New Product Development in Thai Agro-Industry: Explaining the Rates of Innovation and Success in Innovation[*]

Pisit Dhamvithee [a][①], Bhavani Shankar [b], Anuvat Jangchud [c] and Phaisarn Wuttijumnong [d]

[a] *Lecturer, Department of Product Development, Faculty of Agro-Industry, Kasetsart University, Jatujak, Bangkok 10900, Thailand.*

[b] *Lecturer, Department of Agricultural and Food Economics, PO Box 237, University of Reading, Reading RG6 6AR, United Kingdom.*

[c] *Assistant Professor, Department of Product Development, Faculty of Agro-Industry, Kasetsart University, Jatujak, Bangkok 10900, Thailand.*

[d] *Assistant Professor, Department of Product Development, Faculty of Agro-Industry, Kasetsart University, Jatujak, Bangkok 10900, Thailand.*

Abstract

The Thai food industry is amongst the most dynamic and diverse in the world. Continual innovation in the form of new product development is critical to this industry, and yet new products are more likely to fail than succeed. In this paper, we investigate factors explaining both the rate of new product development as well as the rate of success in products newly introduced into the market, using data from a survey of firms. The methodology involves a Poisson regression to investigate the determinants of innovation and a Least Squares regression to explain success rates in innovation.

Keywords: New product development, Thailand, food industry, innovation.

Motivation and Objectives

The Thai food industry is amongst the most dynamic and diverse in the world. The sector contributes significantly to Thailand's growth and prosperity. 14.4 % of the country's total exports originate from the food sector, and Thailand earns nearly US $10 billion annually from food manufacturing (National Food Institute of Thailand, 2002). The sector has a direct or secondary effect on the employment of some 20 million people. Since the 1970's, the Thai food industry has been moving away from being a traditional primary commodity producer and exporter, to specializing in processed food production for home and export markets. This has been accompanied by very rapid growth in the food sector, with some 9000 food factories in existence currently. Recognizing the potential of the food sector, the Thaksin Shinawatra government has included the food industry in its set of five special 'clusters' that are viewed as drivers of industrial growth (the other four are automotives, fashion, tourism and software). The motto accorded to the food cluster is 'Kitchen to the world'.

The Thai food sector cannot afford to be complacent, however. A host of other countries are competing for the same export markets; nor is the home market particularly captive. With rising incomes and urbanization, Thai consumers are demonstrating sophisticated consumption patterns and choices. In this situation, multinationals are often able to quickly and successfully bring in products developed elsewhere for local adaptation (Suwannaporn and Speece, 2003). Continual innovation in the form of new product development (NPD) is therefore critical for the survival and propagation of firms in this sector.

A very large literature exists on NPD success factors in other industries and countries. Food sector NPD rates and determinants are often quite different from those in many other typically studied industries, such as automotive and 'heavy' industries. However, the literature on factors influencing innovation and innovative success in Thai food production is thin. Suwannaporn and Speece (1998, 2000, 2003) have recently kick-started this research agenda by looking at Thai food NPD success factors from a variety of angles. Their valuable stream of research seems the only NPD work adapted specifically to Thai food sector realities. In Suwannaporn and Speece (1998), they analysed results from a set of in-depth interviews and case studies to qualitatively characterise the NPD process in the industry. In Suwannaporn and Speece (2000), they used similar data to develop a conceptual model of continuous learning in Thai food NPD. In Suwannaporn and Speece (2003), they provided a more quantitative dimension to their research by looking at factors influencing NPD success rates across firms using survey and likert scale data on NPD practices.

In this paper, we attempt to advance this literature in some important ways. First, we quantitatively explore the determinants of product innovation across Thai food firms. The only previous quantitative work, that of Suwannaporn and Speece (2003), related to success factors in NPD. In the first part of our paper, we instead go back to a more basic question: what determines how much innovation happens across in the first place? This is accomplished using a Poisson regression framework on new product counts during our study period. Secondly, we revisit the same question raised by Suwannaporn and Speece (2003), i.e., what determines success rates in NPD across Thai food firms? However, we take a different methodological approach, choosing to continuously model the NPD success rates in a regression framework instead of dichotomizing the success variable as in their case. Thirdly, we also exploit the industrial economics literature on innovation, while their studies have been predominantly based on concepts from the management and marketing literatures.

We proceed by discussing the data in section 2. Section 3 presents the Poisson regression framework and the results explaining the rate of NPD innovation. In section 4, we turn to the results from applying the regression to model new product success rates. Section 5 summarizes and discusses the main implications of the study. Instead of reviewing previous literature in a separate section, we choose to weave such discussion into the individual sections on explaining innovation and innovation success.

Data

Very little secondary firm-level data is available in developing countries, and this is also true of the Thai food industry. Information is not typically available even on basic firm statistics such as turnover, product development expenditure and assets. Firms are also understandably reluctant to release exact numbers and hard data. They are more amenable to providing categorical information and scale ratings. Our data comprise a mixture of categorical information on basic firm level variables, as well as a series of Likert scale ratings on NPD practices and company competencies and links. These data derive from a formal questionnaire-based survey of Thai food companies. A list of such companies compiled by FOSTAT (2002) was used to randomly select 400 firms to which the postal surveys were sent. The questionnaire, administered in 2002/2003, requested information on counts of new products developed during the year 2001, the respondent's rating of proportions of successful products, basic firm level variables (mostly categorical), as well as a series of Likert scale questions on various details relating to NPD and related practices and company competencies. The Likert scale questions were developed on the basis of factors indicated by previous research as important (Suwannaporn and Speece, 1998, 2000, 2003; Song and Parry, 1997). For the purposes of this research, the definition of a new product is based on the definition used in Martin and Mitchell (1998) and Katila and Ahuja (2002). According to this definition, a new product is

one that involves a non- trivial change in a product's design characteristics. This matches broadly with the criteria used by Suwannaporn and Speece (1998), specifying that minor improvements, cost reductions and repositioning do not count.

The survey instrument was developed in several rounds. The first draft was pre-tested with managers from 30 food companies. Particular care was taken to ensure that the meaning of each question was carefully understood, particularly when it came to defining new products and the variables relating to NPD practice. These pre-test respondents made a number of suggestions that incorporated into a second draft. This second draft was again tested on 5 respondents, resulting in further, albeit more minor, modifications. The final, third draft was sent as a postal survey to the randomly selected firms. The cover letter requested that the survey be completed by a senior person or team with substantial involvement in NPD activities in the company. More than 200 responses were received after follow-up reminders. After data cleaning, deletion of records with significant missing data, etc, 93 responses are available for full statistical analysis. Table 1 presents summary statistics for the major variables used in our analysis.

Modeling the Determinants of Innovation

Introduction

There is a substantial literature on modeling the extent of innovation in industries by conducting regression analysis on patent data (e.g., Hausman, Hall and Griliches, 1984.). Patents are only one of a set of several possible indicators of innovation. However, their definition is clear and based on norms established by regulatory authorities. Patent data are also often relatively easy to obtain from secondary sources. These are possible reasons for the predominance of patent-based empirical models of innovation. Occasionally, researchers have studied the determinants of broader definitions of innovation, including product as well as process innovations. For example, Cabral and Traill (2001) attempted to explain 'innovation counts' in the Brazilian food industry.

NPD data are relatively harder to obtain than patent data, and therefore the literature on modeling the level of NPD activity is smaller. Katila and Ahuja (2002) modeled the number of new products introduced in the industrial robotics industry in Europe, Japan and North America, using Poisson regression methods and interpreted their results using concepts from organizational learning theory. Siegel, Westhead and Wright (2003) used count data methods and an UK cross-industry dataset to explain the influence of 'science park' location of firms on the number of new products developed. Rogers (2000) explained new product introduction in Australian manufacturing using variables such as market structure and export status.

Table 1: Summary Statistics of Main Variables

VARIABLES	Mean	Sandard Deviation
Count variables		
• Numbers of new products developed in study period (NEWPRODUCTS)	6.2	6.4
• Number of new products that succeeded	2.6	2.3
Likert scale variables (10=extremely important/followed extremely carefully/very widely used/high intensity, 0=not followed at all/never used/very low intensity)		
Good NPD Practice		
• Intensity of planning in the NPD process (PLANNING)	7.9	1.6
• Frequency of Milestones in NPD process (STEPPING)	7.5	1.7
• Resources devoted to launching the product (LAUNCHING)	7.6	1.8
Cross Functional Communication		
• Strength of relationship and communication between PD and Marketing (PD & MARKETING)	7.9	1.8
• Strength of relationship and communication between PD & Production (PD & PRODUCTION)	8.1	1.7
• Strength of relationship and communication between Production & Marketing (PRODUCTION & MARKETING)	7.9	1.7
Firm Competencies		
• Firm competence in production (PRODUCTION)	8.3	1.5
• Firm competence in management (MANAGEMENT)	7.4	1.9
• Firm competence in PD (DEVELOPMENT)	7.5	1.9
Continuous variables		
• Age in years (AGE)	17.7	11.6

CATEGORICAL VARIABLES	%
• Independence (INDEPENDENCE)	
0 = Independent	88
1 = Part of Conglomerate/Multinational	12
• Firm size (EMPLOYEE)	
1 = Less than 100 persons	26.8
2 = 101-200 persons	10.7
3 = 201-300 persons	10.7
4 = 301-400 persons	7.5
5 = 401-500 persons	6.4
6 = more than 500 persons	37.6
• Number of perceived competitors on market (COMPETITION)	
1 = Less than 5	22.5
2 = 6-10	39.7
3 = 11-15	7.5
4 = More than 15	31.1
• Subsector-wise breakup	
1. Grains and Tubers	15.8
2. Meat and Poultry	3.7
3. Fruits & Vegetables	3.0
4. Dairy	4.6
5. Fat & Oil	7.4
6. Confectionery	2.7
7. Fish	21.3
8. Other	33.4

Poisson Regression Methodology

A special statistical problem arises in modeling 'counts' of discrete data such as new products and patents. In these cases, it is important to recognize that data on the dependent variable are different from data in typical regression models in three ways: non-negativity, the prevalence of a higher proportion of zeros, and the integer nature of the data. Thus basic assumptions of OLS and linear panel data models, such as normality of the residuals are no longer satisfied, and appropriate 'count' data methods have to be used. The most fundamental of these is the Poisson regression model. Suppose NP_i represents the number of new products developed by firm i. The NP_i are assumed to be independently distributed as Poisson, with parameters λ_i, and the λ_i specified as functions of a set of explanatory variables, x_i, i.e.,

$$\text{Prob}(NP=NP_i) = \exp(-\lambda_i) \, \lambda_i^{NP_i} / y_i! \qquad (1)$$
Where
$$\lambda_i = \exp(x_i\beta) \qquad (2)$$
The conditional expected value of NP_{it} is given by
$$E(NP_i \mid \beta, x_i) = \lambda_i \qquad (3)$$

Thus, although the estimated β indicate the direction of the marginal effect of the associated explanatory variables, the magnitude of the marginal effect has to be calculated at a chosen point, such as sample mean values. The variables included to explain the number of new products developed were chosen on the basis of indications from previous literature. These are discussed below.

Previous Literature and Choice of Variables

Firm Size (Number of Employees)

Larger firms are likely to have better cash flow and capital market access essential for introduction of new products, and may be able to spread the fixed costs of innovation more easily. On the other hand, smaller firms may be quicker to recognize opportunities (Rogers, 2000). Mixed results have been found in previous studies of firm size and innovation, and hence generalizations are difficult to draw (Katila and Ahuja, 2002). Cabral and Traill (2001) note that the relationship between firm size and innovation depends on the empirical context, industry or sector, although most food industry studies have found that large firms are more likely to innovate. Galizzi and Venturini (1996) and Huiban and Boushina (1998) are examples of food industry studies that have confirmed a strongly positive relationship between size and innovation. In the specific context of Thai food manufacturing, Suwannaporn and Speece (2003) indicate that smaller Thai firms are unlikely to indulge in much innovation. Hence, we may expect a positive

relationship between firm size and the number of new products introduced in the year, although a contrary result cannot be ruled out. As in Katila and Ahuja (2002) and Cabral and Traill (2001), we use number of employees as proxy for firm size.

Firm Age

An argument could be made that older, more established firms that have established flagship products and brands may be able to 'coast' on such products, finding little need for constant innovation. Newer firms are more likely to face the pressure to experiment and innovate frequently to discover an optimal product profile. On the other hand, Cabral and Traill (2001) hypothesize that older firms may find it easier to innovate due to accumulated knowledge.

Independence

Previous research indicates that ownership structures can influence innovation (Bishop and Wiseman, 1999). Suwannaporn and Speece (1998) have noted that multinationals may be able to quickly adapt products that are successful elsewhere for local Thai conditions, an option that is not easily available to independent local firms. Conglomerate/multinational ownership may thus provide access to a larger pool of financial resources, as well as a transferable pool of ideas to fund and promote innovation. On the other hand, innovative activities are often homespun. Firms that are closer to the ground and that are able to take advantage of immediate opportunities without requiring approval from a long chain of command may be more innovative. Externally owned units often have a low level of autonomy, and decisions regarding innovations are likely to be made at corporate rather than local levels (Hamilton, 1998; Bishop and Wiseman, 1999). For instance, Harris (1988) and Love et. al. (1996) find that externally owned branch entities are often missing R&D functions, resulting in a negative relationship between independence and innovation. To test this hypothesis, we use a simple dummy representation for the independent variable, with 0 indicating independence and 1 representing ownership by a conglomerate or a foreign entity.

Competition

The industrial organization literature has long debated the influence of competition on innovation. The Schumpeterian view holds that limited competition is conducive to innovation. Geroski (1990) divides this market power-innovation relationship into two parts: one, the effect of anticipated market power on innovation, and the second, the effect of actual market power on innovation. Anticipated market power may encourage innovation in the sense that, if the new product confers a degree of monopoly power to the firm that is currently in a competitive market, the firm can enjoy supernormal profits. As Geroski notes, this notion is straightforward and hard to dispute. In the Thai food industry, however, competing firms are quick to copy

successful innovations, and so anticipated market power solely due to the introduction of a new product is unlikely to be significant. This is exacerbated by the fact that intellectual properties are generally inadequately protected in Thailand. Actual market power may influence innovation in two ways. One is a direct effect that is related to the firm size variable discussed above. Firms with market powers tend to be large and possessed of substantial funds. They may thus be able to hire better personnel and have sufficient internal resources to take advantage of potential market opportunities. The indirect actual market power effect arises from the fact that firms that currently have market power are more able to erect barriers to entry that keep away imitators of their innovations. Given their adequate financing, firms currently possessing market power are able to create unique brand images that allow them to enjoy market power from the innovation even in the face of quick imitation.

However, Geroski (1990) has argued against this Schumpeterian view. The first counterargument is based on the familiar notion of monopoly 'x-inefficiency'. The lack of competition can breed a lack of initiative, depressing innovation rates[1]. Secondly, the process of innovation itself can be fostered by several firms searching simultaneously for new breakthroughs. Thirdly, innovations produced by firms with market power are often likely to only displace the market share already enjoyed by their own older products, a factor which could discourage NPD by these firms. The independent variable used in testing the market power-innovation hypothesis here is a categorical variable where each respondent was asked to choose a category containing the number of key competitors they faced in their principal market.

Food Sub-sector

The rate of innovative activity is likely to differ across food industry sub-sectors. Innovation in the Thai food industry has already been shown to be tied to product groupings by Suwannaporn and Speece (1998). For instance, production of confectionery products requires constant innovation to satisfy the demands of bakeries and restaurants, which in turn need to segment their market quite extensively to cater to very heterogeneous tastes. On the other hand, products that serve as ingredients or raw material in further food production are unlikely to require substantial innovation beyond developing a good basic product. We asked all respondents to indicate which of the following groups they felt their firm would fit into best: grain, meat, fruits, dairy, fat/oil, confectionery and fish-based. Those who felt their organization did not fit easily into one of these categories, or those who felt more than one category was appropriate to them, were classified under 'other'. Grain is taken as the 'base' category, and all other categories are introduced as dummy variables measured against this base.

---

[1]In Geroski's own words, 'Managers may exhibit a preference for leisure and become sleepy'!! (Geroski, 1990, page 587).

Results

Table 2 below provides OLS results in the first column, Poisson regression results in the second, and Poisson marginal effects in the third. Goodness of fit and overall model specification tests are reported at the bottom of the table.

Table 2: OLS and Poisson Regression Results for Number of New Products Introduced§

Variable	OLS Estimate	Poisson Estimate	Poisson Marginal Effect
Constant	4.30 (2.69)	1.56 (0.16***)	9.49
Meat	3.38 (2.82)	0.33 (0.15**)	2.01
Fruits	1.50 (2.17)	0.23 (0.13*)	1.39
Dairy	-0.03 (3.00)	-0.07 (0.21)	-0.42
Fat/Oil	-2.38 (2.49)	-0.66 (0.21***)	-3.98
Confectionery	3.30 (3.35)	0.35 (0.19*)	2.10
Fish-Based	2.82 (1.92)	0.38 (0.11***)	2.31
Other	2.34 (1.73)	0.32 (0.10***)	1.96
Independence	0.06 (0.43)	0.01 (0.02)	0.04
Age	-0.03 (0.05)	0.00 (0.00)	-0.03
Employee	0.68 (0.35*)	0.11 (0.02***)	0.65
Competition	-0.86 (0.60)	-0.15 (0.04***)	-0.93
R^2	0.13		
F statistic	1.42		
Chi-squared		112.8***	

§ standard errors in parenthesis
*** significant at the 1% level, ** at the 5% level, and * at the 10% level.

A broad comparison of OLS and Poisson regression results shows striking differences. The OLS model performs poorly overall, with only one parameter significant, and that only at the 10% level. The Poisson parameters are seen to be estimated much more precisely, with 9 out of 12 parameters significant at least at the 10 level, and 6 parameters significant at the 1% level. The R squared for the OLS regression shows that only 13% of the variation in new product introduction is explained by the model, and the F test for the null hypothesis that all variables are jointly insignificant cannot be rejected at the 5% level. On the other hand, the counterpart chi-square statistic for the Poisson regression model is significant at the 1% level, strongly rejecting the null hypothesis that all the model variables are jointly insignificant. Thus we conclude that the Poisson model significantly improves on a simple linear specification.

In accordance with our expectations, there are strong 'sub-sector' specific effects in new product introduction rates in our sample of Thai food firms. Recalling that the

grain and tubers sub-sector is at the base of our estimation, we can see that the meat, fruit, confectionery and fish-based sub-sectors all have higher rates of innovation compared to the grain sub-sector, even controlling for the influence of other variables in our regression. The fat/oil sector is seen to have lower innovation than grain, while dairy is not significantly different. As discussed before, Thai confectionery producers constantly feel the need to keep up with changing consumer tastes and to segment an overall market with very heterogeneous preferences. The meat, fruit and fish-based sub-sectors are strongly export oriented. Much of Thailand's recent success in food exports derives from the processing of fruits, prawns and meats into packaged products for Asian as well as worldwide markets. Given the heterogeneity and sophistication of preferences in these export markets, there is a corresponding need for continuous innovation. On the other hand, the grain/tuber, dairy and fat/oil sub-sectors produce basic, staple commodities largely for domestic consumption, for which there is little need to diversify from a good basic product.

The effect of increasing firm size on innovation is confirmed by the positive and strongly significant parameter attached to the employee proxy variable. This validates the statement by Suwannaporn and Speece (2003) that smaller Thai food firms are not inclined to be innovative. Interestingly, the coefficient for number of competitors is negative and highly significant, suggesting that lowered competition provides impetus for more innovation in the Thai food industry. These signs of the firm size and competition/market power variables can be interpreted as being complimentary to each other. Firms with more market power (less competition) tend to be larger as well, and the signs on the two variables probably reflect a common latent effect. In this Schumpeterian effect, large firms with significant market power have considerable available resources to develop innovations and to successfully erect barriers to entry to enjoy the fruits of such innovation.

Somewhat surprisingly, neither the independence nor the age variables are significant. With both variables, there could be effects working in opposite directions that nullify each other in the final analysis. Multinationals may often be able to bring in products developed elsewhere for the Thai market, but are also liable to hold-ups and delays when opportunities present themselves, due to long chains of commands and centralized decisions about NPD. Similarly for the age variable, the accumulated knowledge effect may well be cancelled out by the tendency for older firms to coast on established products.

Regression model of NPD success rates

Introduction

Having attempted the explanation of levels of innovative activity in the previous section, we now turn to explaining the rates of success in innovation next. In other

words, we attempt to explain the <u>proportions</u> of new products deemed to be successful by respondents. In terms of the characterization of the dependent variable, this is very similar to Suwannanporn and Speece's analysis of the Thai food industry. Here, as in their case, respondents express the proportion of new products developed during the study period that they would categorize as successful. The methodology used in explaining success rates is very different, however. They used a simple cutoff rate of 20% success to categorize respondents into 'high success' and 'low success' groups. Subsequently, they proceeded to associate these groupings, using cross-tabulations and discriminate analysis, with a range of likert scale responses gathered from their survey. We take a different route. One point of divergence with their approach is based on the view that grouping a continuous variable like success rate into dichotomous categories is not always straightforward since there is no easily determined cutoff point between success and failure. Another issue concerns cross-tabulations. While comparisons of simple groupwise percentages and means can be instructive, controlling for other covariates will usually result in a more reliable characterization of bivariate relationships. Thus we choose instead to continuously model the proportion of success by regressing it on the entire set of relevant covariates. A third significant point of departure is that we include among our covariates a set of objective basic firm level data, as well as a scaling variable.

The explanation of NPD success and failure factors has generated a very large literature, encompassing a variety of disciplinary perspectives and a range of methodologies. Quite often, these are at the level of an individual NPD project (i.e., why particular products have succeeded or failed), and involve financial (profit, sales, etc) or technical objectives underlying the dependent variable measurement of success or failure. Case studies are also numerous in this literature. Suwannaporn and Speece (2003) have investigated the case similar to that analyzed in this section, i.e. the determinants of proportions of successful products across Thai food firms, focusing predominantly on marketing factors. Our purpose is to revisit the marketing related factors pinpointed by them, but also to expand the set of explanatory variables to include other factors that may have a bearing on success rates. The determinants of innovation success rates should logically speaking include a marketing and management dimension beyond the determinants of innovation rates itself. Simply developing and releasing new products may not require extensive marketing and management assets and practice. The function of marketing is primarily to increase the probability of the innovation being successful ones.

Underlying this exercise is the view that quantitative measures of causality from an independent variable to a dependent variable are misleading unless other potentially important factors are controlled for. The previous literature on success factors has been extensively reviewed before (e.g. in Suwannaporn and Speece, 2003 with a marketing focus; and in Montaya-Weiss and Calantone, 1994, with a

business management focus). Hence we refrain from an extensive review in this discussion, limiting ourselves to describing the rationale for the variables chosen.

Choice of Variables

The first three sets of variables described here correspond to critical marketing/management-related factors identified by Suwannaporn and Speece:

Good NPD Practice

Methodically executing NPD based upon a carefully planned approach is likely to raise success rates. Brown and Eisenhardt (1995) discuss the importance of planning and frequency of milestones in good NPD practice. Cooper (1994) stresses the need for research to include this as a separate and important category in the study of success factors. Suwannaporn and Speece (1993) refer to this as a 'strategic' factor, and find that it does have a bearing on success rates in Thai food NPD. Here, the 'Good NPD Practice' factor is represented by 3 Likert scale questions, one on the amount of planning that goes into firm NPD (Planning), the frequency of milestones in firm NPD (Stepping), the attention paid to and resources devoted at the launch of a new product (Launching).

Cross-Functional Communication

With marketing, R&D and production departments of a firm all having keys roles to play in NPD, it is vital that all departments share the same vision and understand and complement each other's roles. Investigating a variety of success factors in Japanese NPD, Song and Parry (1997) find this to be the most critical element. Suwannaporn and Speece's study also finds this to be a vital factor in Thai food NPD success. We represent this factor in this study by three simple Likert scale questions querying the strengths of relationships and frequency of communications between the three pairs of departments: PD and Marketing, PD and production, Marketing and Production.

Firm Competencies

The notion that the quality and ability of key departments should have a bearing on NPD success is easy to accept. However, the measurement of such competencies is more problematic. Song and Parry (1997) attempt to capture these factors in their study of Japanese NPD success by asking managers to rate firm competencies in the three departments involved in NPD. We follow a similar approach, asking for Likert scale ratings on PD competence, Marketing competence and Production competence.

While the marketing/management factors listed above are evidently important in investigating NPD success rates, there appears no reason why more 'basic' firm level variables included as determinants of innovation rates before, should be excluded here. Plausible arguments can be made that each of <u>Independence</u>, <u>Age</u>, <u>Employee</u> (firm size) and <u>Competition</u>, as defined before, should be included in our regression. For instance, increased competition typically provides alternative choices and spurs imitation, and may hence lowers NPD success rates. The same abundance of resources that enables larger firms to carry out more innovation, could also work towards boosting new product success rates. Larger firms may have the reserves to ride out the initial months of turbulence faced by a new product, before the product can establish itself and realize its potential. Smaller firms may not have the luxury of waiting very long, and may be more likely to cut their losses and terminate promotion at an earlier stage.

In addition to the variables on marketing & management practices & competencies, and the firm & market's inherent characteristics above, we also included a scaling variable. The number of new products is included on the right hand side to investigate whether innovation success rates depend on innovation rates in the first place. Such scaling variables are often important when attempting to explain rates of growth or averages or proportions data, as in our case[2].

Methodology

In addition to counts of new products developed during the study period, respondents were also asked to provide information on the number of such products deemed to be 'successful'. Since success can be a subjective and fuzzy term, respondents were prompted to think about a set of common financial (profits, market shares, sales targets) and technical factors that underlie success, for each newly introduced product in turn. The rate of success in new product development is thus a proportion between 0 and 1.

One problem with operationalizing the proposed regression is the large number of independent variables and the consequent lowering of degrees of freedom. This arises particularly because of the large number of Likert scale items. Multicollinearity is another problem that arises due to the proliferation of variables measuring similar latent characteristics. Factor analysis and principal components analysis are common methods for reducing the dimensionality problem in such cases. A typical way to proceed would then be to take the entire set of likert scale items, perform exploratory factor analysis on them, choose a limited number of factors on the basis of eigenvalue criteria, and then set about interpreting the factor/components and using them in the regression. One recurring problem with

---

[2] An obvious example being the average cost function, C/Q being expressed as a function of output, Q.

this approach in applications is that interpretations are not always straightforward when items measuring very different constructs load heavily on to the same factor.

We choose a simpler, more intuitive approach in our case. Instead of performing principle components/factor analysis on the entire set of Likert scale variables, we take each subset (Good PD practice, cross-functional communication, and firm competencies) in turn and perform principal component analysis on the variables within each, attempting to find a single component/factor to represent the subset in each case. Each subset has 3 Likert scale variables, and collapsing these to one factor each would reduce the Likert scale variables from nine to three, considerably easing our dimensionality and co-linearity problems. Since each subset has a natural definition already, the usual interpretation problems do not arise. We are thus using principal components merely as an intermediary step to the regression analysis, rather than as an end in itself. Our purpose is not the uncovering and defining of latent factors. The only function of the analysis is to find linear combinations of variables within already defined subcategories that will explain a significant proportion of the variance (we use a 70% rule of thumb for this) within the subset.

Table 3: Principal Components Analysis of Likert Scale Variables

Principal Component	Eigen-value	Cumulative Proportion of Variance	Variable 1: Loadings	Variable 2: Loadings	Variable 3: Loadings
PD Good Practice					
			Planning	Steps	Launching
1	6.7	0.70	0.59	0.59	0.56
2	2.1	0.91	-0.35	-0.44	0.82
3	0.8	1.00	0.74	-0.66	-0.04
Cross Functional Communication					
			PD & Marketing	PD & Production	Production & Marketing
1	7.6	0.79	0.64	0.54	0.53
2	1.4	0.93	-0.23	-0.53	0.81
3	0.6	1.00	-0.72	0.65	0.21
Firm Competencies					
			Production Competence	Mgmt. Competence	PD Competence
1	7.2	0.71	0.41	0.64	0.63
2	1.5	0.87	0.81	0.05	-0.58
3	1.3	1.00	0.41	-0.75	0.50

Results

Results from the principal components analysis are summarized in table 3. Since each subcategory contains 3 Likert scale variables, the maximum number of components in each case is 3. The results indicate that, in each case, a single component adequately captures the total variance. This is along expected lines since we have only 3 variables in each case, with all three variables designed to measure a common, broader latent variable. In the first subcategory (PD Good Practice), the first component contains 70% of the total variance, and loadings are approximately equal on all 3 variables. In the second subcategory (Cross-functional Communication), the first component explains almost 80% of the total variance, with loadings being broadly of the same magnitude. This pattern is repeated in the third subcategory (Firm Competencies) as well, the first component containing in excess of 70% of total variance, and significant positive loadings for all 3 variables. Thus we are able to confidently proceed in using the 3 principal components in the place of the 9 likert scale variables in the regression.

Regression results are presented in Table 4. In order to further explore the importance of the scaling variable, number of new products (NEWPRODUCTS) on success rates, two regressions are computed: Model one with the scaling variable and the other one, Model two, without. The regression not including NEWPRODUCTS is presented in the second half of the table. Note that sectoral dummies have not been included in these regressions. A full set of such dummies was originally included, but all dummies proved insignificant, and were subsequently dropped since they took up too many degrees of freedom. Thus, unlike in the case of innovation itself, success in innovation appears not to be explicitly sub-sector specific.

Table 4: Regression explaining proportion of successful new products

Variable	Model 1: Including Number of New Products			Model 2: Excluding Number of New Products		
	Estimate	T stat	P value	Estimate	T stat	P value
Intercept	0.78	8.71	<.0001	0.64	5.52	<.0001
Newproducts	-0.03	-7.83	<.0001			
Independence	-0.009	-0.63	0.53	-0.01	-0.47	0.64
Age	0.002	0.98	0.33	0.00	1.11	0.27
Employee	0.02	1.57	0.12	-0.01	-0.62	0.54
Competitor	-0.02	-0.92	0.36	-0.01	-0.22	0.83
PD Good Practice	0.01	1.39	0.17	0.03	1.68	0.10
Cross Communication	0.02	1.85	0.07	0.02	0.99	0.32
Competencies	-0.01	-1.13	0.26	-0.03	-1.58	0.12
R^2	0.47			0.07		

The most striking factor emerging from the regression is the importance of the scaling variable, the number of new products developed, on the proportion of new products that are successful. The estimate for NEWPRODUCTS has a very large t statistic of -7.83, and the coefficient value is negative. This indicates that firms that release the most new products also enjoy the lowest success rates. One interpretation of these results is as follows. One can conceive of two approaches to innovation within the Thai food industry: one in which the NPD budget is used to create a number of new products, in the anticipation that at least some will catch on and succeed. Another in which the budget is used to create fewer new products, but bringing them along with greater care so that their chances of success are maximised. The importance of the scaling factor is seen in the fact that the R^2 in model 2, not including the scaling variable, is 0.07, while the R^2 in model 1 is 0.47.

Of the marketing and management variables encapsulated in the principal components variables, cross-functional communication is clearly the most important, being positive and statistically significant. This corroborates the finding of Suwannaporn and Speece (2003) that this element is of considerable importance in enhancing success in Thai food industry. Our results also fit well with the findings of Song and Parry (1997) that cross-functional integration is more important than other variables such as marketing and technical proficiency in Japanese NPD. In our case, we can observe that PD Good Practice is the only other marketing/management variable that can considered even marginally significant, and that only with a p-value of 0.17. The Competencies variable is more strongly insignificant, and has a counter-intuitive sign.

As for the 'basic' firm & market variables, none appear significant apart from firm size. Competitiveness is surprisingly not a significant determinant of success rates. However, there is much prior evidence of just such insignificance in previous studies. In their review of new product success factors, Montoya-Weiss and Calantone (1994) find that despite theoretical plausibility, there is very little empirical evidence that competitiveness affects success factors. They echo the hypothesis of Cooper (1985) that multiple effects of competitiveness on success and performance tend to cancel each other out. In Cooper's own words, 'One might speculate that the reason markets are so competitive in the first place is because they are so lucrative…thus the market attractiveness has been well read by competitors, the end result being a lucrative but competitive market. The positive and negative aspects cancel each other, and performance is neither heightened nor diminished by market competitiveness' (Cooper, 1985, page 16).

Firm size, proxied by the number of employees, emerges as a significant determinant of NPD success rates. It is not strongly significant, having a p-value of 0.12, but is admissible as a significant factor if a less stringent significance criterion is allowed. Since firm size has also been found to be a significant, positive determinant of innovation rates, our results suggest that larger firms will continue

to drive innovation in the Thai food sector. By innovating more and generally being more successful at innovation (despite the depressing effect of increased innovation on success rates), large firms will only continue to increase their competitive edge over time.

Conclusion

In this paper, we have attempted to advance the literature on new product development in Thai food industries. Taking the view that the extent of innovation is an essential first step to be understood before attempting to explain success factors in innovation, we quantitatively investigated the factors influencing innovation rates. Several findings emerged from this. First, we found a strong sub-sector specific influence on innovation, in accordance with expectation. More interestingly, we found support for a Schumpeterian hypothesis that lowered competition encourages innovation, which may also be tied to a firm-size innovation effect that we found. Also somewhat surprisingly, we concluded that innovation rates were not strongly influenced by the independence of firms. In other words, local and MNC firms are likely to develop new products at similar rates, once we control for all other mediating variables such as sub-sector specificity and competitive status.

Turning to the explanation of success rates, we found that the most significant determinant of the rate of success in innovation is the rate of innovation in the first place. This relationship is negative, indicating that some firms follow a strategy of releasing several new products, but pay a cost in terms of lowered success rates. Other firms spend their NPD budgets on nurturing smaller number of new products more carefully, achieving higher success rates. Cross-functional communication and to a lesser extent, good NPD practice, were also seen to be important in explaining NPD success rates. Larger firms are not only likely to be more innovative, but were also found to be more successful.

Since innovation is viewed as a critical factor for long term competitive advantage, one implication of the findings is that the future looks most promising for the larger firms in the Thai food industry. Not only are they able to innovate more than smaller firms, but they are also able to more successfully convert innovation into successful innovation. Taken together with the fact that lowered competition further spurs innovation, continued consolidation in the food industry looks like an inevitable trend. Smaller firms may be sustainable in the more 'basic' food sectors such as grains and dairy, but are likely to quickly fall behind in more dynamic sectors, particularly those catering to export markets and to the processed food sales from supermarkets. The current government's Science and Technology Action Plan that commenced in 2003 sees a key role for small entrepreneurs in Thai industry. Special tax incentives have been introduced that provide tax relief explicitly conditional on the firm undertaking R&D activity and providing workforce

training and education. This is a welcome move to improve the innovation profile and success of smaller firms. However, these firms also need better access to a pool of technical knowledge, which perhaps the University sector is best placed to provide.

References

Bishop, P. and N. Wiseman, 1999. "External ownership and innovation in the United Kingdom". *Applied Economics*, 31:443-450.

Brown, S. L. and K. M. Eisenhardt, 1995. "Product Development: Past Research, Present Findings, and Future Directions". *Academy of Management Review*, 20(2): 343-378.

Cabral, J. and W. B. Traill, 2001. "Determinants of a firm's likelihood to innovate and intensity of innovation in the Brazilian food industry". *Chain and Network Science*, 1(1): 33-48.

Cooper, R. G., 1985. "New Product Strategies: What distinguishes the top performers?" *Journal of Product Innovation Management,* 1(1): 5-18.

Cooper, R. G., 1994. "New Products: The factors that drive success." *International Marketing Review*, 11(1): 60-76.

FOSTAT. 2002. Directory 2002 Food Processors and Packaging. Food Science and Technology Association of Thailand.

Galizzi, G., and L. Venturini, 1996. Product innovation in the food industry: nature, characteristics and determinants, in *Economics of Innovation: The case of the food industry*. (eds. G. Galizzi and L. Venturini): Physica-Verlag, Heidelberg.

Geroski, P., 1990. "Innovation, technological opportunity, and market structure." *Oxford Economic Paper*s, 42: 586-602.

Hamilton, F. E., 1998. Multinational enterprises, in *Industrial Change in the United Kingdo*m, W. F. Lever (Ed.), Longman, London, pp. 167-195.

Harris, R. I. D., 1988. "Technological change and regional development in the UK: evidence from the SPRU database on innovations." *Regional Studie*s, 22, 361-374.

Hausman, J., B. H. Hall and Z. Griliches, 1984. "Econometric Models for Count Data with Applications to the Patents-R&D Relationship". *Econometrica,* 52(4): 909-938.

Huiban, J. and Z. Boushina, 1998. "Innovation and the quality of labour factor: an empirical investigation in the French food industry." *Small Business Economics,* 10: 389-400.

Katila, R. and G. Ahuja, 2002. "Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction." *Academy of Manangement Journal*, 45(6): 1183-1194.

Love, J. H., Ashcroft, B. and S. Dunlop, 1996. "Corporate structure, ownership and the likelihood of innovation." *Applied Economics*, 28: 737-746.

Martin, X. and W. Mitchell, 1998. "The influence of local search and performance heuristics in a new product market." *Research Policy*, 26: 753-771.

Montoya-Weiss, M. and R. Calantone, 1994. "Determinants of New Product Performance: A review and meta-analysis." *Journal of Product Innovation Management,* 11(5): 397-417.

National Food Institute, 2002. "Overview of Thai Food Industry".
http://www.nfi.or.th/domestic/thai-food-industry/food-sector02.html

Rogers, M., 2000. "Understanding Innovative Firms: An Empirical Analysis of the GAPS". Melbourne Institute Working Paper No. 8/00. Melbourne: Melbourne Institute of Applied Economic and Social Research.

Siegel, D.S., Westhead, P. and M. Wright, 2003. "Assessing the Impact of University Science Parks on Research Productivity: Exploratory Firm-Level Evidence from the United Kingdom." *International Journal of Industrial Organization,* 21: 1357-1369.

Song, X. M. and M. E. Parry, 1997. "The Determinants of Japanese New Product Success". *Journal of Marketing Research*, 34 (February): 64-76.

Suwannaporn, P. and M. Speece, 1998. "Organization of New Product Development in Thailand's Food Processing Industry." *International Food and Agribusiness Management Review*, 1(2): 195-226.

Suwannaporn, P. and M. Speece, 2000. "Continuous Learning Process in New Product Development in the Thai Food-Processing Industry." *British Food Journal*, 8: 598-614.

19

Suwannanporn, P. and M. Speece, 2003. "Marketing Research and New Product Development Success in Thai Food Manufacturing." *Agribusiness*, 19(2): 169-188.