Heliyon 8 (2022) e10726

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Innovative price-setting approaches to high-value products: A pricing method for agribusiness farmers

Phaninee Naruetharadhol [a,b,c], Chavis Ketkaew [a,c], Wutthiya Aekthanate Srisathan [a,c,*]

[a] International College, Khon Kaen University, 123 Mitrphap Road, Khon Kaen, Thailand 40002
[b] Hincks Centre for Entrepreneurship Excellence, Munster Technological University (MTU), Cork, Ireland
[c] Center for Sustainable Innovation and Society, 123 Mitrphap Road, Khon Kaen, Thailand 40002

ARTICLE INFO

Keywords:
High-value products
Innovative price-setting approaches
Multigroup structural invariance
Agribusiness farmers
Segmented (tiered) pricing
Peak-load pricing

ABSTRACT

Despite being determined by global market prices, the majority of Thai farmers have never become innovative price setters. Not many Thai farmers considered a pricing approach that would maximize the value of their agricultural products. To this end, this study provides empirical evidence regarding the impact of marketing-based variables on pricing. This study aims to identify marketing-based determinants involved in innovative, dynamic price settings for value-added agricultural products. We consider two approaches to innovative pricing – segmented (tiered) pricing and peak-load pricing – to see if there is a possibility for such pricing. A sample of 840 agribusiness farmers was collected from different regions of Thailand. Using multigroup structural invariance analysis, the sample was grouped into four types of farmers: rice, sugarcane, maize, and cassava, to see if there were any differences between them in each of the proposed pricing propensities. Our study finds that cassava farmers tend to pay significant attention to market focus, customer and product differentiation, brand orientation, and segment-based mass customization. Other groups of farmers, like rice and sugarcane, tend to set segmented (tiered) pricing as a result of brand orientation and mass customization. As for peak load pricing, market demand and seasonality are significant factors that can be found among four crops. No matter how prices are set on the global market, this study suggests that agribusiness farmers should think about marketing-related factors to stand out from their competitors.

1. Introduction

Pricing is one of the essential elements in product marketing. The change in price-cost margin results in a percentage change in the innovative business's profitability (Panda and Nanda, 2018). It is possible that setting a price that is either too low or too high will have a detrimental effect on profitability (Radhi and Zhang, 2018). This study refers to agribusiness farmers as smart farmers. Any smart farmer must recognize the significance of reasonably pricing a high-value product. In both the marketing and economics literature, previous studies (e.g., San-José et al. (2019) and Ho et al. (2018)) have assessed price optimization through field experiments or cost function experiments. Under an optimal pricing strategy, the seller sets a reasonable price, and consumers pay that affordable price (Chen et al., 2019). Farmers who practise this form of pricing are expected to receive enough revenue to cover their costs. When it comes to agricultural products, most of them are set by contract pricing. Specific crop prices are determined using the global market price as a reference.

Still, the problem is exacerbated when the global market price is lower than the cost of production. There is no pricing power for individual agribusiness farmers, making them unprofitable. The government has attempted to devise a measure to appropriately stabilize production factors' prices and promote production efficiency methods (Srisompun et al., 2020). The Thai government has recently announced *Farming 4.0* under the Thailand 4.0 policy agenda. Through innovative agriculture practices as solutions, the Ministry of Agriculture and Cooperatives aims to promote value-added agriculture development (TIR, 2020). This is because smart agriculture results in increased production, lower operation costs, and improved crop production quality. With these benefits, we doubt whether smart farmers can set a price for their value-added products with less reliance on the global market price. This research comes up with the idea of increasing the economic value and consumer appeal of an agricultural product. Aspects of marketing and market

* Corresponding author.
E-mail address: wutthiya_s@kkumail.com (W.A. Srisathan).

https://doi.org/10.1016/j.heliyon.2022.e10726
Received 20 October 2021; Received in revised form 7 January 2022; Accepted 16 September 2022

intelligence are necessary for smart farmers. When talking about economic value, we refer to this value as its price. Thus, pricing as one of the marketing elements is brought up for discussion. Relying on the economic aspect of the *demand-and-supply mechanism* may cause too much instability and ineffectiveness in pricing since the price mechanism has given them a minimal relevant portion of profit (Abokyi et al., 2020). It would be a better option if agribusiness farmers were encouraged to value those products first, then price them. This will lead to the learning process of understanding value creation. In the end, an educated farmer would have good marketing and pricing skills.

Most empirical evidence on price mechanisms is primarily derived from quantitative methods, either field surveys or field experiments. Abokyi et al. (2020) conducted field surveys on the effects of output price support on small farmers' income in Ghana. Through buffer stock operations initiated by the government, Abokyi et al. (2020) unveil that promoting output price support, especially in developing countries, can increase the income of small-holder farmers. Using choice models, Suchato et al. (2021) consider alternative crop production (i.e., switch from rice to sugarcane growing) as a solution during the price-fluctuated time. It is further suggested that effective public policy is required to incentivize farmers to switch from rice to sugarcane production and to implement price control in the early phases of the shift. However, both studies do not take the value-added marketing perspectives into account. As seen, both paid attention to the support of government intervention while such a support especially in the context of Thailand is still ineffective and unsuccessful. This evidence was reflected in the 30–40% increase in poverty and debt among farming households (Tanakasempipat, 2020; Udomkerdmongkol, 2020). Besides, the lack of upskill and reskill of Thai farmers resulted in their inability to increase the value of their crop products (TIR, 2021). Based on our pilot study on 5 new generation farmers, we found that, during the crisis of price fluctuation, they have used online channels to reach more customers and suppliers of processed agricultural products than they could have before. As a result, this study assumes that farmers who understand marketing concepts are more likely to set a fair price for their products so that they can keep making money. We then question whether, if thinking of value-added products as product innovation, it is also possible to have innovative prices. This current research undertakes an evaluation of innovative pricing possibilities among smart agribusiness farmers. In turn, it examines the effect of marketing-based variables on innovative, dynamic price-setting possibilities and assesses the implications for agribusiness farmers.

This study considers whether innovative price-setting approaches can generate positive profits and yield profits in excess of those intervened using price support. From the viewpoint of farmers, this study looks into two new ways to set prices — peak-load pricing and segmented (tiered) pricing. This paper poses two central questions: Is there a possibility to set peak-load pricing and segmented (tiered) pricing for value-added agricultural products? (2) What factors influence peak-load pricing and tiered pricing for value-added agricultural products? This study aims to determine the variables involved in innovative, dynamic pricing (i.e., peak load pricing versus segmented (tiered) pricing) for value-added agricultural products. In other words, this study seeks to understand if there is a potential for smart agribusiness farmers and what determinant features are for setting such pricing strategies.

Apart from the *general* determinant of demand and supply mechanism, the research offers the empirical determinant mechanism of peak-load pricing and segmented (tiered) pricing on success in both dynamic pricing strategies. To achieve this contribution, the research model and hypothesized relationships are empirically tested using 840 Thai smart agribusiness farmers through an SEM-based approach, supported by SPSS Amos 28. To the best of our knowledge, our paper is the first to look at how marketing-based determinants work and how they work together with segmented pricing and peak-load pricing. Our main findings provide a holistic approach to innovative price-setting possibilities that come from marketing ideas that recognize the importance of pricing based on value but also include a cost-based system.

The remainder of the study is organised by Section 2, which examines the theoretical background and hypotheses of this study, while Section 3 discusses the research methodology. Section 4 discusses the multigroup SEM approach, followed by Section 5 addressing the study's findings. Finally, section 6 concludes the study and suggests potential future research directions.

2. Literature review

2.1. Innovative pricing theory: segmented (tiered) pricing and peak-load pricing

The literature on pricing has been dominated by economics theory, cost accounting, psychology, and marketing. It takes more thought to figure out how much to charge for the product than just how much it costs and adds a mark-up. For sellers such as farmers, choosing a pricing strategy is essential to a business model innovation (Tadesse and Bahiigwa, 2015). Agricultural products are challenging to price because the global market determines them, causing low profitability because of price volatility (Banse et al., 2008). This study takes a marketing-oriented approach, focusing on innovative pricing strategies to address this issue.

Elizabeth Marting argued the concept of *creative pricing* in 1968, and it was from this concept that *innovative pricing* has its origins (Hinterhuber and Liozu, 2018, p. 4). According to Piercy et al. (2010), creative pricing refers to a *creative,* strategic approach to pricing by making the products stand out from competitors while also increasing revenues and profits, in addition to cost-based calculations. The possibility for creativity exists for pricing strategists and price setters, despite the fact that this form of pricing is in direct opposition to the existing explanation of most economic theorists (Hinterhuber and Liozu, 2018, p. 4).

Hinterhuber and Liozu (2014) define *innovation in pricing* as an approach to pricing strategies, pricing tactics, and organized pricing structures that are new to the industry to boost consumer satisfaction and firm profitability. The new-to-the-industry system refers to a method of pricing by market segmentation, performance, market expansion, new metrics (customer goals), zero as a special price (freemium), and participative pricing (e.g., pay-what-you-want). Our study defines it as a notion emphasising the entrepreneurial process of establishing a high-valued product and a price level that allows the product to be charged. This is because we believe that the dynamics of various pricing combinations are related to the pricing choice and decision. For product marketing, pricing is the key to answering it (Ingenbleek et al., 2010). However, the terms innovation in pricing, innovative pricing, or pricing innovation are interchangeably used in this study.

Our research framework (see Figure 1) starts with a selection of possible innovative pricing strategies and their determinants. Using concepts under economics and marketing, segmented (tiered) pricing and peak-load pricing are addressed. *Segmented pricing*, also known as *tiered pricing*, is when a firm charges different prices to different groups of customers even though the costs for each market segment are identical (Friedman and Lewis, 1999). Indeed, a farmer who sells commodities (e.g., basic agricultural products) will find it difficult to charge more for its products, where all the products are recognized as basically homogeneous. Without the ability to price the product, it is not necessarily the best way when the farmer struggles with a few percentages to maximize profits. Thus, high-value products cannot be charged by the market mechanism since these products are expected to create superior value for customers or clients. In this study, high-value products refer to *agricultural products* that have a high market value or are value-added to be sold through specialized markets, frequently but not always as a result of their processing (Weinberger and Lumpkin, 2005). Segmented (tiered) pricing is an appropriate pricing strategy to test in this phenomenon. To maintain crop production capacity over time, peak-load pricing is another possible innovative pricing approach allowing to deal with peak and off-peak demand of crop production as high-value products. Peak-load pricing can be defined as a method of charging a high price when the demand for

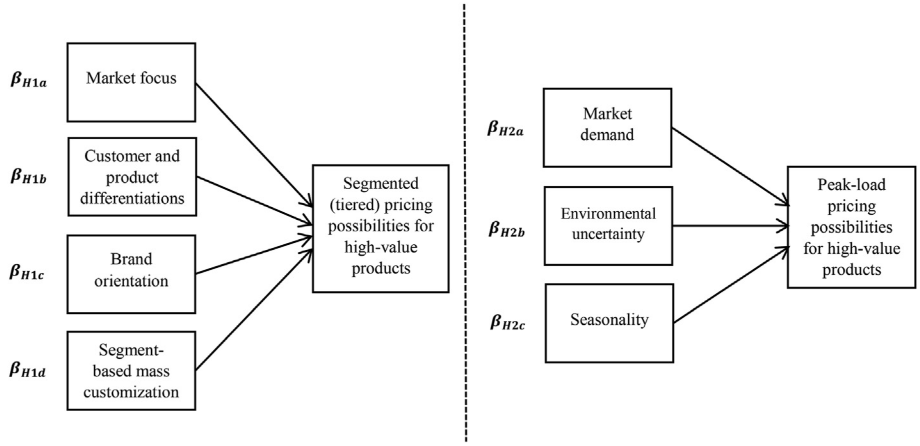

Figure 1. A research model for innovative price-setting approaches for high value products.

high-value products is at the peak and a lower price when the demand is off-peak (Friedman and Lewis, 1999; Shy, 2008). Seasons, cycles, and costs (e.g., fixed costs, marginal capacity cost etc.) play essential roles in determining the current load pricing (Shy, 2008). Farmers' whole year of work is at stake during harvest, so what they do is important. For that reason, all of the revenue comes from taking advantage of the value it has created in the market. There is no other way to sustain that value than pricing (Raju and Zhang, 2010, p. 201).

However, some determinants must be considered when both innovative pricing approaches are set up. Thus, concerns have arisen about defining marketing-oriented determinants that enable agribusiness farmers to price products effectively. Therefore, the second stream of literature will look at innovative pricing propensities affected by marketing-oriented determinants in the next section.

2.1.1. Determinants of segmented (tiered) pricing

2.1.1.1. Market focus. According to Porter's generic strategies, the term *focus* — one strategic approach to how a firm outperforms others in an industry — refers to a choice to focus on a specific type of geographic market, product, or customer (Porter, 1980). Market focus (also referred to as market orientation) helps a firm better understand its target market and its need to decrease the chance that its product will not work (Fernando and Wah, 2017). There are significant implications for the farmers' crop production when choosing a *broad* versus a *niche* market focus for their competitive strategy (Laosirihongthong et al., 2009). For agribusiness firms with a market focus, Wu et al. (2013) argued that consumer segmentation and portfolio would help firms determine market demands for high-value crops according to those high-value segments. As for a segment-based pricing system, Khandeparkar et al. (2020) further argued that understanding price-sensitive levels and behavioural characteristics across different customer segments are critical to successfully implementing pricing policies. Accordingly, market focus will likely affect segmented (tiered) pricing propensity. We assumed that:

H1a. Market focus positively affects agri-business farmers' possibility to set segmented (tiered) pricing.

2.1.1.2. Customer and product differentiations. Pelham (1997) illustrated the commodity-market quadrant that unveils the two primary forms of differentiation dimensions — customer and product differentiations. In commodity markets, agri-business farmers would use either a production or a market orientation, depending on low or high customer and product differentiation levels. Thus, both production and market orientations are considered a source of sustainable competitive advantage (SCA) (Flenskov, 2017). For example, if customer insights are not significant and are not complicated, market orientation may not be necessary. Instead, those farmers must understand market dynamics, needs, size, and purchase criteria (Trienekens et al., 2012; Weinstein, 2013). To be outstanding, those need to consider customer and product differentiations contingent on how strategy is linked with crop production performance (Allen and Helms, 2006). Customer or client segments are classified as differentiated if their needs vary from one another. At the same time, products are recognized as distinguished if the features and benefits of competitive products create a significant difference between them. However, Le Pape & Wang, (2020) argued that price and quantity competition could be used to look at the effect of product differentiation. Looking at the light of price, Hammami et al. (2021) found that product differentiation could lead to significant price differentiation. To price-differentiate, it is important to take customer and product differentiations into account, thereby assuming that:

H1b. Customer and product differentiations positively affect agribusiness farmers' possibility to set segmented (tiered) pricing.

2.1.1.3. Brand orientation. Brand orientation is a marketing orientation which focuses on the importance of branding to a firm's success (Chang et al., 2018). Agribusiness firms with brand-oriented strategies are more likely to have distinct brand visions and identities to effectively communicate and link their brands with their primary stakeholders (Lee, 2013). Brand orientation values brand intelligence (Piha et al., 2021). Brand orientation implies a method of brand management characterised by an offer that is relevant to the buyer and differentiated from competitors (Baumgarth, 2010). In a closer look at the relationship between brand orientation and pricing, Foxall et al. (2013) argued that brand-related characteristics influenced price elasticity. It can be explained that pricing could be elastic for branded products emerging as extensively dynamic. When products are unlikely to be homogeneous, the market is more likely to provide space for strategic and specific branded products (Canan and Cotterill, 2006). In a differentiated product market, Canan and Cotterill (2006) suggested that recognizing competitors' pricing reactions improves the own-price elasticity of demand and increases the price-cost margin. Taking all the above into account, the hypothesis was formed:

H1c. Brand orientation positively affects agri-business farmers' possibility to set segmented (tiered) pricing.

2.1.1.4. Segment-based mass customization. A quick examination of the historical progression from conventional market segmentation to mass customisation would assist in defining the idea of segment-based mass customization (Jiang, 2000). As a result, we took this concept to indicate that an agribusiness farmer produces uniform (standardized) products but that they also can offer the market differentiated (adaptive-customized) products in a variety of ways to various segments of customers or clients. Even if only one unique feature was found according to market coverage, that could be considered a second source of consumer choice and utility benefiting from the use of mass customization systems. As for Industry 4.0, mass customization brings more value to customers/clients and agribusiness producers (Wang et al., 2017). This is because mass customization increases the value of the products while enabling those farmers to increase product variety by supplying customers with customized products.

On the other hand, understanding customer segments and insights are critical because farmers need to assess their *possible* mass customization capability and adaptive behavioural responses to these external changes (Huang et al., 2008). In turn, an effective mass customization capability assessment would impact financial performance (e.g., agricultural product sales and profit growth) (Deshpande, 2018). To optimize price, Jost & Süsser (2020) suggested that differentiated demand and the degree of mass customization should be balanced. This is because the farmers would have pricing options, either to set higher prices with a rise in profit margins as a result of increased margins per unit of sold goods or to set lower prices when a fall in profit margins due to decreased demand as a result of a price rise. Accordingly, it is possible for agribusiness farmers to price their customized products by segmenting and maximizing profit. We then came up with the next hypothesis that:

H1d. Segment-based mass customization positively affects agri-business farmers' possibility to set segmented (tiered) pricing.

2.1.2. Determinants of peak load pricing

2.1.2.1. Market demand, environmental uncertainty, and seasonality. In today's business environment, agribusiness firms and farmers are forced to have flexible strategies for their specific products and processes as a result of intense market rivalry (Lin et al., 2013). One of the most critical factors is market demand. The demand-based perspective is based on the premise that demand dynamics such as customer value heterogeneity will inevitably influence customer choices and firm strategies and, as a result, a firm's competitive advantage (Zhou et al., 2009). The literature reveals that market segmentation, price flexibility of demand, and customer benefits and requirements (for high-value products) are critical aspects of determining market demand (Kammerer, 2009; Lin et al., 2013; Zhou et al., 2009). Anning-Dorson (2017) argued that product innovation (e.g., highly innovative products) and firm performance (e.g., farmers' sales and profit growth) would be diminished when market demand for those products does not significantly peak enough. Therefore, those farmers may not be able to price a product optimally. What matters is whether the agribusiness farmer has enough capacity to supply the flow of high-value products demanded at any given time. It is proposed as a solution to peak-load pricing with seasons of unequal lengths (Shy, 2008). Hence.

H2a. market demand positively affects agri-business farmers' possibility to set peak-load pricing.

A situation that cannot be predicted (such as climate change or natural disasters) or the rate of change in the market (such as customer desires, challenges from competitors, and technological change) that prompt a firm to respond either now or in the future is referred to as environmental uncertainty (Latan et al., 2018) in agribusiness. Environmental uncertainty is a critical contextual variable in peak-load pricing. As for retail-based price discrimination, Nojavan et al. (2017) argued that selling price can be optimal when uniform price, time-of-use price (weekly or monthly), time-of-year price (seasonal), and on-demand price are used to client group demand. Under uncertainty relating to costs, the load profile has been flattened because a portion of the load can be shifted from peak periods to off-peak periods, resulting in an expected reduction in operation costs. After all, the price is higher in peak periods than in off-peak periods, compared to off-peak times (Nojavan et al., 2017). Yet, Khodaei et al. (2018) suggested that firms should have to consider market price and load uncertainty in industrial consumer agricultural production/product procurement.

H2b. Environmental uncertainty negatively affects agri-business farmers' possibility to set peak load pricing.

In the agricultural industry, seasons, cycles, and costs are critical. These are related to how peak-load pricing is set up (Shy, 2008). Some unprofitability is caused by seasonality in agricultural production and volatile prices, which may have been linked to the seasonality of futures contracts on agricultural commodities (Pereira et al., 2012). Given lengths of either short or long times of environmental differences of farm arrangements and climate variations, Kong et al. (2015) argued that seasonality is predictable because it happens every year in the same way. Therefore, farmers can manage the effects of seasonality. Foteinaki et al. (2020) showed that customer demand response is important to reflect the (agricultural) producers' marginal production costs. We interpret this as meaning that when the marginal capacity fee (capital) will be charged to the peak-season consumer, it is vital to balance crop capital investment and production capacity to meet demand in the peak season. To our knowledge, most studies have focused on a dynamic pricing scheme in the energy, hotel, and airline industries. Still, it is interesting how we could use dynamic pricing (peak load pricing) to motivate customers to buy more during off-peak and peak seasons. Thus, seasons are an input variable for implementing profitable peak-load pricing schemes. We hypothesized that:

H2c. seasonality positively affects agri-business farmers' possibility to set peak-load pricing.

2.2. Integrating research frameworks and gaps to answer research questions

In this study, the positivist paradigm is used because we believe that dynamic pricing tendencies are a complex, administered price phenomenon in the agricultural industry that can only be adequately described through quantitative assessments within a (positivist) conceptual framework. The literature on pricing reveals that most existing studies employ pure mathematical treatment to assess pricing systems (e.g., Foteinaki et al., 2020; Khodaei et al., 2018; Nojavan et al., 2017). Pricing phenomena should be viewed and investigated as marketing-oriented determinants of social facts that influence farmer behaviours, but they may also be a product of unintentionally priced actions. Hence, empirical evidence is required to reduce pricing innovation phenomena to a statistical explanation.

A detailed study of Boyaci and Ray (2003) has been made to extract in more detail on the optimal prices and market characteristics. They considered how capacity costs impact product differentiation choices and how a firm's differentiation strategy should be adjusted in response to a change in its operational dynamics using mathematical optimization. They figure out what kind of market condition affects the best pricing structure (Boyaci and Ray, 2003). But further research is also needed with the current methods of structural invariance, where structural relationships of pricing possibilities could be exemplified by the set of observed measures.

Concerning the Context of Thai smart farmers, Jansuwan and Zander (2021) argued that traditional farming has many risks, such as fluctuating agricultural markets and product prices, rising product costs; labor shortages; deteriorating soil quality; climate change; natural disasters, and fraud by intermediaries. They showed that smart farming would be a good solution to such issues because the agricultural outputs could be easily predicted and transparent. Although they have pointed out the pricing issues of agricultural products, most of their focus was on smart farming programs solely. To survive in the competitive markets, innovative pricing should be considered to capture value-added product prices as they cannot always depend on contract pricing systems. This is because of fluctuating global commodity markets and product prices

(Sukpanich et al., 2021). The total or partial breakout from contract pricing systems motivates us to question whether Thai farmers may be able to find new markets as they understand marketing and pricing knowledge. This is the essential motivation for this study to investigate the innovative pricing aspects.

Unlike those previous studies, this study carried out a survey to confirm proposed pricing tendencies among the real target groups of farmers. Through the analysis of innovative pricing, it is, therefore, possible to understand how the object of interest in relation to each other can respond to new social needs only through interpreting reality. Aiming to address the pricing tendencies predicted by marketing-oriented and contextual variables, we propose innovative pricing approaches for high-value products under which the final pricing results are tied to the outcome of the farmers' applications. So far, the influence of market-oriented and contextual variables on innovative pricing possibilities for high-value products has not been investigated in the literature. Most studies have conducted dynamic pricing schemes in energy industries (e.g., Foteinaki et al., 2020), but it is interesting to see how we would use dynamic pricing (peak load pricing) to motivate customers to buy more during off-peak seasons. This is identified as another gap in this study. Figure 1 summarizes and connects the conceptual models presented thus far as a basis for a survey given to the farmers under consideration in order to facilitate a better understanding of the analysis.

3. Research design and methodology

3.1. Data collection and sample selection

Rice, sugarcane, maize, and cassava smart agribusiness farmers were selected to test the research models. Rice farmers were the first group to be looked at because the government has launched the Rice Farmer 4.0 campaign using smart technologies. This campaign aims to improve rice farmers' rice yield and income (Phasuk, 2020). Rice farmers still suffer from price fluctuations depending on harvest season and peaks. Maize farmers were selected as the second research target. Maize is one of the primary high-value crops for Thai policy controversy due to its volatile price (TDRI, 2016). Regardless of price volatility, it is essential to find new solutions for maize farmers to increase incomes through a marketing perspective. The third research target is sugarcane farmers (Daniel, 2021). Sugarcane is an example of a high-value product among existing economic crops linked with Thailand's bioeconomy plans (Daniel, 2021).

On the other hand, sugarcane farmers are confronted with several difficulties, including price fluctuations, debt, water scarcity, soil deterioration, and crop disease. Furthermore, the production price of sugarcane is dependent on the mill destination. Therefore, cassava farmers were selected as the fourth research target. Cassava is an example of an economic, agricultural product used for food, feed, fuel, and factories (Sowcharoensuk, 2020). But farm prices are frequently subject to fluctuations based on the number of roots that reach the market and the starch content of the roots themselves. In addition, the cost is usually variable due to seasonal price volatility (i.e., a low-price during February and March). From the situation analysis, it's found that selecting four crops that are subject to domestic and global market mechanisms is extremely important. Because production costs are not covered by sales revenue, most Thai farmers are in debt. The government has embraced "smart farming" to encourage the deployment of technological innovation in key economic areas, including the agriculture industry. Agriculture 4.0, as part of Thailand 4.0, is considered to develop enabling factors in agriculture and support new generation farmers (NESDB, 2017; Phasuk, 2020). In this study, new generation farmers are referred to as "smart agribusiness farmers," who are likely to use technology for their agricultural practices with higher productivity and profit. With smart farming, solution benefits are that farmers can increase crop production quality, improve water conservation, visualize real-time data, and evaluate accurate farm and field (Mohamed et al., 2021; Walter et al., 2017). As a result of smart agricultural practices, it is possible that such farmers would have some knowledge to set prices innovatively to increase their prosperity.

Once the causal relationships of innovative price-setting approaches are hypothesized, the next step is to set out the research design and methodology. This study was based on the *field* survey design. This design helps us achieve the primary purpose of this study by empirically evaluating whether the determinants of segmented (tiered) pricing and peak-load pricing predict the potential to set segmented (tiered) pricing and peak-load pricing in a sample of economic, agricultural crop farmers.

According to the National Statistical Office (NSO), the nationwide population size was around 7,554,562[1] farm households registered by province (NSO, 2019). As important as it is to know the appropriate sample size for SEM, there is no exact consensus in the literature about what that size should be. Thus, this study applied Kline's suggestion (2015) that the rule of thumb is 100 observations per group for multi-group modeling analysis. Therefore, the minimum sample size should be 400 farmers (4 groups x 100 observations). To reach at least 400 samples, the purposive random sampling was applied to incorporate area sampling because the known population size is defined by the region of the planting zone for this study. The regional areas covered by the survey include Northern, Central, and Northeast Thailand.

Regarding the purposive random sampling method, inclusion and exclusion criteria were considered. The data were collected using a field questionnaire, which means that research teams gathered information using an in-person self-administered questionnaire. The team took farms in the Northern, Central, and North-eastern provinces of Thailand randomly. While taking them into the study, those farmers must use at least a low-cost platform for smart farming monitoring systems. This study used such criteria to recruit farmers as greenhouses, drones, irrigation, sensors, land levelling, and farm design. If they miss one of these criteria, they will be removed from the study. The pilot study on 5 smart agribusiness farmers was carried out before the whole survey was distributed. After the data collection stage, this study distributed 915 responses, but there were 840 valid responses to the questionnaire. This is because 23 responses had no completion, and 52 respondents were rejected at the recruitment stage. The response rate of this study was 91.8% (840/915*100). Table 1 exhibits the characteristics of the sample.

3.2. Instruments and variable measurement

The survey instruments consist of a demographic sample and questions measuring the determinants of innovative price-setting approaches. The demographic part with *seven* questions was used to scan the sample characteristics and meet the criteria for sample inclusion. The second part, with *thirty-six* items, assessed the determinants that led farmer respondents to set segmented (tiered) pricing and peak-load pricing as the smart farmer's innovative price-setting approaches. All of the items in Part 2 were assessed using 7-point Likert scales (1 = totally disagree; 7 = totally agree).

Independent latent variables included market focus, customer and product differentiations, segment-based mass customization, brand orientation, market demand, environmental uncertainty, and seasonality. *First*, market focus refers to understanding and determining target market and needs (Fernando and Wah, 2017) for highly valued products. To measure it, four items were modified from Fernando and Wah's research (2017) (α = 0.875). *Second*, customer and product differentiations refer to determining an offering to be differentiated from other traditional/conventional farmers in the market to make it more desirable to the target customer (Pelham, 1997). Four items were minor changes from Pelham (1997) and Swink and Hegarty (1998), asking crop-benefit needs, purchasing size, capacity costs, and purchasing criteria (α = 0.866). Third, segment-based mass customization capability refers to the

[1] http://statbbi.nso.go.th/staticreport/Page/sector/EN/report/sector_11_3_EN_.xls.

Table 1. The characteristics of the sample.

Demographic characteristics			Rice (n = 296)		Sugarcane (n = 191)		Maize (n = 104)		Cassava (n = 249)	
			Frequency	%	Frequency	%	Frequency	%	Frequency	%
Gender		Male	188	63.50%	114	59.70%	73	70.20%	171	68.70%
		Female	108	36.50%	77	40.30%	31	29.80%	78	31.30%
		Total	**296**	**100%**	**191**	**100%**	**104**	**100%**	**249**	**100%**
Size and type of farm or firm		Small farmer	244	82.40%	154	80.60%	69	66.30%	216	86.70%
		Large farmer	37	12.50%	31	16.20%	22	21.20%	32	12.90%
		Small agribusiness firm	8	2.70%	5	2.60%	5	4.80%	0	0%
		Large agribusiness firm	7	2.40%	1	0.50%	8	7.70%	1	0.40%
		Total	**296**	**100%**	**191**	**100%**	**104**	**100%**	**249**	**100%**
Age		24–39	122	41.20%	90	47.10%	37	35.60%	152	61.00%
		40–55	123	41.60%	55	28.80%	48	46.20%	74	29.70%
		56–74	51	17.20%	46	24.10%	19	18.30%	23	9.20%
		Total	**296**	**100%**	**191**	**100%**	**104**	**100%**	**249**	**100%**
Income (THB)		Below 49,999	1	0.30%	0	0%	1	1.00%	1	0.40%
		50,000–99,999	226	76.40%	146	76.40%	65	62.50%	208	83.50%
		100,000–299,999	41	13.90%	32	16.80%	13	12.50%	37	14.90%
		250,000–749,999	21	7.10%	8	4.20%	13	12.50%	2	0.80%
		750,000–1,499,999	2	0.70%	0	0%	4	3.80%	0	0%
		1,500,000–2,999,999	4	1.40%	4	2.10%	6	5.80%	1	0.40%
		Above 3,000,000	1	0.30%	1	0.50%	2	1.90%	0	0%
		Total	**296**	**100%**	**191**	**100%**	**104**	**100%**	**249**	**100%**
Geographical region by province	**The Northern region**	Phrae	54	18.20%	34	17.80%	0	0%	7	3%
		Chiang Mai	11	3.70%	10	5.20%	12	11.50%	40	16.10%
		Chiang Rai	8	2.70%	2	1%	7	6.70%	3	1.20%
	The North-eastern region	Khon Kaen	39	13.20%	40	20.90%	19	18.30%	27	10.80%
		Kalasin	39	13.20%	26	13.60%	12	11.50%	22	8.80%
		Mukdahan	33	11.10%	30	15.70%	7	6.70%	28	11.20%
		Udon Thani	38	12.80%	14	7.30%	7	6.70%	32	12.90%
		Nong Khai	30	10.10%	11	5.80%	8	7.70%	31	12.40%
		Roi Et	20	6.80%	15	7.90%	12	11.50%	26	10.40%
		Nakhon Ratchasima	5	1.70%	1	0.50%	2	1.90%	32	12.90%
	The Central region	Prachin Buri	10	3.40%	3	1.60%	8	7.70%	0	0%
		Bangkok	7	2.40%	4	2.10%	5	4.80%	1	0.40%
		Nakhon Pathom	2	0.70%	1	0.50%	5	4.80%	0	0%
		Total	**296**	**100%**	**191**	**100%**	**104**	**100%**	**249**	**100%**

ability to offer a volume of *high-value* product options for a relatively large segment that requires customisation without significant compromises in terms of cost, delivery time, or product quality (Wang et al., 2016). This study adapted a four-item scale to measure segment-based mass customization capability from Wang et al. (2016), Huang et al. (2008), and Deshpande (2018) (α = 0.86). *Fourth*, brand orientation refers to differentiating (high-valued agricultural) products — through name, symbol, sign, colour etc. — from those of competitive price-setters to serve market segments for various purposes (Boso et al., 2016; Jevons, 2005). The four-item scale was modified from research by Baumgarth (2010) and Chang et al. (2018) (α = 0.867). *Fifth*, market demand refers to the current level of demand assessment from the market over time (Anning-Dorson, 2017). The measurement scale for market demand was taken from Lin et al. (2013) and Anning-Dorson (2017) (α = 0.852). *Sixth*, environmental uncertainty refers to the unpredictability of external forces affecting the decision unit (Liao et al., 2011) in farm performance. For analysis, the responses were reversed since we assume a negative correlation. The environmental uncertainty assessment was adapted from Liao et al. (2011) and changed to fit the research context (α = 0.919). *Seventh*, seasonality refers to seasonal pattern movements of crop cultivation and price (Devereux et al., 2012, p. 5). To measure seasonality, this study applied the four-item scale from Gilbert et al. (2017) and Sassi (2019) (α = 0.905).

Dependent latent variables were segmented (tiered) pricing and peak-load pricing being tested to investigate whether the above independent variables cause changes in the potential of segmented (tiered) price-setting and peak-user price setting. First, segmented (tiered) pricing refers to the ability to provide price offerings for different potential segments depending on consumer characteristics (Iyer et al., 2002). To measure the phenomenon of segmented (tiered) pricing, this study modified the four-item scale from Friedman and Lewis (1999), Moon et al. (2011), Iyer et al. (2002), Thach and Olsen (2015), and Seufert (2014) (α = 0.883). Second, peak load pricing refers to the ability to provide price offerings during periods of high/peak demand (Iyer et al., 2002). To identify if there's a possibility to set this kind of price-setting, this study measured the peak load pricing phenomenon based on the work of Friedman and Lewis (1999) and Iyer et al. (2002) (α = 0.89). The content details of all item measurements for both dependent and independent latent variables are exhibited in **Appendix**.

4. Data analysis

Multigroup structural invariance was selected as the method to recognize determinants of segmented (tiered) pricing and peak-load pricing across four high-value crops such as rice, maize, sugarcane, and cassava. Given that multigroup structural invariance is assumed to predict on the concept of group heterogeneity (Klesel et al., 2019), it is beneficial for examining dissimilarities across crops. To justify statistical analysis method, multigroup structural invariance is the most appropriate because the study's group moderator is a categorical variable (i.e., crop-farmer types), its predictive model allows to look into farmers interaction and meaningful dissimilarities in multiple relationships across crop-specific results. SPSS Statistics 28.0 and Amos 28.0 were used to analyze the survey data. The motivation of such determinants was driven by the holistic view of two innovative price-setting approaches. The establishment of a holistic view is linked to the theoretical explanation and practical utilization of price-setting approaches to data as a component for evaluation.

This study performed several data analysis steps, such as exploratory factor analysis (EFA), confirmatory factor analysis, measurement invariance, and multigroup structural invariance.

4.1. Step 1: exploratory factor analysis (EFA)

The exploratory factor analysis allows observed variables to be first seen as standardized common factors. In Exploratory factor analysis (EFA), principal axis factoring (PAF) is applied to estimate the factor loadings and unique variances of the research model. The total variance extracted by one factor was 40.136% which is lower than the recommended threshold of 50% (Malhotra et al., 2006). This study claims that this data has no problem with common method bias. Using EFA, we can determine the underlying factors for a set of measured variables. Next, we will perform CFA if there is a relationship between the observed variables and their underlying latent constructs.

4.2. Step 2: confirmatory factor analysis (CFA)

In CFA, fitting procedures (e.g., construct reliability and validity) were employed to estimate the model. To assess convergent validity, the analysis showed that factor loadings ranged from 0.733 to 0.846 for the segmented (tiered) price-setting model and from 0.712 to 0.878 for the peak-load price-setting model. Table 2 illustrates construct validity and reliability of measurement for segmented (tiered) pricing model, while Table 3 illustrates for peak load pricing model. Referring to Table 2 and Table 3, the results of factor analysis showed that factor loadings were higher than a rule of thumb of 0.7 (Hair et al., 2018); this indicates that each factor could gain adequate variance to explain such a variable. The average variance extracted (AVE) is a way to measure how much variance a construct captures in comparison to how much variance there is in the measurement process. In the segmented (tiered) price-setting model, the results ranged from 0.609 to 0.655, while those of the peak-load price-setting ranged from 0.596 to 0.74. Their values exceed the recommended threshold of 0.5 (Hair et al., 2018), indicating that items explain *fewer errors than the constructs' variance*. Composite reliability is another requirement of convergent validity. Values for the segmented (tiered) price-setting model were from 0.862 to 0.884, while those for the peak-load price-setting model were placed in the range of 0.855–0.919. Thus, the CR values went up to a relevant threshold of 0.7 (Hair et al., 2018), indicating that items are reliable to measure the same construct constantly. With reference to Table 4 and Table 5, the discriminant validity was assessed using Fornell and Larcker (1981). The results indicated that the square root of each AVE in the diagonal was higher than the correlation coefficients (off-diagonal) for each construct in the relevant rows and columns. As for the heterotrait-monotrait (HTMT) ratio of the correlation method, the results indicated no disputes because the values passed the recommended threshold of the HTMT 0.85 criterion (Henseler et al., 2014). Overall, both methods of discriminant validity can be satisfactorily supported for this measurement model, allowing us to claim no multi-collinearity problems existed. In a look at the variance inflation factor (VIF), it was found that there were also no issues with multi-collinearity because its scores were not above 10 (O'Brien, 2007).

In CFA, it is also essential to assess how well the model matches the data. The model fit indices for both overall measurement models indicated that they were greatly adequate:

- The overall measurement model of the segmented (tiered) price setting model had good model fit indices: χ^2/df = 2.96; DF = 160; SRMR = 0.031; GFI = 0.945; AGFI = 0.928; NFI = 0.956; IFI = 0.97; TLI = 0.964; CFI = 0.97; and RMSEA = 0.048, indicating that the model fits the data fairly well (Hair et al., 2018).

Table 2. Construct validity and reliability for segmented (tiered) pricing model.

Constructs	Factor loadings	AVE	CR	α	VIF
Market focus					
MF4	0.803				1.712
MF3	0.821				1.832
MF2	0.796				1.672
MF1	0.773	0.637	0.875	0.875	1.557
Customer and product differentiations					
CPD4	0.776				1.568
CPD3	0.81				1.755
CPD2	0.773				1.554
CPD1	0.791	0.62	0.867	0.866	1.641
Brand orientation					
BO4	0.763				1.515
BO3	0.818				1.81
BO2	0.733				1.407
BO1	0.842	0.624	0.869	0.867	2.011
Segment-based mass customization					
SMP4	0.772				1.551
SMP3	0.812				1.768
SMP2	0.781				1.593
SMP1	0.756	0.609	0.862	0.86	1.486
Segmented (tiered) pricing					
SEG1	0.846				2.052
SEG2	0.807				1.736
SEG3	0.808				1.743
SEG4	0.775	0.655	0.884	0.883	1.565

Table 3. Construct validity and reliability for peak load pricing model.

Constructs	Factor loadings	AVE	CR	α	VIF
Market demand					
MD4	0.793				1.651
MD3	0.791				1.644
MD2	0.803				1.712
MD1	0.698	0.597	0.855	0.852	1.311
Environmental uncertainty					
EU4	0.878				2.475
EU3	0.874				2.402
EU2	0.836				1.95
EU1	0.853	0.74	0.919	0.919	2.121
Seasonality					
SS4	0.796				1.669
SS3	0.863				2.247
SS2	0.858				2.182
SS1	0.842	0.706	0.906	0.905	2.011
Peak load pricing					
PLP1	0.839				1.983
PLP2	0.81				1.759
PLP3	0.823				1.846
PLP4	0.798	0.669	0.89	0.89	1.683

Table 4. Discriminant validity of segmented (tiered) pricing model.

Fornell-Larcker criterion						Heterotrait-monotrait ratio of correlations					
	MF	CPD	BO	SMP	SEG		MF	CPD	BO	SMP	SEG
MFS	**0.798**	0.72	0.709	0.663	0.619	MF		0.72	0.709	0.663	0.619
CPD		**0.788**	0.669	0.711	0.646	CPD			0.669	0.711	0.646
BO			**0.79**	0.698	0.766	BO				0.698	0.766
SMP				**0.781**	0.689	SMP					0.689
SEG					**0.809**	SEG					

Table 5. Discriminant validity of peak-load pricing model.

Fornell-Larcker criterion					Heterotrait-monotrait ratio of correlations				
	MD	EU	SS	PLP		MD	EU	SS	PLP
MD	**0.772**	0.015	0.538	0.669	MD		0.015	0.538	0.669
EU		**0.860**	0.037	0.011	EU			0.037	0.011
SS			**0.840**	0.699	SS				0.699
PLP				**0.818**	PLP				

- For the peak-load price setting model, the indices of model fit involved SRMR = 0.042; GFI = 0.948; AGFI = 0.928; NFI = 0.96; IFI = 0.971; TLI = 0.964; CFI = 0.971; and RMSEA = 0.056. With the degree of freedom equal at 98, the relative chi-square (χ^2/df) was below 5, indicating a reasonable fit (Marsh and Hocevar, 1985).

In sum, the results confirm the need to implement the structural model in the next step. However, the aggregate structural model will be omitted since our objectives focus on multigroup analysis; it is no need to perform it. Before the analysis of multigroup invariance, measurement invariance is required.

4.3. Step 3: measurement invariance

In CFA, invariance testing is important to imply that the same construct is being assessed across groups that are not related to each other (Vandenberg and Lance, 2000). To evaluate it, groups of interest are set to be equal in the following three hierarchical levels of invariance:

- First, configural invariance tests the default model with unconstrained factor loadings. The model fit for the segmented (tiered) price setting model indicated χ^2/df = 1.65; DF = 640; SRMR = 0.0346; TLI = 0.951; CFI = 0.959; and RMSEA = 0.028, while that for the peak-load price setting model was χ^2/df = 1.829; DF = 392; SRMR = 0.0391; TLI = 0.954; CFI = 0.959; and RMSEA = 0.031.
- Second, metric invariance tests the models with measurement weights. The model fit for the segmented (tiered) price setting model indicated χ^2/df = 1.652; DF = 685; SRMR = 0.0345; TLI = 0.951; CFI = 0.956; and RMSEA = 0.028, while the metric model fit for the peak-load price setting model was χ^2/df = 1.82; DF = 428; SRMR = 0.04; TLI = 0.953; CFI = 0.962; and RMSEA = 0.031.
- Third, scalar invariance tests the models with structural covariances. The model fit for the segmented (tiered) price setting model indicated χ^2/df = 1.852; DF = 730; SRMR = 0.0672; TLI = 0.936; CFI = 0.939; and RMSEA = 0.0973, while the scalar model fit ensures that the supportive indices had χ^2/df = 2.341; DF = 458; TLI = 0.924; CFI = 0.928; and RMSEA = 0.04. The value of standardized RMR, 0.097, was considered adequate because it was less than 0.10 (Meza and Fahoome, 2008).

In a nutshell, all three levels of invariance are satisfied; we can claim that the full measurement invariance is established (see Table 6), meaning that it may be meaningful to compare across groups. The multigroup moderation analysis of the structural invariance will be given in the next step.

4.4. Step 4: multigroup structural invariance

We sought to estimate different structural models for each group after establishing the measurement model's group invariance to check whether there were any meaningful changes in their structural links. The goodness-of-fit indices for the SEM runs with four crop groups appeared to fit fairly well for the segmented (tiered) price setting mode: χ^2/df = 1.65; DF = 640; SRMR = 0.0346; NFI = 0.903; IFI = 0.959; TLI = 0.951; CFI = 0.959; and RMSEA = 0.028. For the peak-load price setting model, the model-data fit indices across crop farmers were: χ^2/df = 1.829; DF = 392; SRMR = 0.04; NFI = 0.92; IFI = 0.962; TLI = 0.953; CFI = 0.962; and RMSEA = 0.031. To determine the structural invariance of a composite model, structural weights must be established. The model fit for the segmented (tiered) price setting model indicated χ^2/df = 1.689; DF = 757; SRMR = 0.035; TLI = 0.948; CFI = 0.948; and RMSEA = 0.029, while the goodness of fit of the peak-load pricing model ensures that the supportive indices had χ^2/df = 2.002; DF = 485; SRMR = 0.0408; TLI = 0.943; CFI = 0.943; and RMSEA = 0.035. Accordingly, the multigroup structural invariance model is *adequate* to present a good fit of rice, sugarcane, maize, and cassava farmer samples. All four steps were supported and confirmed, allowing us to test the hypotheses next.

Using the critical ratio difference, a *Z-test* for loading differences was conducted to compare the factor loadings between structural invariance models (rice, sugarcane, maize, and cassava farmers) (see Table 9). This method yields a list of critical ratios for pairwise comparisons between parameters determined in the multigroup analysis. If the critical ratio is higher than the absolute value of ±1.96 at 5% significance, the factor loadings between the two groups are considerably different (Byrne, 2016; Reisenzein, 1986).

Table 6. Measurement invariance and structural invariance.

Study 1	CMIN/DF	SRMR	TLI	CFI	RMSEA
Unconstrained	1.65	0.0346	0.951	0.959	0.028
Measurement weights	1.652	0.0345	0.951	0.956	0.028
Measurement intercepts	1.686	0.0346	0.948	0.949	0.029
*Structural weights	1.689	0.035	0.948	0.948	0.029
Study 2	CMIN/DF	SRMR	TLI	CFI	RMSEA
Unconstrained	1.796	0.0378	0.955	0.963	0.031
Measurement weights	1.773	0.0374	0.956	0.961	0.03
Measurement intercepts	1.916	0.0394	0.948	0.949	0.033
*Structural weights	2.002	0.0408	0.943	0.943	0.035

5. Results and discussions

While reports (e.g., TIR, 2020, 2021) consider smart farming as agricultural development concerning the government's farming and food development plan that serves the farm marketing policy (TIR, 2021). This is related to *farmnovation* (TIR, 2020) and marketing-based pricing. Therefore, this paper suggests that Thai smart farmers should utilize marketing platforms (especially online platforms) in order to succeed in the economic, agricultural sustainable transition and improve the ease of doing business in the agricultural sector. As argued in the work of Jansuwan and Zander (2021), the farmers need to network to share information about new farming methods, form large-scale farming groups to have more bargaining power when buying inputs and distributing their products, and feedback government agencies directly about their needs and thoughts. This is also related to *open innovation*, which aims to meet the unique (agricultural) requirements in our areas of interest by collaboration and marketing to the innovation community (Jansuwan and Zander, 2021; Leckel et al., 2020; Srisathan et al., 2020). Our findings show that openness to innovative pricing highlights that smart farmers must understand market focus, brand management, customization, and customer and product value quantification; these are insights from Study I. It means those farmers can find the right price using customer knowledge from market segments (also called market insight). As for Study II, innovative pricing should allow uncertainty and demand change management to reassess when market prices are undesirable. When the level of uncertainty and the rate of product innovation in the market is high, choosing a pricing base becomes critical for achieving acceptable profitability. In order to find a good way to price high-value (agricultural) products (Hinterhuber and Liozu, 2018), pricing becomes an act of innovation. Our findings back up what Jansuwan and Zander (2021) found, but what we offer is a look at the marketing side of things. Overall, our research finds that smart farmers are likely to know marketing-based pricing strategies for their own agribusinesses. Still, evidence of agribusiness's exact price setting is restricted in our holistic scope.

In order to demonstrate the effects of market focus, we plotted the relationships among different groups of crop farmers. The results of H1a reveal that the market focus has no significance across rice farmers (β = 0.044; t-value = 0.558), sugarcane farmers (β = -0.079; t-value = -0.619), and maize farmers (β = -0.115; t-value = -0.574) in determining current segmented (tiered) pricing. This is because these products may not be featured as heavily as cassava products since a price guarantee has recently been a short-term remedy during economic stagnation in the country. The government must also enhance the quality of farmers' production and provide them with supportive knowledge to be smart farmers for long-term sustainability. Compared with European countries, this is not the first time European countries have used price guarantees; they have also improved their productivity and quality and monitored the world markets, providing farmers with information so that they can adjust their production capacity to match the demand in the market (Suebpongsang, 2021). Hence, agricultural productivity must be raised through the use of innovation and big data by the government in order to assist farmers in improving their quality (Wolfert et al., 2017). It may not be worth considering that market penetration may not ultimately be the goal to increase volume. This effect of non-significance also means that these products may be more tailored to mass demand of general consumption than niche desire. When H1a was tested, our proposed model appeared to work with cassava farmers (β = 0.252**; t-value = 2.942), which is significant at a 1% significance level. Cassava seems more featured and appealing by segments, while they are also targeted with clear messages that put across high-valued cassava products' unique selling points. In turn, these farmers have the ability to set a price for each unique segment. Similar to H1a, the test of H1b indicated that there were no effects in determining segmented (tiered) pricing by customer and product differentiations. The reason might be that more key benefits or features of these highly valued crops, such as rice, sugarcane, and maize, may not be met by sufficient and specific demand. Differentiation aspects – especially pricing – could not be fulfilled. The effect of customer and product differentiations on segmented (tiered) pricing success was significant (β = 0.185*; t-value = 2.169) at 5% significance level. This implies that the choice of customer and product differentiation is based on the variety of cassava forms, which can help boost the profitability and viability of the agribusiness by providing superior value to customers at a reasonable price. Hence, this confirms that H1b is supported. Also, this can be confirmed by the study of Sukpanich et al. (2021) that in terms of Thai cassava exports, China is Thailand's largest buyer. China imports cassava chips for the production of ethanol and cassava starch for the production of modified starch used in the papermaking and textile industries, respectively. Thai cassava export has strong competitiveness, including its potential, market share and competitiveness against the main competitor, namely Vietnam, Cambodia, Lao, and Indonesia (Sukpanich et al., 2021).

If looking at Table 7, the standardized parameter loadings from H1c in study 1 for rice, sugarcane, and maize farmers were significantly different at an alpha level of 0.1% (p-value $<$ 0.001) while for cassava farmers at an alpha level of 1% (p-value $<$ 0.01). In marketing, these results (H1c grouped by rice, sugarcane, maize, and cassava) supported the segment (tiered) price setting theory, in line with Small et al. (2007). It means that when smart farmers could position their market, there might be a possibility to set prices by segment. This results from brand value creation in terms of market performance (i.e., cost structure, price elasticity, expansion etc.), which enables them to enhance and meet the needs and wants of that target segment. In particular, in order to become smart farmers, our results propose a new solution for those traditional ones by focusing on strategic branding in their business strategy. Compatibly, with the country's position as a leading agricultural goods producer, supported by public funding and policy, and surrounded by innovative startups and research centers, the Thai agricultural sector is moving toward a more intelligent future. Many exciting new agricultural technologies are being implemented in Thai farms following agriculture 4.0 Thailand (TIR, 2020).

Brand orientation has a *significant* effect in determining segmented (tiered) pricing success across rice farmers (β = 0.401; t-value = 4.583), sugarcane farmers (β = 0.717; t-value = 6.567), maize farmers (β = 0.83; t-value = 3.517) and cassava farmers (β = 0.305; t-value = 3.068). Based on our results, in the case of rice as a high-value product through their brand, we found that most Thai rice farmers have shifted their sales channels to social media and e-commerce platforms, which allows them to set prices based on their cost and market segment (e.g., organic consumers, etc.). As for Thai sugarcane industry, Thai sugarcane farmers have indeed faced the problem that the input cost is higher than the sugarcane price set by the world market (Manivong and Bourgois, 2017). Brand orientation may work for the sugar industry rather than the sugarcane industry itself. In some ways, processing sugarcane and sugarcane diversification should be considered. Farmers can set different prices for their sugarcane because of the power of branding. For example, vinegar, sugarcane juice concentrate, sugarcane molasses, sucrose, ethanol, electricity, powder jaggery, and other high-value products can be made from sugarcane. These products are not only nutritious but also have a lot of potential for exporting to other countries such as Indonesia, the United States, and Bangladesh (PCP, 2020). Even for maize, the process of brand orientation to define the brand identity for high-value products becomes more challenging as they expand their maize products internationally to meet new segments; this allows smart farmers to set a very different/unique pricing from the domestic market. Cassava is a versatile crop that may be used for various value-added products ranging from coarse flour to high-tech starch gels (Srivastava et al., 2021). When crop producers face price fluctuations, minimal processing and value addition of tapioca is the only option for them to get an additional price. As supported by the International Trade Center's recommendation, any high-value products aimed at a certain segment will need to be properly positioned in order to optimize their chances of success in a competitive

Table 7. Multigroup structural results.

		Rice		Sugarcane		Maize		Cassava	
Study 1									
Hypotheses	Causal relationships	β (p-value)	Critical ratio	β	Critical ratio	β	Critical ratio	β	Critical ratio
H1a	MF → SEG	0.044 (0.558)	0.587	-0.079 (0.536)	-0.619	-0.115 (0.566)	-0.574	0.252 (0.003**)	2.942
H1b	CPD → SEG	0.145 (0.135)	1.495	-0.15 (0.292)	-1.054	0.055 (0.693)	0.394	0.185 (0.03*)	2.169
H1c	BO → SEG	0.401 (***)	4.583	0.717 (***)	6.567	0.83 (***)	3.517	0.305 (0.002**)	3.068
H1d	SMP → SEG	0.308 (***)	3.369	0.387 (***)	3.834	0.169 (0.138)	1.483	0.128 (0.19*)	1.31
Study 2									
Hypotheses	Causal relationships	β (p-value)	Critical ratio	β	Critical ratio	β	Critical ratio	β	Critical ratio
H2a	MD → PLP	0.395 (***)	5.957	0.282 (***)	4.457	-0.15 (0.259)	-1.13	0.479 (***)	5.212
H2b	EU → PLP	0.025 (0.624)	0.49	-0.007 (0.84)	-0.202	-0.106 (0.374)	-0.89	0.023 (0.723)	0.355
H2c	SS → PLP	0.459 (***)	6.738	0.707 (***)	9.86	0.4 (0.006**)	2.771	0.383 (***)	5.093

and crowded market (ITC, 2020); brand positioning and value are required to reassure a point of competitive price setting.

Regarding segment-based mass customization, H1d was supported in that significant differences in segmented (tiered) pricing propensities in either rice (β = 0.308***; t-value = 3.369), sugarcane (β = 0.387***; t-value = 3.834), and cassava (β = 0.128*; t-value = 1.31) were found. Linking segment-based mass customization to the smart farm idea implies that creating a smart production system with automation may increase the efficiency and flexibility of high-value crop production (Pedzik et al., 2020). The further effect of this is to allow new generation farmers to customize certain features of such products while still keeping costs close to mass production prices. However, there is a key takeaway consistent with the findings of Shao (2020), that a high-level mass customization system makes it possible to offer customized product forms for each segment. Hence, those farmers could earn high-level mass customization of crop production at a higher price, but lower prices do not always accompany standardization. Nonetheless, our findings indicated that a high-level mass customization strategy could always result in increased sales and prices. No effect of segment-based mass customization was significant for maize farmers (β = 0.169; t-value = 1.483).

Study 2 was developed based on the peak load pricing model by introducing market demand, environmental uncertainty, and seasonality. The results of H2b indicated no effect of environmental uncertainty across rice (β = 0.025; t-value = 0.49), sugarcane (β = -0.007; t-value = -0.202), maize (β = -0.106; t-value = -0.89), cassava farmers (β = 0.023; t-value = 0.355). This may be because those farmers might perceive that environmental uncertainty is under their control. Aside from maize farmers, the H2a results favored rice farmers (β = 0.395***; t-value = 5.957), sugarcane farmers (β = 0.282***; t-value = 4.457), and cassava farmers (β = 0.479***; t-value = 5.212) at 0.1% significance level. These groups of farmers may assess market demand; they could price high-value products during peak seasons. This further implies that those farmers who may know about the market demand characteristics for a certain agricultural product can use this knowledge to figure out when to supply their products (Anning-Dorson, 2017; Zhou et al., 2009). With capacity planning, peak demand (load) management can be maintained (Arteconi et al., 2012). Different crops can be grown for different lengths of time. Agricultural production and seasonality are heavily dependent on seasonal and cycle conditions, allowing peak price to play its role. Also, it is seen that Thai farmers start to develop and strengthen agricultural cooperatives so that farmers have greater bargaining power in the markets for farm inputs, and collectively handle production plans, plant diseases and pest prevention plans, logistics and farm mechanization, and warehouse storage of their crops in the peak period (Arunrat et al., 2021; Jansuwan and Zander, 2021). As seen in the testing results of H2c, we confirm that it is true that there is an effect of seasonality on peak-load pricing, supported by Shy (2008). The results reveal the significant differences among rice farmers (β = 0.459***; t-value = 6.738), sugarcane farmers (β = 0.707***; t-value = 9.86), and cassava farmers (β = 0.383 ***; t-value = 5.093) at 0.1% significance level while maize farmers (β = 0.4 ***; t-value = 2.771) at 1% significance level. Most farmers come up with great crop production plans each year. Agribusiness farmers then manage these practices on their farms with their resources. When a marketing plan is used with a farm's production plan, it helps the farmers figure out what prices they want for their grains as the production and storage season goes on.

Our main objective is to accurately predict the response variable's value using the predictor variable, so squared multiple correlations are important. Table 8 summarizes the coefficient of determination, which measures how much of the total variation the proposed pricing model can explain in each group. 67.8% represents a model that explains all the variations to predict the current segmented (tiered) pricing for rice farmers ($R^2 = 0.678$). 70.9% of the total variance explains that sugarcane farmers are more likely to set prices based on market segmentation for high-value products. A squared multiple correlation of 65.3% explains the fact that maize farmers are inclined to apply segmented (tiered) pricing. 51.6% of the variance shows cassava farmers are more likely to be worried about using segmented (tiered) prices. The response data provides useful information about the segmented (tiered) pricing model. The R-squared values were higher than 0.5 and 0.7. It explains that these values are generally considered to have a moderate-to-strong effect size. It appears that 57.5% of the total variance explains that rice farmers are likely to apply peak-load pricing, while 88.3% of the variance explains that sugarcane farmers are. A squared multiple correlation of 13.33% explains the fact that maize farmers are inclined to apply segmented (tiered) pricing. Cassava farmers are more concerned about the usage of segmented (tiered) pricing, as seen by 42.4% of the variation. The response data gives some useful information about the peak-load pricing model. The R-squared values were more significant than 0.1 and 0.8. It explains that these values are generally considered to have a weak-to-strong effect size.

Theoretical implications

The findings of this study have various theoretical implications for scholars in the field of innovative pricing. First, this current study gives a better theoretical understanding of the determinants that lead new generation farmers to apply innovative pricing by identifying important factors and comparing their effects across four groups of crop farmers. Existing studies (see e.g., Boyaci and Ray, 2003; Foteinaki et al., 2020; Khodaei et al., 2018; Nojavan et al., 2017) tend to emphasize a mathematical economic standpoint (e.g., demand function), whereas this

Table 8. Squared multiple correlations across groups.

Model	Squared Multiple Correlations (R^2)			
	Rice	Sugarcane	Maize	Cassava
Segmented (tiered) pricing	0.678	0.709	0.653	0.516
Peak load pricing	0.575	0.883	0.133	0.424

Table 9. Test results for critical ratio differences.

		Critical ratio comparisons between parameters				
Study 1						
Hypotheses	Causal relationships	Rice vs. Sugarcane	Sugarcane vs. Maize	Maize vs. Cassava	Cassava vs. Rice	Thresholds
H1a	MF → SEG	| -0.806 |	| -0.051 |	| 1.727 |	| 1.883 |	| ± 1.96 |
H1b	CPD → SEG	| -1.626 |	| 1.061 |	| 0.656 |	| 0.25 |	| ± 1.96 |
H1c	BO → SEG	| 2.75 |**	| 0.989 |	| -2.53 |**	| -0.817 |	| ± 1.96 |
H1d	SMP → SEG	| 0.802 |	| -1.413 |	| -0.274 |	| -1.182 |	| ± 1.96 |
Study 2						
Hypotheses	Causal relationships	Rice vs. Sugarcane	Sugarcane vs. Maize	Maize vs. Cassava	Cassava vs. Rice	Thresholds
H2a	MD → PLP	| -0.978 |	| -2.866 |**	| 3.806 |**	| 0.999 |	| ± 1.96 |
H2b	EU → PLP	| -0.521 |	| -0.452 |	| 0.892 |	| -0.254 |	| ± 1.96 |
H2c	SS → PLP	| 3.015 |**	| -5.168 |**	| 1.276 |	| -1.275 |	| ± 1.96 |

study's focus is on marketing-oriented and contextual factors. Additionally, this study has successfully determined the innovative pricing of segmentation (tiered) by including market focus, customer and product differentiations, brand orientation, and segment-based mass customization. Market demand and seasonality characteristics probably generate an appropriate determination to explain the context of peak-load pricing. However, our causal findings only provide new insights into marketing-related and contextual factors that can influence innovative pricing tendencies. This means these factors have a tendency to foster segmented (tiered) pricing and peak-load pricing among farmer groups.

Practical implications

From a practical standpoint, this study's findings hold necessary implications for the practical context of the agricultural industry in Thailand in terms of strategies that it can apply to innovative pricing approaches incorporating global market prices of agricultural commodities.

Our findings provide practical implications of the reality if certain conditions are fulfilled. Based on evidence-based results, we use the item measures from factor loadings to recommend some of the following practical implications to promote the dynamic pricing model. For example, how could market focus, customer and product differentiations, brand orientation, and segment-based mass customization be used to design evidence-based actions for segmented (tiered) pricing? The following are the key takeaways from our research.

1. **Emphasizing market focus.** Agribusiness farmers might look at a preliminary market for agricultural outputs, focus on a specific target market, work with stakeholders in the market, and get customer feedback on agricultural product ideas. As a result, they are more likely to apply segmented (tiered) pricing for high-value products. This strategy was derived from MF1 – 4.
2. **Differentiating customer and product.** When agribusiness farmers figure out different customer-and-product characteristics, such as how big they are, how much they need, how much it costs, and how they want to buy it, they might apply segmented (tiered) pricing (CPD1 – 4).
3. **Create a brand strategy.** Once smart farmers start learning more about brand strategy, they may run into marketing activities and communications. Therefore, smart farmers should give importance to branding (BO1 – 4).
4. **Mass-Producing a high-value product.** This can be done by customizing products on a large scale, adding product variety without increasing costs, setting up for a different outcome at a low cost, and counting product variety without sacrificing product quality. Mass production results in segmented prices of goods (SMP1 – 4).
5. **Understanding the potential of segmented (tiered) pricing.** Segmented (tiered) pricing can be used when smart farmers want to charge different prices for different features or products, give different options for quality levels at a reasonable or affordable price, give different values for using products, and offer a freemium (a free price tiered) to specific targets. However, segmented (tiered) prices may be determined by market focus, customer and product differentiations, brand orientation, and segment-based mass customization (SEG1 – 4).

How could market demand, environmental uncertainty, and seasonality be used to design evidence-based actions for peak-load pricing? The following are the key takeaways from our research.

1. **Understanding market demand might be necessary as an underlying factor.** Agribusiness farmers might be looking for new products, seeking technical support that help with specific problems, provide new outcomes, and evaluate the segmentation and price flexibility of demand for agricultural crops. They also need to note the sensitive price segment when prices are adjusted (MD1 – 4).
2. **Assessing environmental uncertainty.** Agribusiness farmers might understand the diversity of business segments, purchasing time of customer demand, dissimilarities of suppliers and technology providers, and crop production estimates and crop yield forecasts (EU1 – 4).
3. **Understanding seasonality.** Agribusiness farmers may need to understand, consider, and figure out what people want at different times of the year (i.e., off-harvest season, harvest season, and peak season). Yet, they are recommended to keep in mind that seasonal variation is not only in periods but also in the fluctuations in labor demand and employment (SS1 – 4).
4. **Understand the potential for peak-load pricing.** Peak load pricing may be recognized when the primary and additional charges set prices during high demand, offered with discounts for the early purchase of specific products, and offered for retail and wholesale products. It is also essential to estimate marginal cost and demand in each period. If the marginal cost is also high during these peak periods due to capacity constraints, prices should be higher during these peak periods. However, peak prices may be determined by seasonality, market demand, and environmental uncertainty (PLP1 – 4).

As findings from this research demonstrated that the possibility for innovative pricing approaches (primarily segmented (tiered) pricing) of Thai agribusiness farmers is highly linked to brand-oriented strategies and segment-based customization within these four types of farmers. Our findings recommend that farmers continue to find out what the product's highlight is, which would assist them in standing out from others. In other words, they are advised to consider storytelling. This would further allow them to succeed in applying segment pricing. However, new generation farmers should also use segmented pricing by thinking about the cost parameters so that they still could make some profits when global market prices are lower than their cost of crop production.

In the case of peak-load pricing, the question arises: is it reasonable to set a peak load price? It is possible to do so. This may recall our findings on segmented pricing (also known as price discrimination) (Bergemann et al., 2015). When farmers sell their high-value products in two markets with different marker segments (Chen and Chen, 2021), farmers can opt between two homogenous prices. They can charge a low price, less than the global market price, thereby serving peak and off-peak seasons. Alternatively, they can charge a higher price than global market prices, excluding all off-peak demand and resorting to peak demand only. They need to remember that such a price (i.e., a higher price) should be reasonable and affordable.

6. Conclusion

As motivated by the market segments observed in the agricultural industry, this study discusses the possibilities to set peak load pricing and segmented (tiered) pricing for value-added agricultural products and what determinants most affect peak-load pricing and segmented (tiered) pricing of value-added farm products. We consider high-value or value-added products in which farmers can be heterogeneous in pricing strategies. When it comes to answering our research questions, our findings suggest key answers that there is a possibility to set peak-load pricing and segmented (tiered) pricing for value-added agricultural products in the emerging markets. What factors should be considered? Our study shows cassava farmers fit our segmented (tiered) pricing model when considering market focus, customer and product differentiations, segment-based mass customization, and brand orientation. Only when sufficient market demand and seasonality are considered, there is a chance for peak load pricing to set in. Farmers could price a product with segmented pricing during off-peak seasons. It implies that they need to sell products to the right segment to stabilize the price level of their high-value products without price-cutting or overload price promotion. Our result suggests that the price should be reasonable or affordable. Hence, innovative pricing approaches can create win-win situations for farmers and customers/clients. However, a few other innovative pricing elements can bring more attention to future research directions. Because our study was based on a field survey to get a holistic marketing-based view, simulation and experimental research are required to illustrate how much these two innovative pricing approaches contribute to the degree of profit maximization. Also, for our research to go further, we need to try things out to see how much these factors affect price optimization and farmers' profits. The setup model of conditional probability for pricing may be called for. Another challenging area that is interesting to look at is the effect of creating pricing conditions for both approaches through price and demand functions while considering these factors when setting up the model.

Declarations

Author contribution statement

Phaninee Naruetharadhol conceptualized the main idea of the study, designed the survey, and wrote the paper.

Chavis Ketkaew analyzed the data.

Wutthiya Aekthanate Srisathan conceptualized the main idea of the study, analyzed and interpreted the data, and wrote the paper.

Funding statement

Phaninee Naruetharadhol was supported by the National Science, Research and Innovation Fund" or "NSRF" (FRB650032/0161).

Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Ethical review of the project

The protocols in this study were reviewed and approved as exempt from full board review by the Ethics Committee for Human Research of Khon Kaen University, No. HE633089.

Acknowledgements

The researchers would like to express their gratitude to the International College and Research Administration Division, Khon Kaen University, for their assistance. The researchers would like to express their gratitude to all the anonymous respondents who took the time to complete questionnaires and to their colleagues who helped us complete this research successfully. Finally, we would like to fully thank Miss Chananya Piratanatsakul, Miss Mawalee Tipsombat, and Mr. Tanat Archariyapibal for their partial data collection.

Appendix

Items	Sources
Market focus	Fernando and Wah (2017)
a preliminary market evaluation of agricultural output supply.	
a focus on a specific target market.	
cooperation with stakeholders in the market.	
obtain customers' views on agricultural product ideas.	
Customer and product differentiations	Pelham (1997) and Swink and Hegarty (1998)
Customer differences in purchasing size	
Customer differences by crop-benefit needs	
Cost differences in products	
product differences by purchasing criteria	
Brand orientation	Baumgarth (2010) and Chang et al. (2018)
Branding is essential to our strategy	
Branding flows through all our marketing activities	
Long-term brand planning is critical to our future success	
The brand is an important asset for us	

(continued on next page)

(continued)

Items	Sources
Segment-based mass customization	Wang et al. (2016), Huang et al. (2008), and Deshpande (2018)
We can customize products on a large scale.	
We can add product variety without increasing the cost.	
We can set mass production up for a different product at a low cost.	
We can add product variety without sacrificing product quality.	
Segmented (tiered) pricing	Friedman and Lewis (1999), Moon et al. (2011), Iyer et al. (2002), Thach and Olsen (2015), and Seufert (2014)
Offer different prices based on different features or products	
Various quality level options at a reasonable or affordable price	
Different values for the consumption of products	
Freemium (free price tiered).	
Market demand	Lin et al. (2013) and Anning-Dorson (2017)
Our farm tends to look for new products all the time	
look into price sensitivity	
We tend to seek technical support that helps regarding specific problems and provide new outcomes.	
We assess the segmentation and price flexibility of agricultural crop demand.	
Environmental uncertainty	Liao et al. (2011)
There is an assessment of uncertainty in …	
a wide range of business segments	
customer demand purchasing time	
dissimilarities of suppliers and technology providers	
crop production forecasts and crop yield estimates	
Seasonality	Gilbert et al. (2017) and Sassi (2019)
In our industry, there is a consideration for…	
off-harvest season	
harvest season	
peak season	
seasonal variations in labor demand and employment	
Peak load pricing	Friedman and Lewis (1999) and Iyer et al. (2002)
Prices are set by the basic and additional charges during high demand	
Prices are offered with discounts for the early purchase of specific products	
Prices are offered for both retail and wholesale products.	
Prices are set by the estimated marginal cost and demand in each period.	

Appendix B. multiple response analysis

Inclusion Criteria: Smart Farming Frequency		
Possible practices	Responses	
	N	Percent
Greenhouses	460	24.7%
Drones	39	2.1%
Irrigation	467	25.1%
Sensors	93	5.0%
Land levelling	390	21.0%
Farm design	410	22.1%
Total	**1859**	**100.0%**

***Please note that the criteria were designed to allow respondents to answer more than one options.

References

Abokyi, E., Strijker, D., Asiedu, K.F., Daams, M.N., 2020. The impact of output price support on smallholder farmers' income: evidence from maize farmers in Ghana. Heliyon 6 (9), e05013.

Allen, R.S., Helms, M.M., 2006. Linking strategic practices and organizational performance to Porter's generic strategies. Bus. Process Manag. J. 12 (4), 433–454.

Anning-Dorson, T., 2017. Moderation-mediation effect of market demand and organization culture on innovation and performance relationship. Market. Intell. Plann. 35 (2), 222–242.

Arteconi, A., Hewitt, N.J., Polonara, F., 2012. State of the art of thermal storage for demand-side management. Appl. Energy 93, 371–389.

Arunrat, N., Pumijumnong, N., Sereenonchai, S., Chareonwong, U., Wang, C., 2021. Comparison of GHG emissions and farmers' profit of large-scale and individual farming in rice production across four regions of Thailand. J. Clean. Prod. 278, 123945.

Banse, M., Van Meijl, H., Tabeau, A., Woltjer, G., 2008. Will EU biofuel policies affect global agricultural markets? Eur. Rev. Agric. Econ. 35 (2), 117–141.

Baumgarth, C., 2010. "Living the brand": brand orientation in the business-to-business sector. Eur. J. Market. 44 (5), 653–671.

Bergemann, D., Brooks, B., Morris, S., 2015. The limits of price discrimination. Am. Econ. Rev. 105 (3), 921–957.

Boso, N., Carter, P.S., Annan, J., 2016. When is brand orientation a useful strategic posture? J. Brand Manag. 23 (4), 363–382.

Boyaci, T., Ray, S., 2003. Product differentiation and capacity cost interaction in time and price sensitive markets. Manuf. Serv. Oper. Manag. 5 (1), 18–36.

Byrne, B.M., 2016. Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming, third ed. Routledge.

Canan, B., Cotterill, R.W., 2006. Strategic pricing in a differentiated product oligopoly model: fluid milk in Boston. Agric. Econ. 35 (1), 27–33.

Chang, Y., Wang, X., Arnett, D.B., 2018. Enhancing firm performance: the role of brand orientation in business-to-business marketing. Ind. Market. Manag. 72, 17–25.

Chen, J., Chen, Y.J., 2021. The impact of contract farming on agricultural product supply in developing economies. Prod. Oper. Manag. 30 (8), 2395–2419.

Chen, K., Zha, Y., Alwan, L.C., Zhang, L., 2019. Dynamic pricing in the presence of reference price effect and consumer strategic behaviour. Int. J. Prod. Res. 58 (2), 546–561.

Daniel, R., 2021. Crushing burden: Small-Scale Sugar Cane Farmers bear the Costs of Thailand's Bioeconomy Drive. Stockholm Environment Institute (SEI). https://www.sei.org/featured/crushing-burden-small-scale-sugar-cane-farmers-bear-the-costs-of-thailands-bioeconomy-drive/.

Deshpande, A., 2018. Relationships between advanced manufacturing technologies, absorptive capacity, mass customization, time to market and financial and market performance: an empirical investigation. Asia-Pacific Journal of Business Administration 10 (1), 2–20.

Devereux, S., Sabates-Wheeler, R., Longhurst, R., 2012. Seasonality revisited: new perspectives on seasonal poverty. In: Devereux, S., Sabates-Wheeler, R., Longhurst, R. (Eds.), Seasonality, Rural Livelihoods and Development, first ed. Earthscan.

Fernando, Y., Wah, W.X., 2017. The impact of eco-innovation drivers on environmental performance: empirical results from the green technology sector in Malaysia. Sustain. Prod. Consum. 12, 27–43.

Flenskov, K., 2017. From production-orientation to customer-orientation-modules of a successful airline differentiation strategy. In: Strategic Management in the Aviation Industry, first ed. Routledge, pp. 97–117.

Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Market. Res. 18 (1), 39.

Foteinaki, K., Li, R., Péan, T., Rode, C., Salom, J., 2020. Evaluation of energy flexibility of low-energy residential buildings connected to district heating. Energy Build. 213, 109804.

Foxall, G.R., Yan, J., Oliveira-Castro, J.M., Wells, V.K., 2013. Brand-related and situational influences on demand elasticity. J. Bus. Res. 66 (1), 73–81.

Friedman, H.H., Lewis, B., 1999. Dynamic pricing strategies for maximizing customer satisfaction. Natl. Publ. Account 44 (1), 8–36.

Gilbert, C.L., Christiaensen, L., Kaminski, J., 2017. Food price seasonality in Africa: measurement and extent. Food Pol. 67, 119–132.

Hair, J., Black, W., Anderson, R., Babin, B., 2018. Multivariate Data Analysis, eighth ed. Cengage Learning.

Hammami, R., Asgari, E., Frein, Y., Nouira, I., 2021. Time- and price-based product differentiation in hybrid distribution with stockout-based substitution. Eur. J. Oper. Res. 3 (300), 884–901.

Henseler, J., Ringle, C.M., Sarstedt, M., 2014. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Market. Sci. 43 (1), 115–135.

Hinterhuber, A., Liozu, S., 2018. Innovation in Pricing : Contemporary Theories and Best Practices, second ed. Routledge.

Hinterhuber, A., Liozu, S.M., 2014. Is innovation in pricing your next source of competitive advantage? Bus. Horiz. 57 (3), 413–423.

Ho, J.Y.C., Liang, Y.S., Weinberg, C.B., Yan, J., 2018. An empirical study of uniform and differential pricing in the movie theatrical market. J. Market. Res. 55 (3), 414–431.

Huang, X., Kristal, M.M., Schroeder, R.G., 2008. Linking learning and effective process implementation to mass customization capability. J. Oper. Manag. 26 (6), 714–729.

Ingenbleek, P.T.M., Frambach, R.T., Verhallen, T.M.M., 2010. The role of value-informed pricing in market-oriented product innovation management. J. Prod. Innovat. Manag. 27 (7), 1032–1046.

ITC, 2020. Market Opportunities and Entry Strategies for Cassava and Cassava Related Products in the United Kingdom (08.2020).pdf. https://www.intracen.org/uploadedFiles/intracenorg/Content/Redesign/Projects/WACOMP/Market%20opportunities%20for%20Sierra%20Leone%20cassava%20exports%20to%20UK.

Iyer, G.R., Miyazaki, A.D., Grewal, D., Giordano, M., 2002. Linking Web-based segmentation to pricing tactics. J. Prod. Brand Manag. 11 (5), 288–302.

Jansuwan, P., Zander, K.K., 2021. Getting young people to farm: how effective is Thailand's young smart farmer programme? Sustainability 13 (21), 11611.

Jevons, C., 2005. Names, brands, branding: beyond the signs, symbols, products and services. J. Prod. Brand Manag. 14 (2), 117–118.

Jiang, P., 2000. Segment-based mass customization: an exploration of a new conceptual marketing framework. Internet Res. 10 (3), 215–226.

Jost, P.J., Süsser, T., 2020. Company-customer interaction in mass customization. Int. J. Prod. Econ. 220, 107454.

Kammerer, D., 2009. The effects of customer benefit and regulation on environmental product innovation.: empirical evidence from appliance manufacturers in Germany. Ecol. Econ. 68 (8–9), 2285–2295.

Khandeparkar, K., Maheshwari, B., Motiani, M., 2020. Why should I pay more? Testing the impact of contextual cues on perception of price unfairness for the price-disadvantaged segment in dual pricing. Tourism Manag. 78, 104075.

Khodaei, H., Hajiali, M., Darvishan, A., Sepehr, M., Ghadimi, N., 2018. Fuzzy-based heat and power hub models for cost-emission operation of an industrial consumer using compromise programming. Appl. Therm. Eng. 137, 395–405.

Klesel, M., Schuberth, F., Henseler, J., Niehaves, B., 2019. A test for multigroup comparison using partial least squares path modeling. Internet Res. 29 (3), 464–477.

Kline, R.B., 2015. Principles and Practice of Structural Equation Modeling, fourth ed. Guilford Publications.

Kong, Z., Dong, X., Zhou, Z., 2015. Seasonal imbalances in natural gas imports in major Northeast asian countries: variations, reasons, outlooks and countermeasures. Sustainability 7 (2), 1690–1711.

Laosirihongthong, T., Tan, K.C., Kannan, V.R., 2009. The impact of market focus on operations practices. Int. J. Prod. Res. 48 (20), 5943–5961.

Latan, H., Chiappetta Jabbour, C.J., Lopes de Sousa Jabbour, A.B., Wamba, S.F., Shahbaz, M., 2018. Effects of environmental strategy, environmental uncertainty and top management's commitment on corporate environmental performance: the role of environmental management accounting. J. Clean. Prod. 180, 297–306.

Le Pape, N., Wang, Y., 2020. Can product differentiation mitigate conflicts of interest between principal stakeholders? A cournot-bertrand comparison. Econ. Modell. 91, 341–346.

Leckel, A., Veilleux, S., Dana, L.P., 2020. Local Open Innovation: a means for public policy to increase collaboration for innovation in SMEs. Technol. Forecast. Soc. Change 153, 119891.

Lee, Z., 2013. Rebranding in brand-oriented organisations: exploring tensions in the nonprofit sector. J. Market. Manag. 29 (9–10), 1124–1142.

Liao, C., Chuang, S.H., To, P.L., 2011. How knowledge management mediates the relationship between environment and organizational structure. J. Bus. Res. 64 (7), 728–736.

Lin, R.J., Tan, K.H., Geng, Y., 2013. Market demand, green product innovation, and firm performance: evidence from Vietnam motorcycle industry. J. Clean. Prod. 40, 101–107.

Malhotra, N.K., Kim, S.S., Patil, A., 2006. Common method variance in IS research: a comparison of alternative approaches and a reanalysis of past research. Manag. Sci. 52 (12), 1865–1883.

Manivong, P., Bourgois, E., 2017. White Paper: Thai Sugarcane Sector and Sustainability. https://www.bonsucro.com/wp-content/uploads/2017/08/Thai-White-Paper-FINAL-LowRes.docx.pdf.

Marsh, H.W., Hocevar, D., 1985. Application of confirmatory factor Analysis to the study of self-concept. First- and higher order factor models and their invariance across groups. Psychol. Bull. 97 (3), 562–582.

Meza, J.P., Fahoome, G.F., 2008. The development of an instrument for measuring healing. Ann. Fam. Med. 6 (4), 355.

Mohamed, E.S., Belal, A.A., Kotb Abd-Elmabod, S., El-Shirbeny, M.A., Gad, A., Zahran, M.B., 2021. Smart farming for improving agricultural management. The Egyptian Journal of Remote Sensing and Space Science.

Moon, S., Jambert, E., Childs, M., von Schoen-Angerer, T., 2011. A win-win solution?: a critical analysis of tiered pricing to improve access to medicines in developing countries. Glob. Health 7 (1), 1–11.

NESDB, 2017. Thailand Twelfth National Economic and Social Development Plan (2017-2021).

Nojavan, S., Zare, K., Mohammadi-Ivatloo, B., 2017. Optimal stochastic energy management of retailer based on selling price determination under smart grid environment in the presence of demand response program. Appl. Energy 187, 449–464.

NSO, 2019. Number of Farm Households Registered by Province: 2014 - 2020. National Statistical Office (NSO). http://statbbi.nso.go.th/staticreport/page/sector/en/11.aspx.

O'Brien, R.M., 2007. A caution regarding rules of thumb for variance inflation factors. Qual. Quantity 41 (5), 673–690.

Panda, A.K., Nanda, S., 2018. Working capital financing and corporate profitability of Indian manufacturing firms. Manag. Decis. 56 (2), 441–457.

PCP, 2020. Cluster Development Based Agriculture Transformation Plan Vision 2025: Sugarcane Cluster Feasibility and Transformation Study. https://www.pc.gov.pk/uploads/report/Sugarcane_Cluster_Report.pdf.

Pedzik, M., Bednarz, J., Kwidzinski, Z., Rogozinski, T., Smardzewski, J., 2020. The idea of mass customization in the door industry using the example of the company porta KMI Poland. Sustainability 12 (9), 3788.

Pelham, A.M., 1997. Market orientation and performance: the moderating effects of product and customer differentiation. J. Bus. Ind. Market. 12 (5), 276–296.

Pereira, L.M., De Oliveira Ribeiro, C., Securato, J.R., 2012. Agricultural commodities pricing model applied to the Brazilian sugar market. Aust. J. Agric. Resour. Econ. 56 (4), 542–557.

Phasuk, S., 2020. Improving Skills of Rice Farmers in Thailand. https://tdri.or.th/wp-content/uploads/2020/12/Impoving-skill-of-rice-farmer-in-Thailand-MICRO-2-pdf-1.pdf.

Piercy, N.F., Cravens, D.W., Lane, N., 2010. Thinking strategically about pricing decisions. J. Bus. Strat. 31 (5), 38–48.

Piha, L., Papadas, K., Davvetas, V., 2021. Brand orientation: conceptual extension, scale development and validation. J. Bus. Res. 134, 203–222.

Porter, M.E., 1980. Competitive Strategy : Techniques for Analyzing Industries and Competitors. Free Press.

Radhi, M., Zhang, G., 2018. Pricing policies for a dual-channel retailer with cross-channel returns. Comput. Ind. Eng. 119, 63–75.

Raju, J., Zhang, Z., 2010. mart Pricing: How Google, Priceline, and Leading Businesses Use Pricing Innovation for Profitabilit. Pearson Prentice Hall.

Reisenzein, R., 1986. A structural equation Analysis of weiner's attribution-affect model of helping behavior. J. Pers. Soc. Psychol. 50 (6), 1123–1133.

San-José, L.A., Sicilia, J., Cárdenas-Barrón, L.E., Gutiérrez, J.M., 2019. Optimal price and quantity under power demand pattern and non-linear holding cost. Comput. Ind. Eng. 129, 426–434.

Sassi, M., 2019. Seasonality and nutrition-sensitive agriculture in Kenya: evidence from mixed-methods research in rural lake naivasha basin. Sustainability 11 (22), 6223.

Seufert, E.B., 2014. Freemium economics: leveraging analytics and user segmentation to drive revenue. In: Freemium Economics: Leveraging Analytics and User Segmentation to Drive Revenue, first ed. Elsevier.

Shao, X.F., 2020. What is the right production strategy for horizontally differentiated product: standardization or mass customization? Int. J. Prod. Econ. 223, 107527.

Shy, O., 2008. Peak-load Pricing. In: How to Price: A Guide to Pricing Techniques and Yield Management. Cambridge University Press, pp. 181–226.

Small, J., Melewar, T., Yin Wong, H., Merrilees, B., 2007. Multiple roles for branding in international marketing. Int. Market. Rev. 24 (4), 384–408.

Sowcharoensuk, C., 2020. Industry Outlook 2020-2022 : Cassava Industry. Krungsri Research. https://www.krungsri.com/en/research/industry/industry-outlook/agriculture/cassava/IO/io-cassava-20.

Srisathan, W.A., Ketkaew, C., Naruetharadhol, P., 2020. The intervention of organizational sustainability in the effect of organizational culture on open innovation performance: a case of Thai and Chinese SMEs. Cogent Business & Management 7 (1).

Srisompun, O., Simla, S., Boontang, S., 2020. Influential factors for the decision to participate in a rice-pledging scheme: evidence from jasmine rice farmers in northeast Thailand. World Rev. Enterpren. Manag. Sustain. Dev. 16 (3), 262–275.

Srivastava, R.K., Shetti, N.P., Reddy, K.R., Kwon, E.E., Nadagouda, M.N., Aminabhavi, T.M., 2021. Biomass utilization and production of biofuels from carbon neutral materials. Environ. Pollut. 276, 116731.

Suchato, R., Patoomnakul, A., Photchanaprasert, N., 2021. Alternative cropping adoption in Thailand: a case study of rice and sugarcane production. Heliyon 7 (12), e08629.

Suebpongsang, P., 2021. Contract Farming Regulations and Situations in Thailand. FFTC Agricultural Policy Platform (FFTC-AP). https://ap.fftc.org.tw/article/2842.

Sukpanich, S., Wang, W., Sukpanich, S., Wang, W., 2021. Analysis of the export competitiveness of Thai cassava in the Chinese market (2010-2020). Open J. Bus. Manag. 10 (1), 337–349.

Swink, M., Hegarty, W.H., 1998. Core manufacturing capabilities and their links to product differentiation. Int. J. Oper. Prod. Manag. 18 (4), 374–396.

Tadesse, G., Bahiigwa, G., 2015. Mobile phones and farmers' marketing decisions in Ethiopia. World Dev. 68, 296–307.

Tanakasempipat, P., 2020. World Bank Says Thai Poverty Rate Increases, Farm Income Slides. Reuters. https://www.reuters.com/article/thailand-worldbank-idUSL4N2AY22P.

TDRI, 2016. Liberalizing Thailand's Maize Trade: Reduce/Eliminate the Non-tariff Barriers (NTBs). https://tdri.or.th/wp-content/uploads/2016/09/Liberalizing-Maize-Trade_Policy-Brief_EN-1.pdf.

Thach, L., Olsen, J., 2015. Profiling the high frequency wine consumer by price segmentation in the US market. Wine Economics and Policy 4 (1), 53–59.

TIR, 2020. Farmnovation Technologies in the Field. Thailand Investment Review (TIR), p. 30. https://www.boi.go.th/upload/content/TIR7AwSmartfarming5e5dc88fa8284.pdf.

TIR, 2021. Making Future Food in Thailand: Farm and Food Innovations. Thailand Investment Review (TIR), p. 31. https://aust-thai.org.au/LargeTIR/TIRNewsletterMar2021.pdf.

Trienekens, J.H., Wognum, P.M., Beulens, A.J.M., Van Der Vorst, J.G.A.J., 2012. Transparency in complex dynamic food supply chains. Adv. Eng. Inf. 26 (1), 55–65.

Udomkerdmongkol, M., 2020. Thai Agricultural Sector: from Problems to Solutions. United Nations in Thailand. https://thailand.un.org/en/103307-thai-agricultural-sector-problems-solutions.

Vandenberg, R.J., Lance, C.E., 2000. A review and synthesis of the measurement invariance literature: suggestions, practices, and recommendations for organizational research. Organ. Res. Methods 3 (1), 4–69.

Walter, A., Finger, R., Huber, R., Buchmann, N., 2017. Opinion: smart farming is key to developing sustainable agriculture. Proc. Natl. Acad. Sci. U. S. A. 114 (24), 6148.

Wang, Y., Ma, H.S., Yang, J.H., Wang, K.S., 2017. Industry 4.0: a way from mass customization to mass personalization production. Advances in Manufacturing 5 (4), 311–320.

Wang, Z., Zhang, M., Sun, H., Zhu, G., 2016. Effects of standardization and innovation on mass customization: an empirical investigation. Technovation 48–49, 79–86.

Weinberger, K., Lumpkin, T.A., 2005. High Value Agricultural Products in Asia and the Pacific for Small-Holder Farmers: Trends, Opportunities and Research Priorities. http://www.dangtimes.vn/Portals/0/Docs/130154119-3ced_weinberger_lumpkin_2006.pdf.

Weinstein, A., 2013. Handbook of Market Segmentation : Strategic Targeting for Business and Technology Firms. In: Handbook of Market Segmentation: Strategic Targeting for Business and Technology Firms, third ed. Taylor & Francis.

Wolfert, S., Ge, L., Verdouw, C., Bogaardt, M.J., 2017. Big data in smart farming – a review. Agric. Syst. 153, 69–80.

Wu, J., Guo, B., Shi, Y., 2013. Customer knowledge management and IT-enabled business model innovation: a conceptual framework and a case study from China. Eur. Manag. J. 31 (4), 359–372.

Zhou, K.Z., Brown, J.R., Dev, C.S., 2009. Market orientation, competitive advantage, and performance: a demand-based perspective. J. Bus. Res. 62 (11), 1063–1070.