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 a supply chain. 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.

Key Words: First-mover strategy, food product innovation, entropy, organic

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Innovation in Food Products

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. Intangible resources of the firm, such as intellectual property, are more likely to lead to a sustainable competitive advantage over rivals than tangible assets. The cost of building and maintaining a differentiation strategy tends to undervalue returns to the R&D expenditures.

A successful differentiation strategy through R&D expenditures results in subsequent first-mover decisions. That is, if a first-mover possibility arises for the food manufacturer as a result of their R&D then it confers the right 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.

The objective of this research is to investigate food product innovation in the context of the first-mover strategy among food manufacturers within a supply chain. 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.

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, et al). 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. 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.

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. Finally, 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.

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 (Lieberman; 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.

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 are often sustainable for the pioneering product. In the aggregate, market pioneers deploy innovative strategies with high initial costs and risks, but yield high potential returns.

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 new products or developing new markets. First-mover strategy is a common dilemma for managers and has special importance when the product is in the experience goods category.

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). 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. Useful levels of analytic aggregation include product lines that are grouped into food categories, industry sectors, and even national boundaries. Each food category is a mutually-exclusive element of a particular food industry sector.

Entropy Applied to 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 agribusiness's product/brand manager made a decision: whether to adopt organic practices or not.

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 agribusiness. Expectations and anticipations can be impacted 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 impacts expectations and anticipations.

For example, the National Organic Program (NOP) was initiated in 2002 by the USDA with the intent of defining what it means to be *organic* and to establish a national-level third-party voluntary quality assurance certification process quality standard. The goal of NOP is to substantiate and standardize organic labeling in order to provide all 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, which 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 of entry to the adopter's current and future potential competition and a substantiation of the quality of the adopter's product line.

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. 2006). It is also 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 anticipated cost at the *100% Organic* level is expected to be the highest among the set of organic levels, it is expected that an increasing share of the organic product innovations released into the market will claim to be *Organic*, or only exert enough effort to achieve the 95% organic content threshold in order to get 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. Specifically, expectations about potential net earnings from adoption will 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 (i.e.; milk, cheese, yogurt, bread products, cola, etc). 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 industry sector, where each food category is an exclusive element of the industry sector. Similar agribusinesses are aggregated into food-type categories (which roughly denote the firm's industry) and further grouped into food-processor sectors (five-digit NAISC sectors).

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 firms and sectors. Further, adoption will be impacted 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 to be a viable source of a sustainable advantage, adoption rates across food categories and industry sectors should converge. Thus, it is expected that the relative variance in process innovation adoption rates across food categories and industry sectors will decrease over time.

Designing entropy metrics to analyze food innovation allows 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.

Calculation of Entropy

The probability of the occurrence of a given event is inversely related to the uncertainty, or the degree of expected surprise. An event that is certain to occur implies that the event occurring has a probability of one. As a consequence, the information content or degree of surprise and knowledge gained is zero in this instance. As the probability of an event occurrence decreases from one to zero, surprise goes from zero to infinity at an exponentially decreasing rate.

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:

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

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:

$$(2)\quad H(X) = \sum_{m=1}^{M} P_m * \log_2 P_m^{-1}$$

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

$$\sum_{m=1}^{M} 1/M * \log_2 M = M * 1/M \log_2 M = \log_2 M .$$

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* $k = 1 \ldots K$*).*

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:

$$(3)\quad H(X) = H_b(W_k) + \sum_{k=1}^{K} P_k * H_w(W_k)$$

Total between-set entropy is:

$$(4)\quad H_b(W_k) = \sum_{k=1}^{K} P_k * \log_2 P_k^{-1}$$

and total within-set entropy is:

$$(5)\ H_w(W_k) = \sum_{m \in k} {P_m}/{P_k} * \log_2 {P_k}/{P_m}$$

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:

$$(6)\ H(X) = \sum_{m=1}^{M} P_m * \log_2 P_m^{-1},\ P_m = \sum_{n=1}^{N} P_{mn}$$

$$(7)\ H(Y) = \sum_{n=1}^{N} P_n * \log_2 P_n^{-1},\ P_n = \sum_{m=1}^{M} P_{mn}$$

Total two-dimensional entropy is

$$(8)\ H(X,Y) = \sum_{m=1}^{M}\sum_{n=1}^{N} P_{mn} * \log_2 P_{mn}^{-1}$$

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:

$$(9)\ H(X \mid Y_n) = \sum_{m=1}^{M} {P_{mn}}/{P_n} * \log_2 {P_n}/{P_{mn}}$$

Entropy in Y given X_n:

$$(10)\quad H(Y \mid X_m) = \sum_{n=1}^{N} P_{mn}/P_m * \log_2 P_m/P_{mn}$$

The average conditional entropies are:

$$(11)\quad H(X \mid Y) = \sum_{n=1}^{N} P_n * H(X \mid Y_n)$$

$$(12)\quad H(Y \mid X) = \sum_{m=1}^{M} P_m * H(Y \mid X_m)$$

Average conditional entropy is always less than or equal to unconditional marginal entropy or $H(X \mid Y) \leq H(X)$ and $H(Y \mid X) \leq H(Y)$. $H(X \mid Y) = H(X)$ 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.

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 M = 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

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

and the probability of W_k is

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

where Y_{ne} is the event that a product line innovation is organic and is of food type n where N = 58, the number of food type categories n. Each Y_m can be aggregated into mutually exclusive sets of related event variants Z_l, which is the event that a product line innovation is organic and is produced by industry sector l where $l = 1\ldots L$, L = 9 food industry sectors. The probability of Y_n is

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

and the probability of Z_l is

$$P_l = \sum_{n\in l} P_n = \sum_{n\in l}\sum_{m=1}^{M} P(X_m \cap Y_n) = \sum_{n\in l}\sum_{m=1}^{M} P_{mn}\ .$$

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

$$P_{mn} = P(X_m \cap Y_n)\ ,$$

the probability an organic adoption is X_m and Z_l is

$$P_{ml} = P(X_m \cap Z_l) = \sum_{n\in l} P(X_m \cap Y_n)\ ,$$

the probability an organic adoption is W_k and Y_n is

$$P_{kn} = P(W_m \cap Y_n) = \sum_{m\in l} P(X_m \cap Y_n)$$

and the probability an organic adoption is W_k and Z_l

$$P_{kl} = P(W_m \cap Z_l) = \sum_{m\in 1}\sum_{n\in l} P(X_m \cap Y_n)\ .$$

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:

$$(17)\ H(X,Y) = H(W,Z) + \sum_{k=1}^{K}\sum_{l=1}^{L} P_{kl} * H(X,Y \mid W_k, Z_l)$$

Total between-set entropy:

$$(18)\ \ H(W,Z) = \sum_{k=1}^{K}\sum_{l=1}^{L} P_{kl} * \log_2 P_{kl}{}^{-1}$$

and total within-set entropy:

$$(19)\ \ H(X,Y \mid W_k, Z_l) = \sum_{m\in k}\sum_{n\in l} \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} P_{mn}}{P_{kl}} \log_2 \frac{P_{kl}}{\sum_{m=1}^{M}\sum_{n=1}^{N} P_{mn}}\ .$$

As stated above, absolute rates of adoption across organic content levels, food categories and industry sectors will inherently vary 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 will also vary and carry little additional information pertaining to changes in adoption rates. In order 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:

$$(20)\ \ R(...)_t = \frac{H(...)_t}{\log_2 N_t}\,,$$

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 (20), relative entropy metrics per time period can be derived in order to empirically test whether relative adoption rates across a particular dimension, set of dimensions, or across a particular dimension given the occurrence of a particular variant of another event dimension are behaving in accordance to preliminary expectations. The chosen functional form of the proposed relationship between relative entropy and time will be linear unless otherwise stated. Below is the list of propositions this study will examine and test for statistical significance.

R(X) and *R(W)* is initially increasing over time, reaches a maximum value, and then decreases. This reflects the temporal shift away from non-qualifying process adoptions and toward qualifying adoptions. Before 2002, most organic product innovations will not be certified because the process innovation was introduced in 2002. Over time, more product innovations will bear the seal, reflecting product manager's rising expectations of benefits and lower costs faced by the decision maker.

R(Y) and *R(Z)* is increasing over time due to intra- and inter-industry learning. Yet since information diffuses through food categories and industry sectors at different rates due to external market factors, expectations and anticipations still vary. Competitive advantages tied to path dependency and inter-industry learning network complexity fuels variance in adoption rates across food categories and organic qualification levels, which are also reflected in the categorical variance in the cumulative number of previous adopters. Thus, it is expected that relative two-dimensional entropy will also decrease over time. (*R(X,Y)*, *R(X,Z)*, *R(W,Y)* and *R(W,Z)* is decreasing over time)

To compare adoption trends across food categories or industry sectors given a particular organic level, the calculation of relative conditional entropies are needed. If we assume that relative entropy in Y given X_m ($R(Y|X_m)$) and Y given W_k ($R(Y|W_k)$) to be a linear function of time or

(21) $$R(Y \mid X_m)_t = \alpha_{Ym} + \beta_{Ym} * t$$

and

(22) $$R(Y \mid W_k)_t = \alpha_{Yk} - \beta_{Yk} * t$$

where Δ_{Ym} is the change in relative conditional entropy in Y given X_m, and Δ_{Yk} is the change in relative conditional entropy in Y given W_k.

Hypotheses

It is expected that the variance in seal qualified adoption rates across food categories will decrease over time. Thus, the likelihood that a given product innovation will bear the organic seal will become less dependent on the industry origin of the product. In order to test this, we explore the relative conditional entropy in Y given X_m, when $m = 1$ or 2, and if the relative conditional entropy in Y given W_k, when $k = 1$, is positively related to the time period of the product innovation's release into the market.

It is also expected that the variance in non-qualified adoptions across food categories will increase 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. In order to test the above proposition, we explore the relative conditional entropy in Y given X_m, when $m = 3$ *or* 4, and if the relative conditional entropy in Y given W_k, when $k = 1$, is negatively related to the time period of the product innovation's release into the market.

Given the above relative conditional entropies hold, the relative average entropy in Y given X and the relative average entropy in Y given W over time will reflect the temporal shift away from lower organic qualification levels and toward seal-certified organic process adoptions. Thus, the relative average entropy in Y given X and the relative average entropy in Y given W will initially decrease as early adopters are just beginning to learn of the certification process and will reach a local minimum entropy at some point within the observed time period and increase thereafter.

A clustering of adoptions at the 95% organic content level is apparent over time. In addition, there is a clustering of adoptions occurring at the 95% level of organic qualification and above level over time and in turn an increasing number of new organic processed foods that are eligible to use the NOP seal over time.

It is expected that a given food category's innovativeness (in terms of the rank of the absolute number of product innovations released during the observed time period) is negatively related to relative conditional entropy in the organic content level dimension given the occurrence of each food category. Thus, the dominance of a particular organic level variant within a particular food category decreases as the number of new products per food category increases. This may be expressed as OLS regression

$$R(X \mid Z_l)_t = \alpha_{Xl} - \beta_{Xl} * t$$

where Δ_{Xl} is the change in *r*elative conditional entropy in *X* given $Z_{l.}$

Data and Results

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. The data consist of a total global population of over 320,000 innovations since 2000 and a total US population of over 57,000 innovations as of July of 2006. A simple search function can separate products using certain quality claims with results including: product name, description, time of product release, variants (flavors, sizes, etc.), ingredients and nutritional information, food categories and subcategories which closely correlate to food manufacturing industries, distribution channels in which the new product is offered and price in local currency and Euros. There are 25,340 new US food products within the 14 chosen food categories (out of GNPD's 29 defined categories). These data are used to empirically estimate entropy metrics for organic food products in the United States. These regressions empirically test selected hypotheses regarding innovation, the role of innovation propagators, and first-mover strategy.

Results of the OLS regressions are provided in Figures 2 and 3. The graph of Figure 2 illustrates the relationship and robustness of predicting the number of organic new products within a food category. The horizontal axis of the graph indicates the number of new organic products per food category. The vertical axis is the entropy metric of relative conditional entropy. In a similar way, Figure 3 provides the outcome from predicting the number of organic products within a five-digit NAICS food industry. Figure 3 is based on the industry compared to the results of Figure 2 which are based on individual food product categories. The two graphs illustrate the usefulness of calculating relative conditional entropy based on meaningful categories or divisions within the GNPD data.

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 is relying on a pharmaceutical company ingredient supplier for technological application knowledge. Such cross-chain relationships carry important implications for 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.

Figure 2. Firm Strategy Matrix Across Market and Product Alternatives

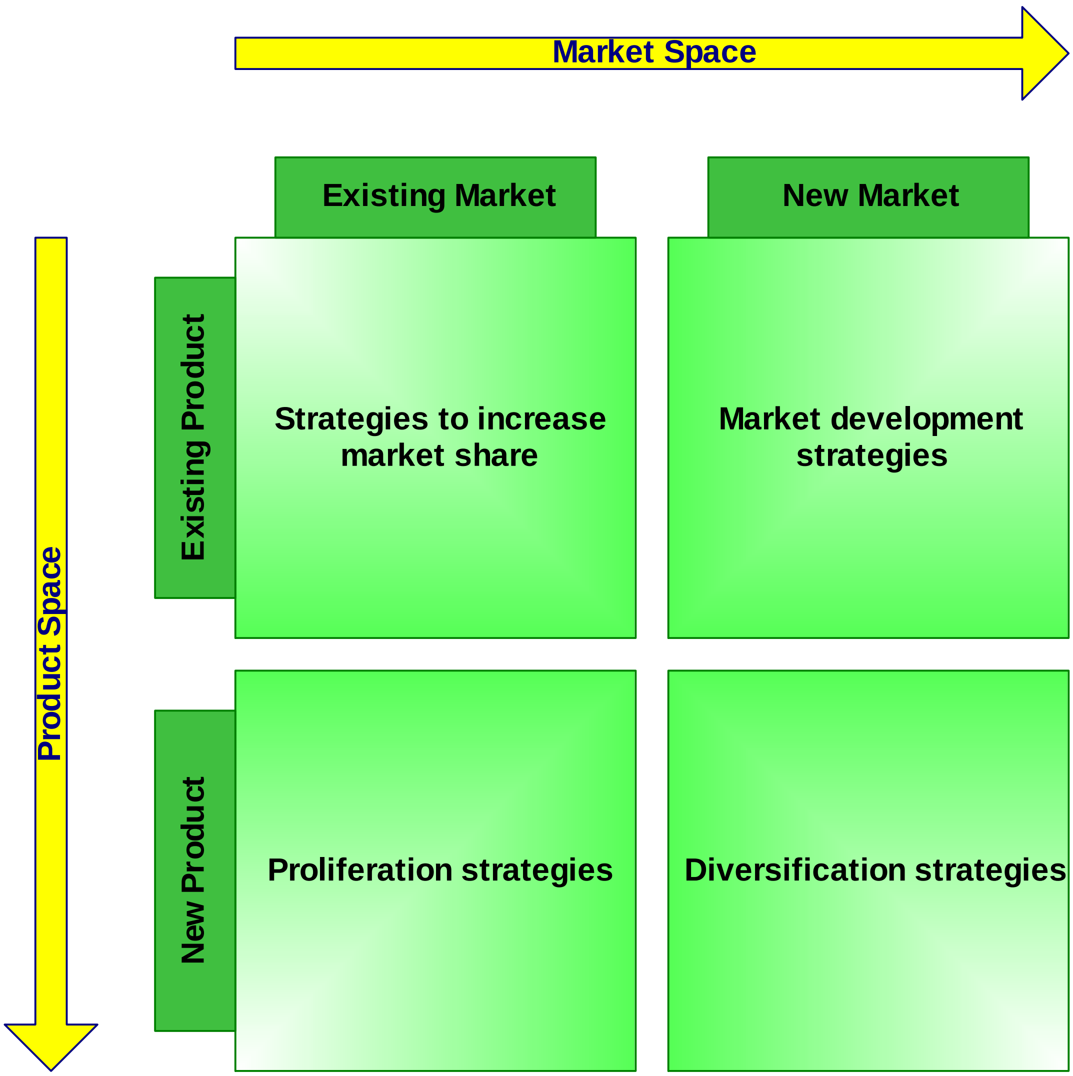


Figure 2. Relative Conditional Entropy in Xm given Yn: All Years

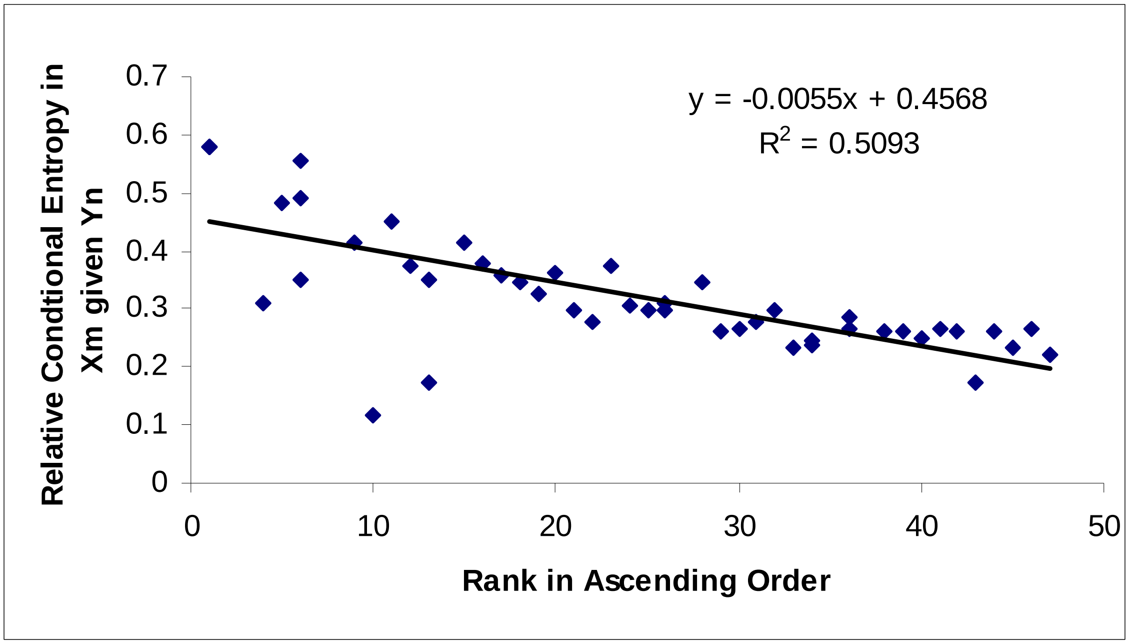
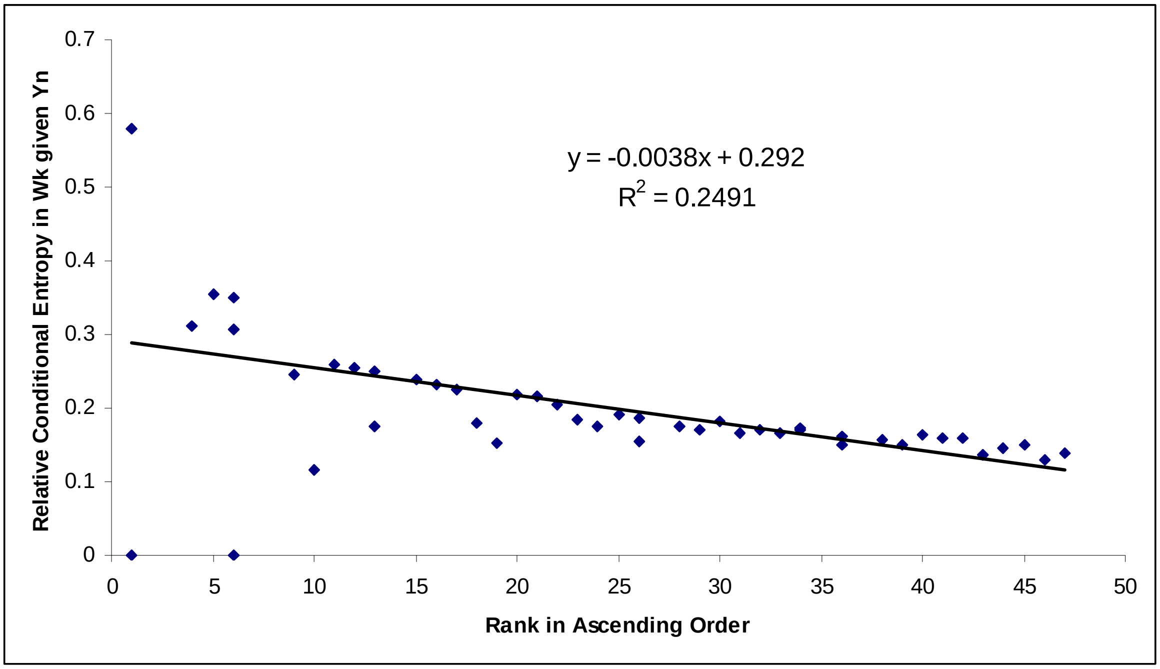


Figure 3. Relative Conditional Entropy in Wk given Yn: All Years



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