วารสารเศรษฐศาสตร์ประยุกต์และกลยุทธ์การจัดการ Journal of Applied Economics and Management Strategy
ปีที่ 12 ฉบับที่ 2 กรกฎาคม-ธันวาคม 2568 Vol. 12, No. 2, July- December 2025

R&D, Innovation and Profit in Food Firms in Thailand

Areeya Areegul[1], and Athakrit Thepmongkol[2]

Received: May 24, 2025
Revised: October 5, 2025
Accepted: October 24, 2025

ABSTRACT

This study investigates the impact of R&D expenditure on firm performance using panel data from 42 food firms listed on the Stock Exchange of Thailand (SET). We first analyze the effect of R&D spending on gross profit and find that its second lag has a strong positive impact. Next, we examine innovation outputs including patent applications and new product launches and observe that both have a negative effect on gross profit. Finally, we construct an Innovation Index using factor analysis to capture latent innovation activities. The index shows a significant positive relationship with gross profit, highlighting the multidimensional nature of innovation in the food industry. Based on these findings, we recommend that the government and Thai food firms continue to strengthen support for R&D to enhance long term competitiveness.

Keywords: Innovation, R&D expense, food firms, Stock Exchange of Thailand, gross profit.

[1] Ph.D. Candidate, Graduate School of Development Economics, National Institute of Development Administration, E-mail: areegul@hotmail.com, areeya.are@stu.nida.ac.th

[2] Lecturer, Graduate School of Development Economics, National Institute of Development Administration, E-mail: athakrit.t@nida.ac.th

Background and Significance of the Research Problem

Innovation is widely recognized as a critical driver of firm performance, particularly in enhancing gross profits. Theoretically, innovation enables firms to develop new products and improve production processes, thereby increasing revenue and reducing costs. Research and development (R&D) serves as a primary driver of innovation. Thailand's Gross Domestic Expenditure on R&D (GERD) as a percentage of GDP has shown a steady upward trend since 2012. According to the 2024 survey report by the National Research Council of Thailand (NRCT, 2024), Thailand's total R&D expenditure in 2022 was 201,415 million baht, equivalent to 1.16% of GDP, with the private sector accounting for the majority share (73%). The food industry has consistently ranked among the top sectors in R&D spending, leading all sectors in 2022 with an expenditure of 22,314 million baht. The food industry is an important sector for Thailand's economy due to its strong interconnections with other supply chains. Given the economic significance of the food industry, its prominent role in national R&D investment, and the influence of factors such as stringent food safety regulations, evolving consumer preferences, intense competition, market trends, and shifting demographics, this study investigates how R&D expenditure and the resulting innovation outputs impact firm performance at the micro level.

This topic has been rarely explored in Thailand, primarily due to the limited availability of public R&D data and the challenges of obtaining relevant quantitative panel data, especially considering the impact of the COVID-19 pandemic. Additionally, the limited research on the relationship between R&D expenditure and their outputs, such as patent applications and new product introductions, as well as their effect on gross profit, makes this study particularly relevant.

To address the research gaps, this paper first examines the relationship between R&D expenditure and gross profit, followed by an analysis of how innovation outputs, such as patent applications and new product launches, affect gross profit. The final part of the study applies advanced statistical techniques to construct an Innovation Index, aiming to provide a more comprehensive representation of innovation and its potential impact on firm performance.

Research Objectives

The main objectives of this paper are to examine how R&D expenditure affects the gross profit of food firms operating in Thailand, specifically those listed on the SET. Furthermore, the paper aims to explore the relationship between R&D expenditure and innovation outputs, namely patent applications and new product launches, and how these factors impact gross profit.

Scope of Research

The dataset covers 42 food firms listed on the Stock Exchange of Thailand from 2015 to 2023, using unbalanced panel data. Firm-level data, including R&D expenses, were collected from annual reports, financial statements, Securities and Exchange Commission filings, sustainability reports, and the Structured Data One Report, which is publicly available on the Stock Exchange of Thailand website.

For patent applications, the data is obtained from the Department of Intellectual Property of Thailand. For new product launches, we also gather data from various sources, such as annual reports, company websites, and news released online.

For the analysis in this paper, we focus on firms that disclose R&D expenses or few firms that do not reveal R&D expenses but spin off their R&D into subsidiary firms, retaining 100% of the shares in those subsidiaries. In this case, we use the expenses of those subsidiaries as a proxy for the R&D expenses of the parent firms. We also include firms that do not invest in R&D in our analysis.

Literature Review

The endogenous growth theory emerged in the 1980s , it is developed to overcome the limitation of the neoclassic growth model refined by Solow and Ramsey (Salvadori, 2003), The internal investment decision which is considered as endogenous factor drive technology progress (Grossman & Helpman, 1991; Romer, 1990). The endogenous growth theory also incorporates the concept of creative destruction concept, as proposed by Schumpeter (1934) who argued that economic development is driven by entrepreneurs who introduce new products, processes which explained how's innovation disrupts the existing market structure or industries and leads to the creation of new ones. This falls within the context of an endogenous theory that growth is driven by technology change that arises from investment decisions made by profit-maximizing agents (Romer, 1990). The stock of human capital, the development of new technology and innovations help to accelerate growth faster. The Theory has many implications for firms to engage in R&D and innovation activity in order to generate growth. The Oslo Manual (OECD & Eurostat, 2018) provides the definition of innovation as a new or improved product or process or combination of both that significantly different from the previous ones and also has been made available to potential users or brought into use by unit in any sector such as firm via process. Additionally, innovation activities can take on various forms such as engineering design or any creative activities, R&D, intellectual property, marketing and brand equities, software or database development, employees training, acquisition or lease tangible asset and others innovation management activities. Firms make their decision regarding how's much resources such as time and budget should be allocated to support this innovation creation activities.

Even if R&D is widely used as indicator for innovation but this also subjected to critic by others scholars due to its limitation. Many scholars attempt to find factors that determine firm's innovation capability in order to gain better understanding of firm's conditions and resources that are essential for implement new ideas effectively, which can result in improving overall performance. Wang and Kafouros (2009) applied regression analysis to determine innovative performance by including R&D, FDI, exports and imports as independent variables for emerging economy in China. Their study showed that these explanatory variables did not always result in positive consequences. Innovation inputs can be both tangible and intangible. Tangible inputs have physical characteristics and incur costs such as buying equipment, machinery, computers and support facilities, as well as building the factory or office. On the contrary, intangible inputs may not have physical characteristics, but they may have costs (Gamal, 2011) such as R&D, software development, market development such as marketing expense on advertising and market research.

Wolff (2007) wrote an article entitled "Forget R&D Spending-Think Innovation". This article summarized evidence from other papers which suggested that spending too much on R&D did not always lead to superior growth for a company. It also highlights that other factors, such as a firm's ability to integrate processes and establish a supportive culture, were crucial in creating a competitive advantage. However, spending too little on R&D could put a company behind its competitors. In this paper. We also include other expenses such as capital expenditure as factors affecting firm performance. However, as highlighted in studies such as Caballero and Engel (1999), investment may exhibit nonlinear patterns. Therefore, this paper also accounts for potential nonlinearity in capital expenditure as well.

Bobillo et al. (2006) used panel data analysis to estimate the impact of R&D expenditures, employment efficiency, tangible capital, and intangible capital on firm performance in terms of sales and net profit for firms in Spain during the period 1991-2001. They found mixed results from various industries when both level and first-difference estimates were used. Another evidence was presented by Chaddad and Mondelli (2013), who utilized hierarchical linear modelling for panel data of US food economy firms during the period 1984-2006. Their study investigated the influence of R&D

expense intensity and advertising expense intensity on firm performance, measured by return on assets (ROA). The results revealed a significantly positive effect of R&D expenditure intensity on firm performance differences, in contrast to advertising expense intensity, which showed no significant effect on firm performance. Lastly, Manogna and Mishra (2021) applied system generalized method of moments to investigate the relationship of R&D expenses and technology purchase expenses on the sales growth of Indian food and agricultural firms. The regression results showed that both R&D expenses and technology purchase expenses have a significantly positive effect on the growth of sales. To measure R&D efficiency, many scholars suggest using patents, which are considered an output of R&D expenditure and serve as an indicator of innovation. Thomas, Sharma, and Jain (2011) analyzed R&D efficiency in the United States using patents granted, providing valuable data for policymaking. Nagaoka, Motohashi, and Goto (2010) provided an overview of how patent statistics can be used to measure and understand innovation. However, they also highlight the limitations of patent data, such as the fact that not all innovations are patented, and not all patents lead to commercially successful products. R&D can serve as a key driver of both process innovation and the introduction of new products (Parisi et al., 2006). In addition to R&D, other variables such as firm age, firm size, foreign ownership, export activity, and number of employees have also been widely studied for their contribution to innovation output.

Research Methodology

We study 42 food firms using unbalanced panel data from 2015 to 2023. As explained in the scope of study, data were collected from various sources, and the monetary expenditure values were adjusted from nominal to real terms using the Producer Price Index for food products from the Trade Policy and Strategy Office in Thailand, which uses 2015 as its base year.

Since financial statement figures are affected by changes in price levels, this adjustment ensures greater accuracy and allows for meaningful comparisons over time. We then employed panel data analysis to compare the fixed effects model with the random effects model and determine which model is most suitable for the data. The Hausman test (Hausman, 1978) is used for this purpose. The null hypothesis of the Hausman test states that the fixed effects coefficients are not significantly different from the random effects coefficients, implying that the random effects model is preferable to the fixed effects model. Parts 1 to 3 of this paper are based on the conceptual framework presented in Figure 1:

The input factors in our model are shown in Figure 1. These include employees, firm age, foreign ownership, exports, assets, and additional investments such as sales and marketing, software, and capital expenditure. R&D expenditure is treated as a key driver of innovation, leading to outputs such as patents, new products, and others improvements such as processes or practices. These outputs are expected to enhance firm performance by increasing gross profit.

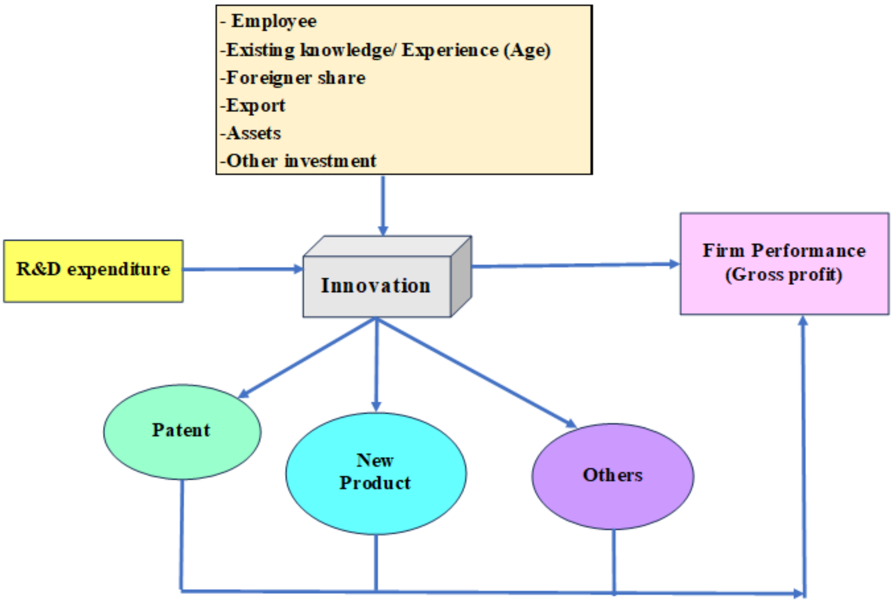

Figure 1 Conceptual Framework: the Pathway from R&D to Innovation and Firm Performance
Source: Developed by Authors

The rationale for selecting these variables, apart from R&D expense and innovation outputs, is as follows. Gross profit was chosen as the performance measure because it reflects profitability from a firm's core operations and excludes expenses not directly tied to production, unlike operating or net profit. Firm age represents accumulated experience. Employees and assets serve as inputs to production. For assets, we include only tangible assets as capital inputs, excluding intangible assets to avoid double counting with R&D and software. Foreign shareholding may provide additional experience and funding, while exporting can expose the firm to new knowledge and enhance market competitiveness. In addition, other investments, such as software expense, sales and marketing expense, and capital expenditure, are key resources that enable firms to generate revenue and profits. While this study explicitly controls for the impact of COVID-19 through a dummy variable, other contemporaneous events such as trade conflicts or the Russia–Ukraine war are not included due to data and model complexity. This is acknowledged as a limitation, as these events may also have influenced firm performance during the study period.

For Part 1: We base our theoretical framework on the quality ladder model in growth theory, as proposed by Grossman and Helpman (1991). By adopting this framework, investing in R&D is expected to have a positive impact on a company's performance. Consequently, we aim to test this concept using empirical data from food firms in Thailand. Additionally, we incorporate insights from other types of expenditures beyond R&D into our model. We examine different lag lengths of R&D and select the optimal lag based on both statistical significance and model fit, using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to guide the selection. Squared terms of capital expenditure is also included in the equation to capture potential nonlinear effects.

Part 2: In this section, we analyze the impact of R&D investments on innovation outcomes. Specifically, we focus on two key proxies for R&D output: patent applications and new product launches, and examine how these factors influence gross profit. To strengthen our analysis, we also employ principal component analysis (PCA) to generate a weighted component that combines patent applications and new product launches. This allows us to assess their joint impact on gross profit in a more integrated manner. The methodology was originally designed in two main parts. However, as the research progressed, we did not find statistically significant positive effects of R&D on patent applications or new product launches, nor did these outputs show a positive impact on gross profit. This suggests that patent applications may not serve as a reliable proxy for innovation output in Thailand’s food industry, possibly due to the sector’s focus on informal or non-patented innovations. Since the results from Part 2 are not consistent with those from Part 1, a third part was introduced. This involves constructing an Innovation Index using advanced statistical techniques to captures the multidimensional nature of R&D and provides a broader, more comprehensive view of innovation activity.

Part 3: We apply factor analysis with varimax rotation (Hair et al., 2010) to identify latent dimensions of innovation and construct a composite Innovation Index. Factor analysis groups together variables that share common variance, thereby reducing dimensionality, minimizing multicollinearity, and enabling a more robust analysis. We then analyze how this index influences gross profit. The notation of variables is shown in Table 1.

Table 1 Notation of Variables

Variables	Notation	Description
Gross Profit	lnGP	Log of gross profit (THB)
New product	lnNP	Log of the number of new products launch each year
Patent application	lnPtA	Log of the number of patents applied each year
The age of the firm	lnAge	Log of the firm's age, measured in years since its establishment
Employees	lnEmp	Log of the number of employees at the end of the year
Assets	lnAsset	Log of the tangible assets
Foreign share intensity	Fshare	The percentage of foreign shareholder to total shareholder
Export intensity	Exp	The percentage of export sales to total sales
R&D Expense	lnRD_lk	Log of lag k of R&D expense
Covid dummy[3]	Covid	The value is set to 1 starting from the year 2020, when the COVID-19 pandemic began, and is 0 otherwise
Interaction R&D and Covid	lnRD_lk xCovid	Interaction of lag k of log of R&D expense and covid dummy
Software expense	lnSoftw_lk	Log of lag k of software expense
Sales and marketing expense	lnMkt_lk	Log of lag k of sales and marketing expense
Capital expenditure	lnCapex_lk	Log of lag k of acquisition or purchasing plant and equipment
Square of capital expenditure	lnCapex_lksq	The square of log of lag k of acquisition or purchasing plant and equipment
PCA of new product and patent	PCAComp	The first principal component from PCA method
Innovation Index	InnoFactor	Innovation Index from factor analysis method

We analyze panel data for firm i at year t where A_0 to G_0 represent intercept terms of each panel regression. The Parameters A_i to G_i are the coefficients associated with each panel regression model. Panel regression for Part 1 is as follows:

$$\begin{aligned} lnGP_{it} = {} & A_0 + A_1 lnAge_{it} + A_2 lnEmp_{it} + A_3 lnAsset_{it} + A_4 Fshare_{it} + A_5 Exp_{it} + A_6\, lnRD\_lk_{it} \\ & + A_7\, Covid_{it} + A_8 (lnRD\_lk_{it} x Covid_{it}) + A_9\, lnSoftw\_lk_{it} + A_{10}\, lnMkt\_lk_{it} + A_{11}\, lnCapex\_lk_{it} \\ & + A_{12}\, lnCapex\_lksq_{it} \qquad (1) \end{aligned}$$

[3] Note that COVID variable reflects the structural impact of the pandemic on Thai economy from 2020 onwards, not limited to just COVID-19 period during 2020-2022.

Panel regression for Part 2 are as follows:

$$lnNP_{it} = B_0 + B_1\, lnAge_{it} + B_2\, lnEmp_{it} + B_3\, lnAsset_{it} + B_4\, Fshare_{it} + B_5\, Exp_{it} + B_6\, lnRD\_lk_{it} + B_7\, Covid_{it} + B_8\, (lnRD\_lk_{it} x Covid_{it}) \quad (2)$$

$$lnGP_{it} = C_0 + C_1 lnAge_{it} + C_2 lnEmp_{it} + C_3 lnAsset_{it} + C_4 Fshare_{it} + C_5 Exp_{it} + C_6\, lnNP_{it} + C_7 Covid_{it} + C_8 lnSoftw\_lk_{it} + C_9 lnMkt\_lk_{it} + C_{10} lnCapex\_lk_{it} + C_{11} lnCapex\_lksq_{it} \quad (3)$$

$$lnPtA_{it} = D_0 + D_1\, lnAge_{it} + D_2\, lnEmp_{it} + D_3\, lnAsset_{it} + D_4\, Fshare_{it} + D_5\, Exp_{it} + D_6\, lnRD\_lk_{it} + D_7\, Covid_{it} + D_8\, (lnRD\_lk_{it} x Covid_{it}) \quad (4)$$

$$lnGP_{it} = E_0 + E_1 lnAge_{it} + E_2 lnEmp_{it} + E_3 lnAsset_{it} + E_4 Fshare_{it} + E_5 Exp_{it} + E_6\, lnPtA_{it} + E_7 Covid_{it} + E_8\, lnSoftw\_lk_{it} + E_9\, lnMkt\_lk_{it} + E_{10}\, lnCapex\_lk_{it} + E_{11} lnCapex\_lksq_{it} \quad (5)$$

For Model (2), R&D is treated as the input for new product launches, while Model (3) treats gross profit as the output. If we substitute Model (2) into Model (3), we obtain the same functional form as Model (1), with only the coefficients differing. We apply the same conceptual approach to the other models.

At the end of Part 2, we applied principal component analysis (PCA) to patent applications and new product launches to derive a single weighted composite measure. The data were standardized, and following the Kaiser criterion (Kaiser, 1960), only components with eigenvalues above 1 were retained. The first principal component, explaining the most variance, was used. This PCA measure was then included as an independent variable in the panel regression to examine its effect on gross profit, consistent with Part 2's approach.

$$PCAComp_{it} = \lambda_1\, lnNP^*_{it} + \lambda_2 lnPtA^*_{it} \quad (6)$$

Where lnNP* , lnPtA* are standardize variables and λ_1 , λ_2 are PCA loadings.

$$lnGP_{it} = F_0 + F_1 lnAge_{it} + F_2 lnEmp_{it} + F_3 lnAsset_{it} + F_4 Fshare_{it} + F_5 Exp_{it} + F_6\, PCAComp_{it} + F_7 Covid_{it} + F_8 lnSoftw\_lk_{it} + F_9 lnMkt\_lk_{it} + F_{10}\, lnCapex\_lk_{it} + F_{11} lnCapex\_lksq_{it} \quad (7)$$

In Part 3, to construct the Innovation Index, factor analysis was performed to identify the latent factors driving innovation within firms. Based on the Kaiser criterion (Kaiser, 1960), only factors with eigenvalues greater than 1 were retained for further analysis. Varimax rotation (Kaiser, 1958) was then applied to improve interpretability. The Innovation Index was subsequently calculated by combining the factor scores of the retained factors and used as an independent variable in the panel regression.

$$InnoFactor_{it} = \omega_1\, lnAge^*_{it} + \omega_2\, lnEmp^*_{it} + \omega_3\, lnAsset^*_{it} + \omega_4\, Fshare^*_{it} + \omega_5\, Exp^*_{it} + \omega_6\, lnRD\_lk^*_{it} + \omega_7\, Covid^*_{it} + \omega_8\, (lnRD\_lk^*_{it} x Covid^*_{it}) \quad (8)$$

Where: Variables with * are standardized values from factor analysis, ω_i are factor loadings from the rotated solution, i=1,...,8. The resulting factor scores for the Innovation Index were then used as an independent variable to examine their effect on gross profit, following the approach in Part 2.

$$lnGP_{it} = G_0 + G_1 lnAge_{it} + G_2 lnEmp_{it} + G_3 lnAsset_{it} + G_4 Fshare_{it} + G_5 Exp_{it} + G_6 InnoFactor_{it} + G_7 Covid_{it} + G_8 lnSoftw\_lk_{it} + G_9 lnMkt\_lk_{it} + G_{10} lnCapex\_lk_{it} + G_{11} lnCapex\_lksq_{it} \quad (9)$$

This study primarily focuses on the coefficients of the following variables: R&D expense, new product, patent application, PCA of new product and patent and the Innovation Index. We take the natural logarithm[4] of most variables to handle large values, reduce skewness, and address heteroskedasticity. Additionally, logging the variables allows us to interpret the coefficients as elasticities, meaning they represent percentage changes rather than absolute changes. We employ robust standard errors, which adjust the standard errors of the coefficient estimates without altering the estimates themselves. This enhances the reliability of results. The analysis was performed using Stata 17.

Results

As we checked the correlation matrix, the majority of correlations were below 0.5. However, high correlations were observed among lnAsset, lnEmp, lnMkt_l0, and lnCapex_l1. To further investigate potential multicollinearity among these variables, we use Stata software to calculate the Variance Inflation Factor (VIF) (Belsley et al., 2005). All VIF values are below 5, which we consider acceptable. Therefore, we include these variables in the models to avoid omitted variable bias. Subsequently, we incorporate lnCapex_l1sq in the regression models to detect nonlinearity.

[4] For independent variables with zero values that are log-transformed, 1 was added to all observations; for example, lnRD_lk = ln(1+RD_lk).

Table 2 Descriptive Statistics

Variables	Unit	Obs	Mean	Std. dev.	Min	Max
Gross profit	THB	227	4,288,644,841	11,911,185,088	71,905,510	107,458,317,635
The age of the firm	Years	227	42	23	9	132
Employees	Persons	227	7,126	21,403	98	147,198
Assets	THB	227	30,138,409,705	112,901,590,179	752,393,947	829,727,058,129
Foreign share Intensity	%	227	10.915	13	0.000	46
Export intensity	%	227	38.818	35	0.000	99
New product	Number	227	6.907	14	0.000	116
Patent application	Number	227	0.132	1	0.000	5
Covid dummy	-	227	0.709	0	0.000	1
R&D expense	THB	227	75,962,705	344,797,425	0.000	3,040,000,000
Software expense	THB	227	16,482,414	56,670,308	0.000	522,883,077
Sales and marketing expense	THB	227	1,519,495,562	3,540,469,940	26,201,271	23,948,279,559
Capital expenditure	THB	227	1,134,555,601	3,605,783,589	3,682,281	26,576,030,060

Note: Variables are in their original values before taking logs, and expenditure variables are expressed in real terms using the Producer Price Index (base year = 2015).

Table 3 Empirical Result from Part 1: Model (1)

Independent Variables	Dependent Variable lnGP	Independent Variables	Dependent Variable lnGP
lnAge	0.0115	Exp	0.00279
	(0.083)		(0.002)
lnEmp	0.0435	lnRD_l2	0.0451***
	(0.080)		(0.016)
lnAsset	0.274**	lnRD_l2xCovid	-0.0361**
	(0.107)		(0.014)
Fshare	-0.000942	Covid	0.648***
	(0.004)		(0.215)

Table 3 (Continued)

Independent Variables	**Dependent Variable lnGP**	**Independent Variables**	**Dependent Variable lnGP**
lnSoftw_l0	0.002	lnCapex_l1sq	-0.00166
	(0.010)		(0.007)
lnMkt_l0	0.695***	Constant	0.496
	(0.094)		(3.487)
lnCapex_l1	-0.00952	Observations	143
	(0.272)	Number of ID	42
		Hausman Test Result	Random Effects

Note: 1. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.
2. Robust standard errors in parentheses.

In line with theoretical and empirical evidence suggesting that R&D requires time to affect firm outcomes, we tested both one-year (lag 1) and two-year (lag 2) lags of R&D expenditure. Including both lags simultaneously caused high correlation between lag 1 and lag 2, so we tested them separately. The results show that only lag 2 is statistically significant and provides the best model fit (lowest AIC and BIC). Accordingly, we focus on lag 2 in the reported results.

From the results in Part 1, R&D at lag 2 shows a strong and significant impact on gross profit. Based on this, we examine whether R&D may generate innovation outcomes (Models 2 and 4), which could in turn affect firm performance, thereby illustrating a potential transmission mechanism from R&D to innovation and then to gross profit, as reflected in Models 3, 5, and 7. We test this concept, and the results are reported in the following tables.

Table 4 Empirical Result from Part 2: Model (2), (4)

Independent Variables	**(Model 2) lnNP**	**(Model 4) lnPtA**	**Independent Variables**	**(Model 2) lnNP**	**(Model 4) lnPtA**
lnAge	5.625***	-0.0638*	lnAsset	-1.108**	0.0488**
	(1.489)	(0.038)		(0.450)	(0.024)
lnEmp	-0.845*	0.0551**	Fshare	-0.0067	-0.00127
	(0.478)	(0.027)		(0.017)	(0.001)

Table 4 (Continued)

Independent Variables	(Model 2) lnNP	(Model 4) lnPtA	Independent Variables	(Model 2) lnNP	(Model 4) lnPtA
Exp	0.00558	-0.00013	lnRD_l2xCovid	0.00624	0.00086
	(0.005)	(0.000)		(0.012)	(0.002)
lnRD_l2	0.0136	0.00116	Constant	12.31	-1.253***
	(0.015)	(0.003)		(8.236)	(0.438)
Covid	-0.435*	0.0207	Observations	143	143
	(0.234)	(0.024)	Number of ID	42	42
			Hausman Test Result	Fixed Effects	Random Effects

Note: 1. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

2. Robust standard errors in parentheses.

Table 5 Principal Component Loadings for Model (6)

(Component 1: Eigenvalue = 1.30)

Variables	Component 1 Loadings
lnNP*	0.7071
lnPtA*	0.7071

Table 6 Result from Part 2: Model (3), (5), (7)

Independent Variables	Model (3) lnGP	Model (5) lnGP	Model (7) lnGP
lnAge	0.687	0.11	-0.0244
	(0.476)	(0.512)	(0.083)
lnEmp	0.352*	0.406**	0.0889
	(0.204)	(0.197)	(0.083)
lnAsset	-0.641*	-0.628**	0.270**
	(0.319)	(0.307)	(0.116)
Fshare	0.00674	0.0102	-0.00161
	(0.012)	(0.013)	(0.004)
Exp	0.0209***	0.0210***	0.00233
	(0.004)	(0.005)	(0.002)
lnNP	-0.132***		
	(0.042)		

Table 6 (Continued)

Independent Variables	Model (3) lnGP	Model (5) lnGP	Model (7) lnGP
lnPtA		-0.120**	
		(0.058)	
PCAComp			-0.0142
			(0.031)
Covid	0.318**	0.348**	0.276**
	(0.128)	(0.132)	(0.121)
lnSoftw_l0	0.00523	0.00584	0.00711
	(0.010)	(0.011)	(0.009)
lnMkt_l0	0.617***	0.625***	0.676***
	(0.122)	(0.130)	(0.089)
lnCapex_l1	0.579***	0.624***	0.050
	(0.201)	(0.225)	(0.262)
lnCapex_l1sq	-0.0176***	-0.0182***	-0.00324
	(0.005)	(0.006)	(0.007)
Constant	12.42**	12.79**	0.669
	(5.885)	(5.613)	(3.165)
Observations	185	185	185
Number of ID	42	42	42
Hausman Test Result	Fixed Effects	Fixed Effects	Random Effects

Note: 1. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

2. Robust standard errors in parentheses.

Table 7 Part3: Rotated Factor Loadings (Varimax Rotation)

(Factor 1: Eigenvalue =2.538, Factor 2: Eigenvalue = 1.678)

Variables	Factor 1	Factor 2
lnAge*	0.468	-0.154
lnEmp*	0.853	0.251
lnAsset*	0.871	0.048
Fshare*	0.485	0.276
Exp*	0.229	-0.173
lnRD_l2*	0.136	0.897
Covid*	-0.014	0.209
lnRD_l2*xCovid*	0.138	0.762

Factor 1 was used as $InnoFactor_{it}$ in panel regression model (9) because it is the dominant factor, having the largest eigenvalue, and its variable coefficients align more closely with theoretical expectations.

Table 8 Result from Part 3: Model (9)

Independent Variables	Model (9) lnGP	Independent Variables	Model (9) lnGP
lnAge	0.0356	lnSoftw_l0	0.00556
	(0.607)		(0.009)
lnEmp	-0.667	lnMkt_l0	0.797***
	(0.521)		(0.224)
lnAsset	-1.545**	lnCapex_l1	0.313
	(0.725)		(0.257)
Fshare	0.0197	lnCapex_l1sq	-0.00998
	(0.023)		(0.007)
Exp	0.0228***	Constant	41.14**
	(0.004)		(16.920)
InnoFactor	2.464*	Observations	143
	(1.237)	Number of ID	42
Covid	0.466**	Hausman Test Result	Fixed Effects
	(0.175)		

Note: 1. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

2. Robust standard errors in parentheses.

Discussion

Part 1: Models with different lags were tested, and the two-period lag model had lower AIC and BIC, indicating better fit. Panel regression results show that R&D expenses at lag2 have a strong, positive, and significant effect on gross profit. This finding is consistent with theoretical frameworks, such as the Quality Ladder Model, which suggests that firms investing in research and development (R&D) can enhance product quality and gain a competitive advantage. As a result, this leads to increased sales and higher profit margins.

Moreover, R&D during the non-COVID period shows a more positive impact on gross profit compared to the period since the COVID-19 outbreak in 2020. There are several possible explanations for this situation, including disruption of operations, shifts in consumer behavior, and higher costs. However, since the COVID-19 outbreak, firms were compelled to operate more efficiently, leading to higher gross profits than in the non-COVID period. In addition to R&D, sales and marketing expenses exhibit a strong positive impact on gross profit.

However, in Part 2, we found that R&D expenses have a positive effect on new product launches and patent applications, but this effect is not statistically significant. Additionally, new product launches have a significant negative effect on gross profit. This suggests that new product launches may incur short term costs which could reduce immediate gross profit. This result is consistent with the product life cycle concept, which suggests that firms may face financial challenges during the initial stages of a new product launch. The results also show that patent applications have a significant negative effect on gross profit. Even after applying PCA to combine new product launches and patent applications at the end of Part 2, we still did not find a significant effect on gross profit. The results of Part 2 are not consistent with those of Part 1, likely because innovation is multidimensional and not all firms apply for or obtain patents. Relying solely on innovation outputs, as done in Part 2, may not fully capture its true impact.

To address this, Part 3 applies factor analysis to construct latent factors representing underlying innovation activity, resulting in an Innovation Index. Using this approach, the results indicate that the Innovation Index has a significant positive effect on gross profit, which is directionally consistent with Part 1, where R&D expenditure exhibits a strong significant positive effect. These findings contrast with Part 2, which finds that new product launches and patent applications have a negative relationship with gross profit. We propose that using the Innovation Index in Part 3 provides a useful tool for capturing latent dimensions of innovation, such as process innovation, for which direct data may be unavailable.

Suggestions:

The results from Part 1 show that R&D expenditure has a strong and statistically significant positive effect on gross profit. In contrast, the results from Part 2 indicate that while R&D positively influences new product launches and patent applications, these effects are not statistically significant. Moreover, the innovation outputs examined in Part 2 do not yield a positive impact on gross profit, as observed in Part 1. This suggests that such outputs may not fully capture R&D's impact especially in developing countries, where not all R&D leads to patents. To address this, Part 3 uses factor analysis to construct an Innovation Index. The results show a significant positive effect on gross profit, directionally consistent with Part 1, where R&D expenditure shows a strongly positive effect. This index captures latent forms of innovation, such as process innovation, that Part 2 may not reveal.

The analysis also finds that food firms operated more efficiently since the COVID-19 outbreak, leading to higher gross profits, though the effect of R&D was weaker during this time, likely due to short term survival strategies. Sales and marketing expenses consistently show a strong positive effect on gross profit, emphasizing the need for continued investment in this area. Software and capital expenditures should also be aligned with innovation strategies such as automation or digital lean methods to enhance efficiency and performance. These findings offer policy insights for food firms listed on the Stock Exchange of Thailand (SET), stressing the importance of long-term R&D investment. Future research should extend the data period and explore additional innovation outputs to better understand performance drivers in this sector. Finally, we recommend using the proposed Innovation Index, as it better captures the multidimensional nature of R&D.

References

Belsley, D. A., Kuh, E., & Welsch, R. E. (2005). *Regression diagnostics: Identifying influential data and sources of collinearity*. John Wiley & Sons.

Bobillo, A. M., Sanz, J. R., & Gaite, F. T. (2006). Innovation investment, competitiveness, and performance in industrial firms. *Thunderbird International Business Review, 48*(6), 867-890.

Caballero, R. J., & Engel, E. M. (1999). Explaining investment dynamics in US manufacturing: a generalized (S, s) approach. *Econometrica, 67*(4), 783-826.

Chaddad, F. R., & Mondelli, M. P. (2013). Sources of firm performance differences in the US food economy. *Journal of Agricultural Economics, 64*(2), 382-404.

Grossman, G. M., & Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies, 58*(1), 43-61.

Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate Data Analysis: A Global Perspective*. (7th ed.). Pearson Prentice Hill.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 46(6), 1251-1271. https://doi.org/10.2307/1913827

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika, 23*(3), 187-200.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and psychological measurement, 20*(1), 141-151.

Manogna, R., & Mishra, A. K. (2021). Does investment in innovation impact firm performance in emerging economies? An empirical investigation of the Indian food and agricultural manufacturing industry. *International Journal of Innovation Science, 13*(2), 233-248.

NRCT. (2024). *Science, Research, and Innovation Index: A Stepping Stone for National Development 2024.* https://www.nrct.go.th

OECD, & Eurostat. (2018). *Oslo Manual 2018* (4th ed.). https://www.oecd.org/en/publications/oslo-manual-2018_9789264304604-en.html

Parisi, M. L., Schiantarelli, F., & Sembenelli, A. (2006). Productivity, innovation and R&D: Micro evidence for Italy. *European Economic Review, 50*(8), 2037-2061.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy, 98*(5, Part 2), S71-S102.

Salvadori, N. (2003). *The theory of economic growth: A 'classical'perspective*. Edward Elgar Publishing Limited.

Schumpeter, J. A. (1934). The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. *Harvard University Press*. https://www.taylorfrancis.com/books/mono/10.4324/9781315135564/theory-economic-development-joseph-schumpeter (1911)

Wang, C., & Kafouros, M. I. (2009, 2009/12/01/). What factors determine innovation performance in emerging economies? Evidence from China. *International Business Review, 18*(6), 606-616. https://doi.org/10.1016/j.ibusrev.2009.07.009

Wolff, M. F. (2007). Forget R&D spending-think innovation. *Research Technology Management, 50*(2), 7.