

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Innovation in Food Products

The agrifood sector traditionally is regarded as a low-tech industry. Food manufacturing is characterised by low intensity of research and development (R&D), compared to other manufacturing firms, which is reflected by relatively low R&D investment per dollar of sales (Grunert et al). Compared to the pharmaceuticals sector or the information technology sector, food manufacturing industries consistently exhibit lower R&D spending (Morgan et al), yet there is enhanced interest in product innovations in this sector. Currently, numerous applications of modern biotechnology focus on engineering input traits in the development of arable crops. Designer genes in arable crops already are important on the business-to-business level. However, agrifood firms increasingly are alert to the potential for differentiating bulk food products by adding useful functionalities relevant to specialized business-to-consumer markets (Bröring, Cloutier, and Leker). Hence, food product innovation through new product development is an important economic driver of the dynamics within agrifood chains. R&D expenditures lead to innovation by food manufacturers and may be driven by a differentiation strategy. A consequence of this is that intangible resources of the firm, such as intellectual property, are more likely to lead to a sustainable competitive advantage over rivals than tangible assets.

A successful differentiation strategy through R&D expenditures results in subsequent first-mover decisions. That is, if a first-mover opportunity arises for the food manufacturer as a result of their R&D then it confers the right, but not an obligation, to develop a product (and/or perhaps even an entire market) within a future time period. To obtain this right for management the firm paid a premium in the form of R&D expenditures committed during prior time periods.

The objective of this research is to investigate food product innovation in the context of the first-mover strategy among food manufacturers within agrifood supply chains. The emphasis of the analysis is on developing a useful metric for tracking new product development in the context of first-mover strategy. Entropy is introduced as a novel and useful means of examining first-mover strategy and new product development (NPD) in general. Understanding the complexities of the first-mover strategy and tracking NPD with entropy metrics holds promise for enhancing the analysis of agrifood supply chains and assisting firms in deciphering first-mover strategies of their rivals.

There is modest development of first-mover advantages compared to second-movers based on economic theory (Lieberman and Montgomery; Lieberman). Some analysts have examined first-mover with regard to barriers to entry (Briggeman, et al). There also is some development of diffusion and sustainable strategies with regard to food product innovation (Bröring; Shanahan, Sporleder, and Hooker). Integrating these concepts with the first-mover theory, particularly with a focus on tracking new food product innovation using entropy metrics, is the unique contribution of this research.

Firm Strategy by Markets and Products

A general view of firm strategy may be based on the combination of products and markets (Ansoff). The managerial strategy, in a simplified way, becomes evident when considering the products the firm either currently has or may develop combined with the current markets for the products or markets the firm may develop for its products, Figure 1. For example, when the relevant circumstance is to manage current or existing products in current or existing markets, the general strategy is to increase market share. Thus, tactics employed are devoted to enhancing market share for these products.

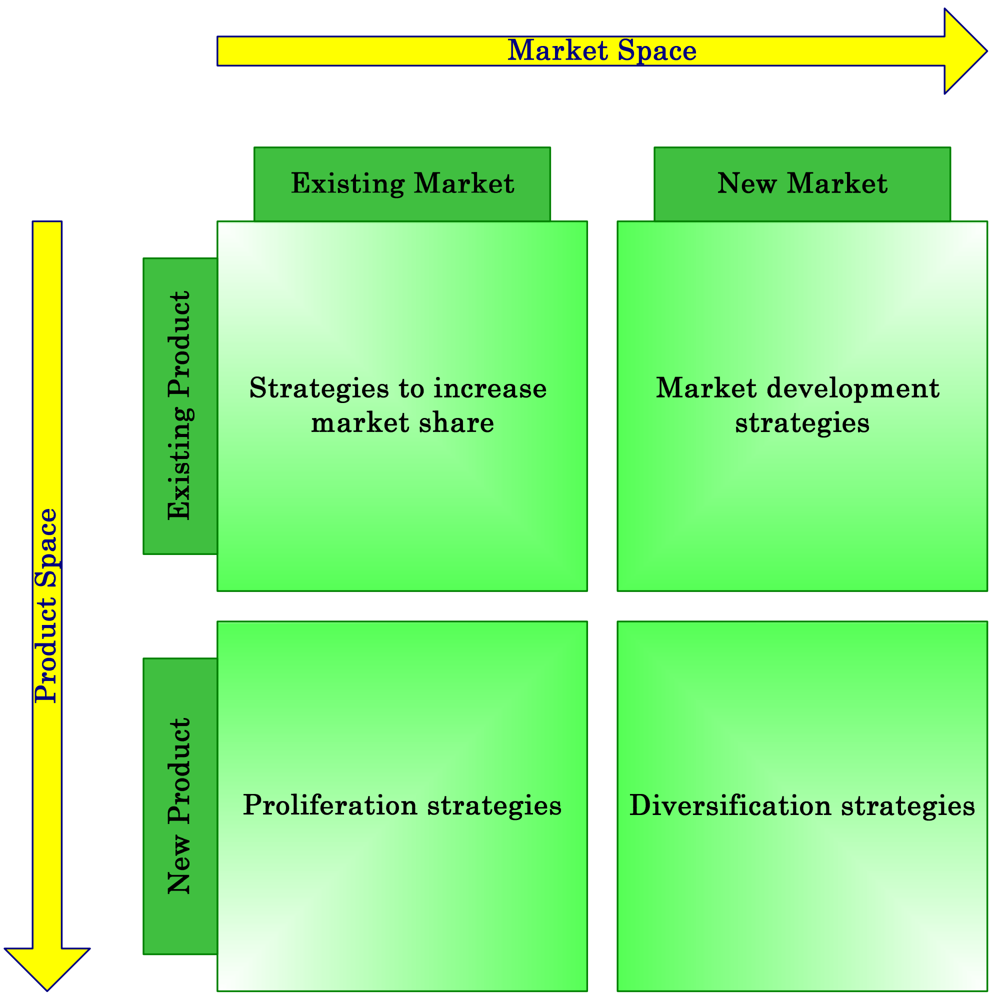

Figure 1: Firm Strategy Matrix across Market and Product Alternatives

Another circumstance may be the managerial challenge of marketing existing products in new markets. For example, a nutraceutical drink initially marketed to health care professionals in hospitals and nursing homes may be rolled out to the general public and marketed through retail grocery stores. Providing customer information on the product's benefits to this market segment is clearly different compared with the existing market. The managerial challenge here is to deploy strategies that will enhance sales of the product in this new product space.

In NPD, strategies also differ depending on whether the market is established or new. In the cell denoting established markets of the strategy matrix (Figure 1), the strategy is to proliferate products by deploying specific strategies such as line extensions or re-positioning products within existing markets. Introducing a new product in a new market is the most uncertain challenge. Here the predominant strategy is diversification. New products aimed at new markets diversify the portfolio of the firm (Ansoff; Madique and Zirger).

First-mover Strategy

First-mover firms in a market are thought to have an initial advantage of high price while second-mover firms have the advantage of lower costs (Montgomery and Lieberman). Pioneer firms face falling prices from firms that enter the market with imitations. Pioneer firms make their first-mover advantage sustainable through developing superior resources and capabilities compared to second-movers (Briggeman, Gunderson, and Detre).

Pioneer firms are first-movers typically thought to gain advantages over rivals from being first. These first-mover advantages may include strong image and reputation, brand loyalty, technological leadership, and being in an advantageous position relative to the 'learning curve' involved in managing a specific product or process innovation. Lieberman and Montgomery argue that there are three primary advantages that may accrue to pioneer firms: the preemption of rivals, the imposition of switching costs on buyers, and the benefit that accrues from being seen by customers as a technological leader compared to rival firms. Second-mover or follower firms have the advantage of lower costs through less expensive imitation of first-mover products or processes and the resolution of market or technological uncertainties faced by first-movers. In the aggregate, market pioneers deploy innovative products or processes with high initial costs and risks, but yield high potential returns. This also implies that second-movers or followers experience lower costs because imitation is less expensive than innovation.

Other potential advantages to second-movers include the ability of followers to free-ride on the first-mover's pioneering costs (such as the expense of gaining regulatory approvals, informing potential buyers of the innovation's advantages, and generally developing the infrastructure necessary to support commercializing the innovation).

Another factor may be the ability of followers to capitalize on first-mover mistakes and operate with less market or technological uncertainty when compared to the first-mover (Kerin, Varadarajan, and Peterson).

Capture and sustainability of first-mover advantages are related to complementary assets (Teece, 1986). Commercialization of innovation requires linking with complementary assets such as marketing expertise, brands, and logistics and supply chain networks, all in support of the innovation. In general, a firm's competitive advantage is a function of the unique organizational skills that determine how it combines and orchestrates assets over time (Teece, 1992). The extent to which a new product innovation can be mastered by existing complementary assets depends on the degree of innovativeness. Following Veryzer, product innovations can be distinguished along the dimensions "technological capabilities" and "market capabilities." Depending on the degree to which an innovation requires new capabilities, it may create conflicts within the existing firm. This view can be extended to include the capability requirements of an innovation on the customer side or even along the entire value chain (Bröring, Leker, and Rühmer). The more disruptive an innovation is from a customer's view, the more assets need to be changed; hence, the less likely is the adoption of that innovation. This is because the customer may not want to build complementary assets to make adopting the innovation feasible (in case of B2B markets), or the customer may not want to invest in extra search and information costs (in case of B2C markets). Sustainability may depend on the nature of the idiosyncratic investments induced by the innovation as well as the aggregate portfolio of tangible and intangible assets possessed by the first-mover firm (Teece, Pisano, and Shuen). The factors influencing capture and sustainability of economic rents not only include complementary assets required to support commercialization but also the nature of the technology (the complexity of the technology) and the legal protections that may be available for insulating the technology from second-movers through patents, copyrights, or trademarks.

The strength of appropriability regimes also may be a factor in determining the sustainability of economic rents to innovators (López and Roberts). Appropriability refers to the ability of various stakeholders to retain the economic rents generated from the commercialization of an innovation. Weak appropriability regimes imply that stakeholders will have difficulty in capturing sustainable economic rents from their innovation. Economic rents from commercializing an innovation are potentially shared among the innovator, customers buying the innovation, suppliers to the innovation, and second-movers or followers (Teece, 1986). Commercializing innovation by firms that lack complementary assets, or in the event that only 'generic' general-purpose assets are required, leads to weak appropriability.

Food products are in the experience goods category. Empirical evidence indicates that first-mover firms in experience goods tend to shape consumer tastes and preferences in favor of the pioneering brand (Robinson, et al). Such preferences often are sustainable for the pioneering product. First-mover strategy is a common dilemma for managers and has special importance when the product is in the experience goods category. A priori, weak appropriability regimes are likely to characterize new product innovation by food manufacturers partly because they are manufacturing experience goods. The exception to this generalization about weak appropriability regimes may be when food manufacturers already possess one or more category-dominant brands. If the new product innovation is then introduced as a brand extension, strong appropriability may better characterize the situation.

In the context of the product/market strategy matrix, Figure 1, the cells that represent first-mover situations include all but the existing product-existing market cell. That is, first-mover strategy may be deployed by firms either through introducing new products or developing new markets. For example, a food manufacturer that develops a new organic product after developing a conventional product in the same category would be characterized within the product proliferation cell of the matrix. The new product into new markets cell is the most uncertain and potentially the highest relative product launch cost among the four cells.

Entropy Metrics for Tracking Food Product Innovation

Entropy metrics are based on probability distributions and are appropriate for use in analyzing phenomena whenever the target of interest is a heterogeneous population that can be grouped into meaningful categories (Theil). Entropy metrics are employed in a wide variety of calculations in both social and physical sciences. For example, entropy has been used as a measure of firm diversification in the management literature (Hoskisson et al).

The typical analytic measure employed for assessing first-mover is market share. The entropy metric has useful features, compared to simple market shares, because of the disaggregation properties of the metric. Specifically, total entropy can be disaggregated into between-set and within-set entropy measures. This is a convenient feature when applied to food products because data are available for several levels of aggregation, such as product line and more aggregated classifications such as food categories, industry sectors, and even national boundaries. To illustrate, suppose the analytic target of interest is plant sterols (a cholesterol-lowering ingredient). New product development may include plant sterols in product lines such as rye bread, yogurt, and margarine. These product lines are typically aggregated into broader product categories such as bakery and dairy. The power of entropy is the between-set and within-set disaggregation. For this illustration, the between-set entropy would be bakery compared to dairy, while the within-set entropy would be yogurt compared with margarine. The entropy metrics thus coincide with normal and meaningful units of analysis and consequently provide more information-rich measures (the appendix to this article provides a discussion of, and formal definition for, between-set and within-set entropy). A strategist attempting to analyze new product development in sterols would be keenly interested in how rapid and pervasive NPD is between these sets as well as within these sets. Further, the strategist might calculate the decomposed entropy metrics at time t and t+1 to provide insight into the dynamics of sterol ingredient NPD. If one level of aggregation is the firm level, then between-set and within-set entropy metrics also could help monitor sterol ingredient NPD by firm and product line.

To illustrate the utility of entropy in tracking NPD, the trends in new organic food product development are tracked here to assess which innovations are using particular combinations of promotional claims as expressed on product labels. Each food category is a mutually-exclusive element of a particular food industry sector.

Tracking Organic NPD

Organic adoption by food processors *(process innovation adoption)* can be observed by tracking new processed food product lines released into a given market and determining which product lines are using an organic promotional claim (as determined by the informational content of product labels). Use of an organic promotional claim on a new product line implies that the food manufacturer's product/brand manager made a decision concerning whether or not to adopt organic practices.

The product/brand manager's decision to adopt organic practices is a function of factors that maximize the expected benefits from adoption and minimize anticipated costs of adoption. Expectations (the likelihood of earning a given target return) and anticipations (the cost of process innovation adoption given the earning's expectation) are not directly controllable by the adopter. They are exogenous to the food manufacturer. Expectations and anticipations can be influenced by the expected consumer demand for product innovation (thus, the demand for a process innovation is derived from the demand for the product innovation), the current and future actions of potential competitors and the actions of suppliers of the process innovation's inputs. Regulation also influences expectations and anticipations.

For example, the National Organic Program (NOP) was initiated in 2002 by the U.S. Department of Agriculture (USDA) with the intent of defining what it means to be *organic* and to establish a third-party voluntary quality assurance certification standard nationally. The goal of NOP is to substantiate and standardize organic labeling to provide all economic agents in the organic market an assurance of product quality. The NOP also substantiates the certification of multi-ingredient processed goods using a ranked four-tiered labeling system that encodes the relevant product by its level of content of organic ingredients, which include:

- *100% Organic*
- *Organic* (contains at least 95% organic)
- *Made with organic ingredients* (contains at least 70% organic)
- *Some organic ingredients* (contains less than 70%)

Only the first two levels can use the official USDA organic seal on the front of the label. Regulation forbids the use of the word 'organic' on the front panel of products that only qualify for the last level of NOP certification. This may effectively nullify the potential adopter's expected benefits from adopting organic production practices. The benefit of adopting NOP requirements and qualifying for the nationally-recognized seal, for producers able to bear the initial investment costs, is the addition of a government-endorsed barrier to entry by the adopter's current and future potential competition and a substantiation of the quality of the adopter's product line. For the manufacturer, this benefit strengthens what otherwise might be characterized as a weak appropriability regime.

It is expected that consumers are willing to pay a higher price for new organic product lines bearing the USDA seal, yet it is uncertain as to whether consumers perceive a difference between *100% Organic* and *Organic* (or *Made with organic ingredients* and *Some Organic Ingredients*) (Hooker et al). It also is expected that the anticipated investment costs of adopting organic production practices is positively related to the level of organic ingredient content in the adopter's new product line. These expectations suggest that since the likelihood of earning a given target return is lower at the *100% Organic* level (due to uncertainty) and the expected cost at the *100% Organic* level is relatively the highest among the set of organic levels, an anticipated evolution of adoption would be an increasing share of the organic product innovations released into the market claiming Organic and/or only exert enough effort to achieve the 95% organic content threshold to qualify for the differentiating seal.

Uncertainty decreases over time due to the learning effects typical in innovation diffusion systems and the accumulating nature of information within these systems (Shanahan, Hooker, and Sporleder). Specifically, expectations about potential net earnings from adoption increase due to continued information gathering about the extent of the process innovation's market success. Thus, it is expected that the share of the organic product innovations released into the market claiming *100% Organic* will increase over time, yet at a lower rate of adoption relative to the *Organic* level. The rates of adoption among the lower two levels are expected to have decreased over time, as learning of the disadvantages of these marketing strategies' becomes increasingly apparent. Thus, an increasing share of the adoptions will bear the USDA organic seal.

The rate of process adoption is defined as the sum of all process innovation adoptions by all product line managers in all specified product categories at a particular point in time. Useful product category specifications include brand, company, industry of origin, industry sector of origin, and food-type category (e.g. milk, cheese, yogurt, bread products, and cola). Product lines can also be aggregated into geo-space groupings, such as groupings by the origin region of production or distribution and market regions (where the product line is primarily sold). For the purposes of this study, product lines are aggregated up to food-type categories and then further aggregated up into an industry sector, where each food category is an exclusive element of the industry sector. For the purposes of this research, similar food manufacturers are aggregated into food-type categories (which roughly approximate the firm's industry).

Relative adoption rate variance across food categories and industry sectors is a function of the characteristics of the adopter set and the external environment. It appears likely that expected benefits and anticipated costs from the adoption of a given process innovation will vary across food manufacturers and food sectors. Further, adoption may be influenced by market structure, consumer demand, and the power of suppliers. In turn, there is no a priori reason to assume that rates of adoption across food categories will be the same. Certain food categories will be more innovative relative to others. However, due to inter- and intra-industry learning, uncertainty tied to the expected net benefits from adoption of organic practices will decrease over time and, given that the process innovation proves a sustainable advantage, adoption rates across food categories and industry sectors should converge over time. Thus, it is expected that the relative variance in process innovation adoption rates across food categories and industry sectors will decrease over time.

Entropy Metrics Applied to Organic NPD

Designing entropy metrics to analyze food innovation, such as organic NPD, facilitates a more sophisticated framework that permits categorical decomposition; a metric unavailable in simpler statistical comparisons. Entropy metrics facilitate an n-dimensional distribution of product innovations over a defined space at particular point in time. These metrics can capture spatial dispersion of product characteristics by indicating product variety and product category specialization *simultaneously*. This is a powerful and novel trait for any metric to possess. More detail on the specific methods of entropy calculation is provided in an appendix to this manuscript.

Using entropy metrics enhances the ability to indicate the extent of n-dimensional variety at particular moments of time and allows for categorical decomposition analysis. There have been many uses of entropy metrics in industrial organization and technical change (innovation) investigations (Sporleder, Franken). Entropy statistics are based on the properties of any probability distribution and are suitable for use in studying phenomena at any population level of heterogeneous entities that are naturally grouped into categories (Franken).

Suppose the following events are observed:
X_m = The event that a product line innovation is organic at organic level m where m =

- 1 if *100% Organic*
- 2 if *Organic*
- 3 if *Made with organic ingredients*, and
- 4 if *Some organic ingredients*

Each X_m can be aggregated into mutually exclusive sets of related event variants; W_k, is the event that a product line innovation is organic at organic level k where $k = 1$ if $m \leq 2$ and $k = 2$ if $m > 2$. When k = 1, the product line is able to bear the USDA organic seal. The probability of X_m is

$$(1)\quad P_m = \sum_{n=1}^{N} P(X_m \cap Y_n) = \sum_{n=1}^{N} P_{mn}$$

and the probability of W_k is

$$(2)\quad P_k = \sum_{m \in k} P_m = \sum_{m \in k}\sum_{n=1}^{N} P(X_m \cap Y_n) = \sum_{m \in k}\sum_{n=1}^{N} P_{mn}$$

where Y_{ie} is the event that a product line innovation is organic and is of food type n where $N = 47$, the number of food type categories n. The probability of Y_n is

$$(3)\quad P_n = \sum_{m=1}^{M} P(X_m \cap Y_n) = \sum_{m=1}^{M} P_{nm}\ .$$

The probability that a given combination of event variants occurs in a particular moment in time is calculated by taking the ratio of the total number of occurrences of the event relative to the total number of adoptions at a defined time. Thus, the probability an organic adoption is X_m and Y_n is $P_{mn} = P(X_m \cap Y_n)$, and the probability an organic adoption is W_k and Y_n is $P_{kn} = P(W_m \cap Y_n) = \sum_{m \in l} P(X_m \cap Y_n)$.

In this study, conditional entropy metrics are calculated which measure entropy in one dimension *given the occurrence of a particular variant of another dimension*. For example, the following conditional entropies are calculated for this particular study:

(4) Conditional Entropy in X given Y_n: $H(X \mid Y_n) = \sum_{m=1}^{M} {}^{P_{mn}}\!/\!_{P_n} * \log_2 {}^{P_n}\!/\!_{P_{mn}}$

(5) Conditional Entropy in Y given X_m: $H(Y \mid X_m) = \sum_{n=1}^{N} P_{mn}/P_m * \log_2 P_m/P_{mn}$

(6) Conditional Entropy in Y given W_k: $H(Y \mid W_k) = \sum_{n=1}^{N} P_{kn}/P_n * \log_2 P_n/P_{kn}$

(7) Conditional Entropy in W given Y_n $H(W \mid Y_n) = \sum_{k=1}^{K} P_{kn}/P_k * \log_2 P_k/P_{kn}$

Average conditional entropy is equal to the weighted average of conditional entropies. The average conditional entropies used in this particular study are:

(8) Average conditional entropy in X given Y: $H(X \mid Y) = \sum_{n=1}^{N} P_n * H(X \mid Y_n)$

(9) Average conditional entropy in W given Y: $H(W \mid Y) = \sum_{n=1}^{N} P_n * H(W \mid Y_n)$

As stated above, absolute rates of adoption across organic content levels, food categories and industry sectors will vary inherently because the expected benefits and the anticipated costs of adoption of a given process innovation and the adopter's external environment will vary. As a result, absolute entropy measures over time also will vary but provide sparse additional information pertaining to changes in adoption rates. To control for changes in absolute adoption rates over time and to observe only changes in adoption rate variance across event variants, relative entropy metrics are needed (Sporleder). Relative entropy can be calculated from any absolute entropy measure as follows:

(10) $R(\ldots)_t = \frac{H(\ldots)_t}{\log_2 N_t}$,

where $\log_2 N_t$ is the maximum possible absolute entropy in time t. Decreasing relative entropy over time implies that adoption rates are increasing in variance across event variants and increasing relative entropy implies that adoptions rates are decreasing in variance across event variants. Using equation 10, relative entropy metrics per time period are derived so as to empirically test relative adoption rates across a specific dimension are behaving in accord with a priori reasoning. Relative entropy may be calculated for any particular dimension, set of dimensions, or across a particular dimension given the occurrence of a particular variant of another event dimension. A linear functional form is specified for each proposed relationship between relative entropy and time unless otherwise noted.

Entropy Metric Results for Organic NPD

Data

The dynamic Mintel/GNPD database (www.gnpd.com) lists new food and consumer product information, including label pictures for goods on sale in 49 countries. These data consist of a total global population of over 320,000 innovations since the year 2000 and a total U.S. population of over 57,000 innovations as of July 2006. A simple search function can separate products using certain quality claims with results including: product name, description, time of product release, variants in product characteristics (flavors, sizes, etc.), ingredients and nutritional information, food categories and subcategories (which closely correlate to food manufacturing industries), distribution channels for the new product, and price in local currency and Euros. There are 1,761 new U.S. organic food products within the 47 chosen food categories. These data are used to empirically estimate entropy metrics for organic food products in the United States. Regressions empirically test selected hypotheses regarding innovation, the role of innovation propagators, and first-mover strategy. Table 1 reports the cumulative number of organic adoptions per food category and by level of organic content during all time periods.

Table 1. Cumulative Number of Organic Adoptions per Food Category and by Level of Organic Content; All Time Periods

Food Category	100% Organic	Organic >95%	Made w/ Organic 95% to 70%	Some Organic <70%	Total Organic Adoptions per Food Category	$R(X/Yn)$
Baking Ingredients & Mixes	0	24	9	12	45	0.265
Bread & Bread Products	0	20	20	24	64	0.263
Butter & Yellow Fats	0	4	1	1	6	0.484
Cakes, Pastries & Sweet Goods	0	5	6	10	21	0.346
Cheese	0	15	13	9	37	0.298
Chilled Desserts	0	2	0	1	3	0.579
Chocolate Confectionery	2	20	20	12	54	0.299
Coffee	5	13	10	32	60	0.286
Cold Cereals	0	56	17	5	78	0.171
Cooking Sauces	0	16	11	9	36	0.298
Cream & Creamers	0	2	1	0	3	0.579
Dressings, Vinegar & Mayonnaise	0	22	24	17	63	0.263
Dry Soup	0	0	2	1	3	0.579

Table 1 Continued.

Food Category	100% Organic	Organic >95%	Made w/ Organic 95% to 70%	Some Organic <70%	Total Organic Adoptions per Food Category	*R(X/Yn)*
Eggs & Egg Products	1	7	3	7	18	0.413
Frozen Novelties Impulse Ice Cream	0	4	2	1	7	0.491
Fruit	6	22	5	4	37	0.309
Fruit Snacks	1	7	2	3	13	0.451
Hot Cereals	0	11	0	1	12	0.115
Malt & Other Hot Beverages	0	3	2	6	11	0.415
Meat Products	0	8	2	6	16	0.351
Meat Substitutes	0	11	14	10	35	0.306
Milk	0	29	19	8	56	0.245
Nuts	0	2	3	2	7	0.554
Oils	3	11	14	12	40	0.346
Pasta	2	29	28	13	72	0.267
Pasta Sauces	0	16	7	3	26	0.277
Pickled Condiments	0	0	3	4	7	0.351
Potato Products	0	4	0	1	5	0.311
Rice	1	12	6	4	23	0.361
RTD Iced Tea	0	3	0	13	16	0.174
RTD Juices & Juice Drinks	4	63	15	19	101	0.221
Savory Biscuits/Crackers	0	16	11	20	47	0.278
Savory Spreads	0	13	3	9	25	0.299
Savory/Salty Snacks	1	26	32	21	80	0.260
Seasonings	2	7	10	10	29	0.375
Snack/Cereal/ Energy Bars	0	31	15	21	67	0.251
Snack Mixes	0	8	3	4	15	0.373
Stuffing, Polenta & Other Side Dishes	1	7	9	2	19	0.378
Sugar Confectionery	1	11	2	6	20	0.357
Sweet Biscuits/Cookies	0	22	15	23	60	0.264
Sweet Spreads	1	32	22	21	76	0.262
Table Sauces	0	30	19	7	56	0.239
Take Home Ice Cream	1	3	14	4	22	0.327

Table 1 Continued.

Food Category	100% Organic	Organic >95%	Made w/ Organic 95% to7 0%	Some Organic, <70%	Total Organic Adoptions per Food Category	$R(X/Yn)$
Tea	3	22	35	31	91	0.264
Vegetables	6	46	26	4	82	0.233
Wet Soup	1	33	17	4	55	0.233
Yogurt & Probiotic Drinks	0	14	22	6	42	0.263
Total Organic Adoptions per Organic Level	**42**	**762**	**514**	**443**	**1761**	

Temporal Trends in Relative Average Conditional Entropy

Relative average conditional entropies, $R(X/Y)$ and $R(W/Y)$, are expected to initially increase over time, reach a maximum value at a particular time, and then decrease thereafter. This reflects the organic food industry's temporal shift away from non-seal qualifying process adoptions and toward NOP seal qualifying adoptions. Prior to 2002 organic product innovations were not certified because the process innovation was not yet introduced. After 2002, more product innovations will display the seal, reflecting product/brand managers' increasingly certain expectations of rising benefits and lower costs of using the differentiating seal. The expectation is that there will an increasing number of new organic processed foods eligible to use the NOP seal over time, evident in an increasing clustering of adoptions at the 95% organic content level and a de-clustering of non-seal adoptions over time. The expected temporal trend in U.S. organic adoption among food products can be depicted graphically, Figure 2.

Given the above relative average conditional entropies hold, the relative average conditional entropy in X given Y and the relative average conditional entropy in W given Y over time will reflect the temporal shift away from lower organic qualification levels and toward seal-certified organic process adoptions, independent of the initial food category. Thus, the relative average entropy in X given Y and the relative average entropy in W given Y initially will be relatively low-- reflecting that most organic adoptions will not have the seal. Then entropy will increase, as early adopters are just beginning to learn of the certification process, and will reach a local maximum entropy at some point within the observed time period. Then entropy decreases thereafter as information pertaining to organic seal compliance has effectively diffused through the industry and increases a given organic adopter's ease of seal qualification.

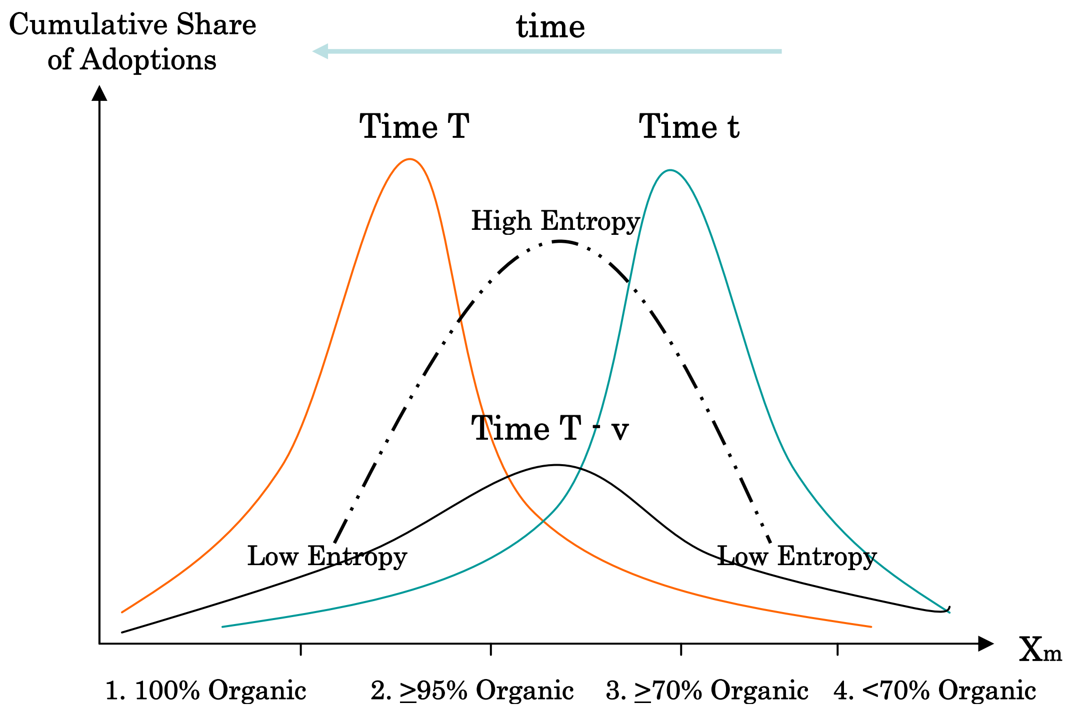

Figure 2. Shift in Cumulative Share of Organic Adopters from Non-Seal Qualified Organic Adoptions to Seal Qualified Organic Adoptions over Time

Below are the specifications used to explore the correlation between the relative average conditional entropy in X given Y and the relative average conditional entropy in W given Y and time, respectively.

(11) $R(X|Y)_t = \alpha_{X|Y} + \beta_{1X|Y} * t + \beta_{2X|Y} * t^2$

(12) $R(W|Y)_t = \alpha_{W|Y} + \beta_{1W|Y} * t + \beta_{2W|Y} * t^2$

where $\beta_{1X|Y}$ and $\beta_{1W|Y} > 0$, $\beta_{2X|Y}$ and $\beta_{2W|Y} < 0$ and each time period is the number of quarters since the inception of the National Organic Program (15 quarters as of May 2006).

Results of the linear models, estimating the temporal relationship of each relative conditional entropy metric is reported in Table 2. The coefficients of determination (adj. R^2) of the relative average conditional entropy in X given Y model is 0.24 and the relative average conditional entropy in W given Y is 0.23. The reported F statistics for the relative average conditional entropy in X given Y is 3.20 and the relative average conditional entropy in W given Y is 3.08. The coefficients describing the change in the relative average conditional entropy $R(X/Y)$ and $R(W/Y)$ given a change in time (0.0075 and 0.0061, respectively) and the relative

Table 2. Results of the Entropy Temporal Trends

Liner Model	α	β1	t-stat	β2	t Stat	F Stat	Adj. R^2
$R(X/Y) = f(t, t^2)$	0.1171	0.0075	1.70	-0.0006	-2.09	0.08	0.24
$R(W/Y) = f(t, t^2)$	0.0621	0.0061	1.95	-0.0003	-1.54	3.08	0.23
E(X) = f(t)	3.0927	-0.0407	-5.72			32.69	0.69
E(W)= f(t)	1.7991	-0.0321	-7.13			50.83	0.78
$R(X/Y_n) = f(CUMA_n^*)$	0.4233	-0.0026	-5.26			34.06	0.42
$R(Y/W1) = f(t)$	0.1054	0.0233	7.20			51.85	0.78
$R(Y/W2) = f(t)$	0.5608	-0.0247	-7.43			55.28	0.79

* $CUMA_n$ = Cumulative Number of Adopters in Food Category i

average conditional entropy $R(X/Y)$ and $R(W/Y)$ given a change in time squared (-0.0006 and -0.0003, respectively) are found not statistically different from zero at the 95% level. These results provide modest evidence that the relative average conditional entropy in X given Y and W given Y did shift along the organic level dimension in the expected direction, away from non-NOP seal qualified organic adoptions and toward seal-qualified adoptions. However, endogenous factors influence the adoption decision, as evident in the degree of variation unexplained, and confirmation that the a priori shift is going in the expected direction needs further empirical verification.

Temporal Trends in Adoption Clustering

The above statistical relationship between X given Y or W given Y and time does show the change in adoption clustering activity along the X/W dimension, but it does not reveal anything about the change in locality along the X/W dimension. In an effort to verify that the adoption clustering activity along the X/W dimension is shifting in the expected direction, temporal change in expected value or location in X and W are explored. Specifically, the trend relationship of the expected organic adoption location on the X/W dimension per time period is calculated. The time period covers the number of quarters since the inception of the National Organic Program (15 quarters prior to and including May 2006).

Results of the linear models describing the correlations between the expected location of organic adoptions on the X/W dimension and time are provided in Table 2. Based on the statistical results, 69% of the variation between the expected location of organic adoptions on the X dimension is explained by time and 78% of the variation in relative the expected location of organic adoptions on the W dimension is explained by time. F statistics indicate statistically significant models. In addition, coefficients describing the change in the expected location of organic adoptions on the X given a change in time (-0.0407) and the change in the expected location of organic adoptions on the W given a change in time (-0.0321) are statistically different from zero at the 95% level and exhibit the correct a priori sign. These findings suggest that the relative average conditional entropy in X given Y

and the relative average conditional entropy in W given Y are shifting in the expected direction. That is, away from non-NOP seal qualified organic adoptions and toward seal-qualified adoptions.

Relative Conditional Entropy and the Cumulative Number of Organic Adopters

The relative conditional entropy in X given Y_n, $R(X/Y_n)$, denotes the variance or entropy in the organic level dimension in each food category I. This metric reveals whether there is clustering occurring at a particular event variant (relatively low entropy) or if organic adoptions are occurring at many levels along the organic level dimension (relatively high entropy) at a particular food category. A priori expectations are that the degree of relative conditional entropy within a particular food category is negatively related to the cumulative number of organic adopters within the particular food category. This is because higher levels of innovation imitation are expected to occur in food categories with higher levels of innovation (organic) adoptions and relatively weak appropriability regimes.

With respect to the organic case, as more organic adoptions occur within a particular food category, it is expected that later adopters will, in general, imitate early adopters and choose the same organic quality level. So, some organic adopters will choose a higher level of organic quality while others will choose to adopt a relatively lower level of organic. But over time, as more products within a particular food category enter the market, the occurrence of organic adoptions will converge onto the market's most successful organic level variant. Diminishing net benefits of adopting a particular level of organic quality per adopter is expected as the cumulative number of organic adoptions increases, due to an increase in the degree of competitive rivalry within a particular food category. However, data availability does not permit empirical tests of this particular hypothesis.

Conversely, it is possible to explore temporal trends between relative conditional entropy in X given Y_n and the cumulative number of organic adoptions per food category Y_n with the model as specified here:

$$(13)\quad R(X \mid Y_n) = \alpha_{X|Y_n} + \beta_{X|Y_n} * CUMA_n$$

where $CUMA_n$ is the cumulative number of organic adoptions in food category n, $\beta_{X|Yn} < 0$ and each time period is the number of quarters since the inception of the National Organic Program (15 quarters as of May 2006).

Results of this temporal trend for relative conditional entropy in X given Y_n and the cumulative number of organic adopters per food category is in Table 2. The coefficient of determination (adj.R^2) of the correlation is 0.42 and the parameter estimate is statistically significantly different from zero at the 95% level, has the correct a priori sign, and this evidence supports the a priori expectations.

Temporal Trends in Seal Qualified Adoption Rates

It is expected that the variance in seal qualified adoption rates across food categories will increase over time. Thus, the likelihood that a given product innovation will bear the organic seal becomes less dependent on the industry origin of the product and there is increased diversity of organic food product types on the store shelves. To test this the relative conditional entropy in Y given W_k, when $k = 1$, or that the product bears the NOP organic seal, is expected to be positively related to the time and this expected relationship is explored. Also, it is expected that the variance in non-qualified adoptions across food categories will decrease over time because some product managers releasing product innovations to particular food categories will find that the obligations of seal-qualification are in excess of their firm's abilities or effort level, due to food category or industry sector-specific external constraints. To test this hypothesis, the relative conditional entropy in Y given W_k, when $k = 2$, or that the product does not bear the NOP organic seal, is expected to be negatively related to time. To compare adoption trends across food categories or industry sectors given a particular organic level, the analysis assumes that relative conditional entropies in Y given W_k ($R(Y/W_k)$) are a linear function of time where β_{Yk} is the change in relative conditional entropy in Y given W_k or:

$$(14)\quad R(Y \mid W_1) = \alpha_{Y|W_1} + \beta_{Y|W_1} * t$$

where $\beta_{Y|W_1} > 0$ and

$$(15)\quad R(Y \mid W_2) = \alpha_{Y|W_2} + \beta_{Y|W_2} * t$$

where $\beta_{Y|W_2} < 0$ and each time period is the number of quarters since the inception of the National Organic Program (15 quarters as of May 2006).

As before, Table 2 contains the results of the linear models describing the correlations between each of explored relative conditional entropy in Y given W_k and time. The coefficients of determination (adj.R^2) for the correlations are 0.78 and 0.79 for the relative conditional entropy in Y given W_1 and the relative conditional entropy in Y given W_2, respectively. Thus, more that three-quarters of the variation in relative conditional entropies in Y given W_k are explained by time alone. The reported F statistics indicates a statistically significant relationships and this evidence supports the a priori expectations.

Most results of this preliminary design of entropy metrics are encouraging. The estimated parameter describing the change in relative conditional entropy in Y given W_1 given a unit change in time has the expected positive sign and is statistically significant at a 95% level of confidence. This evidence suggests an increase in the variety of organic food products on store shelves qualifying for the NOP organic seal. In turn, the estimated parameter describing the change in relative conditional entropy in Y given W_1, given a unit change in time, has the expected negative sign and is statistically significant at a 95% level of confidence. This further implies that some product managers releasing organic products into the market from particular food categories are finding that the obligations of seal-qualification are in excess of their ability to comply due to food category or industry (sector-specific) external constraints.

Conclusions and Managerial Implications

An important aspect of food manufacturing first-mover strategy for firms is to understand the potential entrants that may develop after a firm becomes a pioneer. This analysis suggests that entropy is a useful metric for understanding the market dynamics when product innovation is a key aspect of the rivalry among firms within an industry. Because differentiation strategies are common as a means for gaining a sustainable advantage over rivals, the issue of first-mover strategy is critical to managerial understanding of the implications for R&D budgets and the theoretical relationship between R&D budgets and such factors as the role of innovation propagators.

In addition, supply chains are complex and food manufacturers' within-chain relationships are influenced by strategic planning. First-mover strategy may result in the development of different within-chain relationships. Simultaneously, first-mover strategy also may result in developing novel among-chain relationships as well. For example, recent research by one of the authors of this manuscript focuses on agrifood supply chains relative to nutraceuticals and functional foods. The analysis suggests convergence of food manufacturing and pharmaceutical industries. The supply chain relationships may evolve so that an innovative food manufacturer relies on a pharmaceutical company ingredient supplier for technological application knowledge (Bröring and Cloutier). Such cross-chain relationships carry important implications for first-mover strategy.

This research complements previous work on first-mover strategies and new product innovation which stresses the correct launch tactics, for example in Guiltinan. As the evidence about organic NPD presented here suggests, choosing the right certification scheme as a means to reduce information costs for the consumer (establishing complementary assets) appears to be an important issue to consider during product launch within a first-mover strategy. Clearly, there are several potentially important managerial implications from the research reported in this manuscript.

Finally, the development of entropy metrics useful for analyzing complex and dynamic markets, such as the agrifood industry, is in its infancy. However, there is empirical evidence reported here that at least encourages further development of the methods based on entropy metrics so that complex and interrelated levels and categories of target markets can be better analyzed. In addition, certain entropy metrics provide insight into whether weak appropriability regimes prevail in various food sectors.

Acknowledgements

The authors acknowledge partial financial support for this research from the U.S. Department of Agriculture-NRI (Markets and Trade), Award 2008-35400-19716.

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Appendix A.

Calculating Entropy

Suppose that we observe event X_m out of M possible event variants. Each X_m occurs with a probability of P_m, where $P_m \geq 0$ and $\sum_{m=1}^{M} P_m = 1$ (where $m = 1 \ldots M$). Since P_m inversely influences the degree of surprise, $h(P_m)$ presumes the following relationship:

$$(16)\ h(P_m) = \log_2 P_m^{-1}$$

where $h(P_m)$ exponentially decreases from infinity to zero as the probability of an event variant occurrence increases. The expected degree of surprise of a probability distribution, or entropy, is:

$$(17)\ H(X) = \sum_{m=1}^{M} P_m * \log_2 P_m^{-1}$$

where it is assumed that $P_m * \log_2 P_m^{-1} = 0$ when $P_m=0$ because it can be shown that $\lim_{P_m \to 0}[P_m * \log_2 P_m^{-1}] = 0$ (Theil). Minimum entropy occurs when one event has 100% chance of occurring which means that $H(X) = 0$. This implies maximum concentration and minimal dispersion. Maximum entropy occurs when all n events have an equal chance of occurring and $H(X)$ will equal

$$(18)\quad \sum_{m=1}^{M} 1/M * \log_2 M = M * 1/M \log_2 M = \log_2 M \ .$$

Maximum entropy (and maximum degree of surprise) increases at a decreasing rate as m increases.

Total entropy can be disaggregated into among-set (category) and within-set (category) entropies. Suppose that each event variant X_m can be aggregated into mutually exclusive sets of related event variants W_k (i.e., a subset of X_m exclusively falls into W_k). The probability of W_k occurring is: $P_k = \sum_{m \in k} P_m$ where $P_k \geq 0$ and that $\sum_{k=1}^{K} P_k = 1$ *(where k = 1…K).*

The *Entropy Decompositional Theorem* states that total entropy $H(X)$ is equal to total between-set entropy plus the average within-set entropy (Sporleder; Theil): Total entropy is:

$$(19)\quad H(X) = H_b(W_k) + \sum_{k=1}^{K} P_k * H_w(W_k)$$

Total between-set entropy is:

$$(20)\quad H_b(W_k) = \sum_{k=1}^{K} P_k * \log_2 P_k^{-1}$$

and total within-set entropy is:

$$(21)\quad H_w(W_k) = \sum_{m \in k} P_m / P_k * \log_2 P_k / P_m$$

Using (3) the extent of total spatial dispersion of all product innovations can be derived; with (4) the extent of spatial dispersion product innovations among the product categories can be derived and with (5) the extent of spatial dispersion of product innovations within each product category can be derived.

Multidimensional entropy metrics can also be derived. Suppose that we observe two events, X_m and Y_n, and there are M number of event X variants and N number of Y variants. The marginal entropies of each dimension within a total two-dimensional entropy measure are equal to the total entropy of each dimension:

$$(22)\ H(X) = \sum_{m=1}^{M} P_m * \log_2 P_m^{-1},\ P_m = \sum_{n=1}^{N} P_{mn}$$

$$(23)\ H(Y) = \sum_{n=1}^{N} P_n * \log_2 P_n^{-1},\ P_n = \sum_{m=1}^{M} P_{mn}$$

Total two-dimensional entropy is

$$(24)\ H(X,Y) = \sum_{m=1}^{M} \sum_{n=1}^{N} P_{mn} * \log_2 P_{mn}^{-1}$$

We can also calculate conditional entropy metrics, which measures the amount of entropy in one dimension given the occurrence of a particular variant of some other dimension. The calculation of conditional entropy statistics is similar to the calculation of within-set entropy.

Entropy in X given Y_m:

$$(25)\ H(X \mid Y_n) = \sum_{m=1}^{M} {}^{P_{mn}}\!/_{P_n} * \log_2 {}^{P_n}\!/_{P_{mn}}$$

Entropy in Y given X_n:

$$(26)\ H(Y \mid X_m) = \sum_{n=1}^{N} {}^{P_{mn}}\!/_{P_m} * \log_2 {}^{P_m}\!/_{P_{mn}}$$

The average conditional entropies are:

$$(27)\ H(X \mid Y) = \sum_{n=1}^{N} P_n * H(X \mid Y_n)$$

$$(28)\ H(Y \mid X) = \sum_{m=1}^{M} P_m * H(Y \mid X_m)$$

Average conditional entropy is always less than or equal to unconditional marginal entropy or $H(X \mid Y) \le H(X)$ and $H(Y \mid X) \le H(Y)$. $H(X \mid Y) = H(X)$ and $H(Y \mid X) = H(Y)$ if and only if X and Y are independent.

Defining Multidimensional Entropy

Multidimensional entropy equals the sum of marginal entropies minus expected mutual dependence and expected mutual dependence is equal to marginal entropy in a particular dimension minus the average conditional entropy in a particular dimension given the occurrence variation in another event. Using these defined probabilities, distributions can be constructed and marginal, conditional and total two-dimensional entropy measures per time period calculated.

Total two-dimensional entropy can also be disaggregated into between-set and within-set entropies in the same manner as one-dimensional disaggregation as defined in equations (3) through (5). Suppose we wanted to aggregate the occurrence of organic adoptions at each quality level up to the occurrence of whether they receive the permission to use the NOP seal and to aggregate food categories into their respective industry sectors. Total two-dimensional entropy can be disaggregated into two-dimensional between-set entropy and two-dimensional within-set entropy using the following equations, total 2D entropy:

$$(29)\ H(X,Y) = H(W,Z) + \sum_{k=1}^{K}\sum_{l=1}^{L} P_{kl} * H(X,Y \mid W_k, Z_l)$$

Total between-set entropy:

$$(30)\ H(W,Z) = \sum_{k=1}^{K}\sum_{l=1}^{L} P_{kl} * \log_2 P_{kl}^{-1}$$

and total within-set entropy:

$$(31)\ H(X,Y \mid W_k, Z_l) = \sum_{m\in k}\sum_{n\in l} \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} P_{mn}}{P_{kl}} \log_2 \frac{P_{kl}}{\sum_{m=1}^{M}\sum_{n=1}^{N} P_{mn}}$$

