Demand Elasticities for Selected Seasoning Commodities: An Almost Ideal Demand System with Instrumental Variables*

Elasticidades de la demanda para condimentos seleccionados: Un sistema de demanda casi ideal con variables instrumentales

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Abstract

This study analyzes the consumption elasticities of five key seasoning commodities in Indonesia: cooking oil, red onion, garlic, red chili, and cayenne pepper. A Linear Approximate Almost Ideal Demand System (LA/AIDS) model is employed, incorporating instrumental variables to address potential endogeneity. The results indicate that the unconditional income and own-price elasticities are inelastic, with income elasticities ranging from 0.74 to 0.75 and own-price elasticities from –0.77 to –0.94. No significant evidence of substitution or complementarity among the seasonings is found. Furthermore, elasticity remain similar before and after the COVID-19 pandemic, and across regions with different economic sizes. However, regions known for spicy cuisines demonstrate higher elasticities than those with milder culinary traditions.

Keywords: *Seasoning commodities, Almost Ideal Demand System, Instrumental Variables, Indonesia.*

JEL Classification: *C36, D12, Q11.*

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Resumen

Este estudio analiza las elasticidades de consumo de cinco condimentos clave en Indonesia: aceite de cocina, cebolla morada, ajo, ají rojo y ají picante. Se emplea un modelo del Sistema de Demanda Casi Ideal en su versión Lineal Aproximada (LA/AIDS), que incorpora variables instrumentales para abordar posibles problemas de endogeneidad. Los resultados indican que las elasticidades no condicionadas respecto al ingreso y al precio propio son inelásticas, con elasticidades-ingreso que varían entre 0,74 y 0,75, y elasticidades-precio propias entre –0,77 y –0,94. No se encuentra evidencia significativa de sustitución o complementariedad entre los condimentos. Además, las estimaciones de elasticidad se mantienen relativamente estables antes y después de la pandemia de COVID-19, así como entre regiones con distintos tamaños económicos. Sin embargo, las regiones conocidas por sus cocinas picantes presentan elasticidades notablemente mayores que aquellas con tradiciones culinarias más suaves.

Palabras clave: *Condimentos, Sistema de demanda casi ideal, Variables instrumentales, Indonesia.*

Clasificación JEL: *C36, D12, Q11.*

1. Introduction

Studies on consumption patterns using demand systems have covered a wide range of topics. These include food consumption (Bakhtavoryan & Capps, 2024; Bilgic & Yen, 2013; Marioni et al., 2022; Roosen et al., 2022; Zhuang & Abbott, 2007), energy consumption (Burke & Abayasekara, 2018; Deryugina et al., 2020; Fouquet, 2014; Goetzke & Vance, 2021; Jin & Kim, 2022), health expenditure (Casabianca et al., 2022; Ellis et al., 2017; Farag et al., 2012; Z. Zhou et al., 2011), tourism expenditure (Fleissig, 2021; Fredman & Wikström, 2018; Gatt & Falzon, 2014; Untong et al., 2014), and transportation (Seya et al., 2024; Ventura et al., 2022; S. Wang & Noland, 2021; Wardman, 2024). Meta-analyses have comprehensively examined the elasticity of animal-derived food and energy consumption (Bouyssou et al., 2024; Labandeira et al., 2017). However, certain commodities such as seasonings remain understudied.

Seasonings—although not classified as major staple foods—play a crucial role in shaping cuisine flavours worldwide (Sproesser et al., 2022). These ingredients, which include various spices and flavourings, substantially contribute to the unique culinary identities. For instance, Indian cuisine is renowned for its extensive use of diverse spices and seasonings (Basak et al., 2023), while Chinese culinary emphasize achieving harmonious flavours through the combination of rice with specific aromatics, such as welsh onion, ginger, and garlic (Zhou et al., 2024). Similarly, Malaysian cuisine is characterized by the prominent use of spices, resulting in rich and complex flavour combinations (Abidin et al., 2020). These examples illustrate the importance of seasoning in culinary traditions, beyond the addition of flavour.

My study will examine the consumption patterns of seasoning commodities in Indonesia, a country with a rich culinary heritage. This gastronomic heritage is exemplified by the Mustikarasa Recipe Book, which document 1,600 traditional cuisines from various regions in Indonesia. These culinary preparations feature a wide variety of ingredients and flavours, including red onion, garlic, ginger root, turmeric, galangal, candlenut, lemongrass, red chili, and cayenne pepper (Wijaya et al., 2020). Therefore, this study provides insights into the seasoning consumption patterns within culinary diversity.

This study aims to calculate income and own-price elasticities, as well as identify substitution-complementarity relationships through cross-price elasticities of seasonings in Indonesia. This study contributes to the body of knowledge in several ways. First, it addresses the often-overlooked seasoning consumption patterns that are relevant to other countries with distinctive food consumption characteristics, such as India, Ethiopia, Thailand, and China (Helgy Library, 2023; Sherman & Billing, 1999). Second, this study adopts a multi-stage budgeting process to estimate long-run unconditional elasticity coefficients by assuming separable preferences and stable group price across utility levels (Ramírez, 2013). This approach is particularly unusual in Indonesian demand-system studies. Third, the study incorporated instrumental variables to address endogeneity issues in the model, a method rarely used in demand system modelling (Colen et al., 2018). This method is intended to promote the use of instrumental variables in future research on demand systems. Additionally, this study provides valuable policy insights into how rising prices affect public consumption patterns.

For the remainder, this paper is organized as follows. Section 2 explains the importance of studying seasoning demand elasticity and provides further background. Section 3 presents a brief literature review of the seasoning consumption elasticity. Section 4 introduces the demand system framework and the AIDS model. Section 5 describes the methods used in this study. Section 6 describes the descriptive statistics, model results, heterogeneity analysis, robustness checks, and simulation analysis. Section 7 discusses the research findings and their policy implications. Finally, Section 8 concludes the study and provides recommendations for future research.

2. Seasonings And Indonesian Cuisines

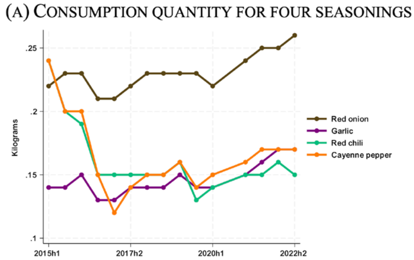
The statistical report on household consumption identified at least 20 commonly consumed commodities. Seven of these were categorized as essential seasonings: cooking oil, red onions, garlic, red chili peppers, cayenne pepper, coconut, and sugar. Five of these seasonings are widely used in many Indonesian cuisines, such as in stir-fry, *pecel lele*, *rawon*, *nasi padang*, *coto*, *nasi liwet*, and many others. Cooking oil serves as a medium for sautéing basic seasonings and is used throughout the cuisine preparation. Red onions and garlic are often combined to enhance the overall cuisine flavour. Similarly, red chilies and cayenne peppers, although used differently, contribute heat and flavour to a range of dishes. Even, these chilies are also commonly associated with sambal—a traditional Indonesian condiment (Surya & Tedjakusuma, 2022).

Figure 1 shows the consumption patterns of the five major seasonings over eight years. Throughout the observation period, these commodities remained important to the Indonesian diet. Although the consumption quantities fluctuated over time, the overall trend showed a positive trajectory. Notably, red chilies and cayenne peppers deviated from this pattern, indicating a decline in the quantity consumed. However, when considering consumption value (quantity multiplied by price), all commodities—including red chili and cayenne peppers—showed an obvious upward trend.

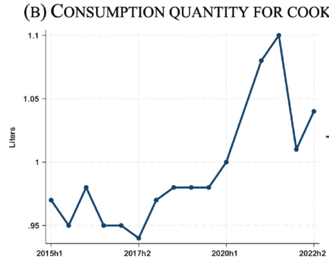
FIGURE 1

CONSUMPTION OF FIVE SEASONINGS

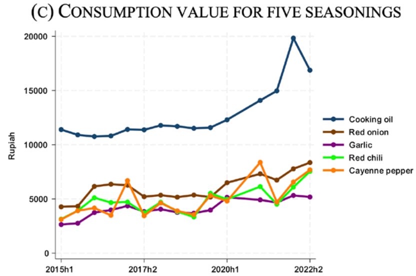
(A) Consumption quantity for four seasonings



(B) Consumption quantity for cooking oil



(C) Consumption value for five seasonings



Given their essential role in Indonesian cuisine, it is unsurprising that the government closely monitors the price fluctuations of these five seasonings. These seasonings—cooking oil, red onion, garlic, red chili, and cayenne pepper—contributed significantly to inflation in 2022. As shown in Table 1, these seasonings experienced multiple price increases throughout the year, with red onions having the highest frequency, with nine occurrences. Several factors contribute to these recurring price increases, including supply chain disruption and crop failure. These fluctuations significantly impact household budgets, prompting the government to oversee prices and ensure the affordability of these essential ingredients.

TABLE 1

PRICE MOVEMENTS DURING 2022

Commodities	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**June**	**July**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Cooking oil	+	–	+	+	–	–	–	–	–	+	○	–
Red onion	+	+	+	○	+	+	+	–	–	+	+	+
Garlic	○	○	+	+	○	–	–	–	○	○	○	○
Red chili	–	–	+	–	–	+	+	–	–	+	–	+
Cayenne pepper	○	–	+	–	–	+	+	–	–	+	–	–

Source: BPS (2022, processing).

Source: sign + denote price increase.
sign – denotes price decrease.
sign ○ denotes constant price.

The impact of rising food prices is inseparably linked to a decline in purchasing power. When income levels remain constant, higher seasoning prices can lead to a reduction in the total quantity of goods purchased or to a shift towards the consumption of lower-quality goods. Consequently, rising prices are often associated with a decline in welfare level. However, there is a lack of data to accurately measure the impact of price increases on consumption patterns in Indonesia. The Socioeconomic Survey (SUSENAS) is the only source of comprehensive per capita consumption data covering expenditures on multiple commodities. However, this survey was conducted on a semiannual basis. Conversely, data for commodity prices are collected more frequently and comprehensively, with weekly collections and being aggregated into a monthly price index. This difference in the frequency of data collection poses significant challenges in establishing a causal relationship between price increases and changes in consumption patterns.

Despite data limitations, analyzing income and price elasticities of demand—both own-price and cross-price—for the five major seasonings remains crucial. In particular, understanding complementary goods through cross-price elasticity is important because these relationships can potentially reduce the purchasing power of other goods. From a public policy perspective, mapping complementary goods can facilitate the formulation of a more comprehensive strategy to mitigate food inflation. Therefore, this study is valuable for informing policy formulation and managing inflationary pressures on seasoning prices.

3. Previous Studies

The existing literature on seasoning consumption elasticity is relatively limited. A thorough review of the available research revealed that only four studies addressed this issue. Among these studies, two examined consumption elasticity in India, while others investigated the United States and Indonesia. This lack of research highlights the need further to explore seasoning consumption patterns across regions and markets.

Parappurathu and Mathur (2006) conducted a comprehensive study of spice demand in India—the country with the largest producer and consumer of spices. Using household data from nationwide surveys in 1987-1988 and 1999-2000, they estimated the demand elasticities. This study employed a multi-stage budgeting framework to model consumer behaviour and used a double-log regression model estimated through Ordinary Least Squares (OLS). The findings revealed that expenditure elasticities for spices in India were positive and inelastic. They also found that lower-income groups would increase their expenditure on spices more than higher-income groups in response to positive changes in income. Notably, the study found no significant difference in spice consumption between rural and urban households, suggesting that consumption patterns were relatively unchanged across regions.

Srivastava et al. (2013) conducted a similar study in India that examined the consumption patterns of six major spice commodities—dry chili, garlic, ginger, pepper, tamarind, and turmeric—using data from 2004 to 2005. The research employed Ordinary Least Squares (OLS) estimation and included demographic variables as controls, such as age, household size, proportion of children, and education. The results indicate that dry chili has the highest income elasticity among the spices studied, with demand increasing more rapidly as household income increases in both urban and rural areas. Conversely, ginger has the lowest income elasticity among the commodities examined.

In contrast to the two previous studies, Nguyen et al. (2019) used the Rotterdam model to assess the United States import demand for source-differentiated spices. Using monthly import data by region from January 1990 to April 2018, this study revealed that imported spices are normal goods in the U.S. market. Their study demonstrated a positive correlation between increases in real income and higher demand for spice imports, particularly those from Asia and South America. In terms of price sensitivity, U.S. demand for spices showed the highest elasticity to North American imports, while demand for Asian and South American spices was stable and less price-sensitive. The study further indicates that an increase in North American spice prices would likely result in a decrease in U.S. demand for these products and a subsequent shift to substitutes from alternative sources.

The most relevant study, both in terms of regional scope and the commodities examined, was conducted by Hamzah and Huang (2023). Using the Quadratic Almost Ideal Demand System (QUAIDS), they examined food consumption patterns in five regions using microdata from 2018. The study covered 12 major commodities in Indonesia, including rice, meat, eggs, red onions, garlic, chili, fish, cooking oil, white sugar, flour, processed foods, and miscellaneous food items. They implemented a two-step budgeting procedure that included demographic variables such as age, education level, household size, and rural-urban classification. The results indicated an absence of heterogeneity in the regional classification.

In summary, the first two studies primarily examined the consumption of seasonings specific to India such as dry chili, tamarind, and turmeric, which are not necessarily consumed in other regions. The third study used aggregate data without specifying the types of seasoning consumed, focusing instead on regional elasticity. The fourth study offered a more comprehensive approach by incorporating commodities of interest, including red onions, garlic, chilies, and cooking oil. However, these four studies have certain limitations that my study aims to address. The improvement encompasses the use of a three-stage budgeting mechanism, the application of instrumental variables, using macro household consumption data with a time series, and focusing on specific commodities with specific uses.

4. Demand System

4.1 Static Demand Analysis

Demand systems based on product space are frequently used in consumption studies. However, this methodological approach has several limitations (Pakes, 2021). First, it assumes that researchers possess the ability to accurately identify product choices from the perspective of the consumer. Second, it assumes that consumers have a comprehensive understanding of their products. Moreover, static demand systems require a significant number of coefficients—$2n^2+n$ for the n goods under study—and are incapable of forecasting the demand for new products. Based on these limitations, Pakes (2021) proposed a shift from product space to characteristic space analysis. This shift offers a more dynamic and flexible framework for understanding consumer behaviour and overcoming the limitations of traditional product space-based demand systems.

To address this criticism, the selection of commodities for this study was based on food consumption data from 2015 to 2022. These data revealed that the five chosen commodities consistently demonstrated high consumption levels and are widely recognized as essential components of daily dietary intake. These commodities fulfil distinct culinary functions and are intuitively understood by consumers without explicit instructions. By focusing on commodity-level data, this study encompasses various brands and variants within each category, despite the published data being in aggregate form. This approach ensures the capture of new products—whether brands or variants—within the same commodity category.

Furthermore, this study employs a multi-stage budgeting scheme to analyse the five main seasoning commodities. The analysis was conducted in three stages, generating a total of 75 coefficients: 10 unconditional coefficients in the first stage, 10 conditional coefficients in the second stage, and 55 conditional coefficients in the third stage. Despite this comprehensive calculation, the study primarily focuses on unconditional coefficients from the third stage.

Therefore, the final number of coefficients is reasonable and ensures an effective interpretation.

To accommodate the characteristic space-based analysis, this study incorporated heterogeneity analysis by classifying regions based on cuisine variations. Certain provinces are known for their spicy flavors, which are closely associated with the consumption of red chili, cayenne pepper, cooking oil, red onions, and garlic. Conversely, other regions are assumed to have relatively lower consumption of these five seasonings. By categorizing provinces according to their culinary characteristics, I was able to analyze and compare spatial variations in seasoning use and flavor preferences across regions.

Of course, implementing a static demand system yields long-run coefficients that capture the consumption response over an extended period of time. Conversely, dynamic demand systems must be implemented to obtain short-term coefficients. However, a dynamic approach was not included in this study due to the unavailability of the STATA commands. In addition, the semi-annual data structure used in this study makes the short-term approach infeasible. The effective implementation of dynamic analysis for food commodities requires a shorter data structure, such as weekly or monthly, for both consumption and price data. Despite these limitations, the static demand system approach offers significant long-term perspectives on the consumption patterns.

4.2 Multi-stage Demand System

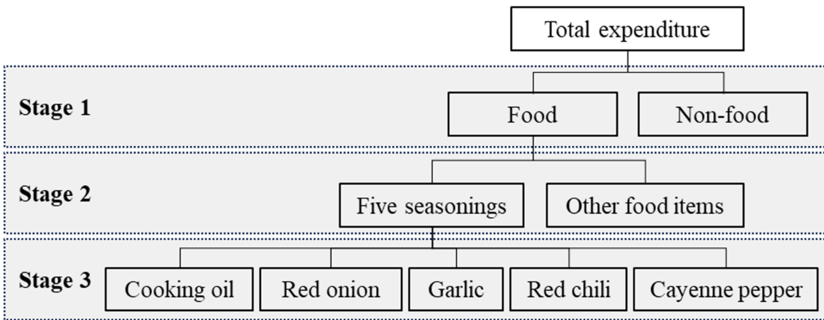
Consumption allocation across income groups was extensively investigated by Chai et al. (2024) and Bonke & Browning (2009). However, the precise stages of household budgeting and expenditure allocation remain unclear. Various studies have proposed different approaches to analyse this process, including the adoption of a three-stage model (Dey et al., 2011; Edgerton, 1997; Ramírez, 2013; Rathnayaka et al., 2021; Wu et al., 2021) and a two-stage model (Hamzah & Huang, 2023; Hasiner & Yu, 2020; Y. Wang & Çakır, 2020; Widarjono & Rucbha, 2016). In addition, some researchers have focused on specific commodity groups without explicitly defining the stages (Čiderová & Ščasný, 2022; Díaz & Medlock, 2021; Suárez-Varela, 2020; Wongmonta, 2022).

As noted by Edgerton (1997), determining the stages of a consumption analysis remains subjective and questionable. Despite this challenge, multi-stage modelling offers significant advantages over single-stage demand analysis. Primarily, it allows for the calculation of unconditional elasticities, which more accurately reflect real-world consumer behaviour. In contrast, single-stage demand analysis, with its narrow focus on specific goods, yields conditional coefficients with limited practical utility. These conditional elasticities depend on higher-level demand functions, which preclude their direct application in understanding consumer behaviour. As a result, although multi-stage modelling is more complex, it provides a more accurate representation of actual consumption decisions.

In this study, a three-stage consumption model was employed, as illustrated in Figure 2. The first stage, grounded in Engel's law, examines the allocation of expenditure between food and non-food commodities. Engel's law, derived from the work of Ernst Engel, postulates that the share of income allocated to food decreases as income increases. Building on this foundation, then the second stage focuses on the allocation of food expenditures between the five seasonings and other food items. The final stage looks more closely at the allocation of expenditure among the five specific seasonings: cooking oil, red onion, garlic, red chili, and cayenne pepper. This hierarchical approach allows for a comprehensive analysis of consumer expenditure patterns, from broad categories to specific food items.

FIGURE 2

CONSUMPTION DECISION STAGE



4.2 Almost-Ideal Demand System (AIDS)

The Almost-Ideal Demand System (AIDS), introduced by Deaton and Muellbauer (1980), provides a framework for analysing consumer spending patterns. This model primarily requires expenditure and price data for its implementation. Overall, the estimation of the demand system equations involves three key variables: total consumption expenditure (M_{ht}), expenditure share (w_{iht}), and commodity prices (p_{iht}). In this study, I implemented the AIDS model for each stage by focusing on different commodity groups. Regarding scope, my study examined five seasoning commodities (*i=5*) across 33 provinces (*h=33*) in Indonesia, ranging from Aceh to Papua. For the data periods, this study encompasses 15 semi-annual periods from 2015h1 to 2022h2 (*t=15*).

To calculate the household share of commodity *i*, I used the following formula:

(1) $$w_{iht} = \frac{p_{iht} q_{iht}}{M_{ht}}, \; 0 \leq w_{iht} \leq 1, \text{ and } \sum_{i=1}^{n} w_{iht} = 1$$

The AIDS formula used in this study was based on the works of Deaton and Muellbauer (1980) and Moschini (1995). Here, I adapted their approach to fit the specific data structure. Thus, the mathematical representation of this formula is as follows:

(2) $$w_{iht} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln p_{jht} + \beta_i \ln\left(\frac{M_{ht}}{P_{ht}}\right) + \varepsilon_{iht}$$

(3) with $\alpha_i = \alpha_{i0} + \alpha_{i1} t + \alpha_{i2} Z_{ht}$

The model incorporates several key components and parameters to analyse household consumption patterns. At its core, the model uses ε_{iht} as an error term, P_{ht} denotes the translog price index, and Z_{ht} denotes the demographic variables, specifically total household members. The parameters in the model serve different functions: α_i represents the average share of good *i*, γ_{ij} measures the effect on the household share of good *i* of an increase in the relative price of good *j*, holding expenditure constant, and β_i indicates the effect on the household share of good *i* of an increase in real per capita expenditure. However, γ_{ij} and β_i are not direct measures of elasticity. Then to simplify the analysis, this study used the Linear Approximated AIDS (LA/AIDS) model. In this approach, the original translog price index P is replaced by the Stone index P, which is expressed by the following formula:

(4) $$\ln P_{ht} = \sum_{i=1}^{n} w_{it} \ln p_{iht}$$

Furthermore, demand theory requires that certain restrictions must be satisfied to ensure consistency with utility maximization.

(5) Additivity $$\sum_{i=1}^{n} \alpha_i = 1, \; \sum_{i=1}^{n} \beta_i = 0, \; \sum_{i=1}^{n} \gamma_{ij} = 0,$$
$$\sum_{i=1}^{n} \alpha_{i0} = 1, \; \sum_{i=1}^{n} \alpha_{i1} = 0, \; \sum_{i=1}^{n} \alpha_{i2} = 0$$

(6) Homogeneity $$\sum_{j=1}^{n} \gamma_{ij} = 0$$

(7) Slutsky symmetry $$\gamma_{ij} = \gamma_{ji}$$

From the above specification, the conditional expenditure elasticity (η_i), conditional uncompensated (Marshalian) price elasticity (e_{ij}^{u}), and conditional compensated (Hicksian) price elasticity (e_{ij}^{c}) in each level are formulated as follows:

(8) $$\eta_i = 1 + \left(\beta_i / w_i\right)$$

(9) $$e_{ij}^{u} = -\delta_{ij} + \left(\gamma_{ij} / w_i\right) - \beta_i \left(w_j / w_i\right)$$

(10) $$e_{ij}^{c} = -\delta_{ij} + \left(\gamma_{ij} / w_i\right) + w_j$$

(11) $$e_{ij}^{c} = e_{ij}^{u} + \eta_i w_j$$

where δ_{ij} is the Kronecker delta with a value equal to one when $i=j$ and zero when $i \neq j$. Then β_i and γ_{ij} are the estimated parameters.

As previously mentioned, this study proposes a three-stage consumption decision-making process that yields two types of elasticity: conditional and unconditional. Conditional elasticity is calculated at the second and third stage using equations 8-10, with interpretations influenced by stage-specific budget constraints. Conversely, unconditional elasticity is derived by modifying the formulation according to Edgerton (1997) and Ramírez (2013), which are expressed as follows:

(12) $$\eta_i^{T} = \eta_{i(stage\,3)} \times \eta_{five\ seasonings\,(stage\,2)} \times \eta_{food\,(stage\,1)}$$

(13) $$\begin{aligned} e_{ij}^{u(T)} &= e_{ij(stage\,3)}^{c} + \left(w_{j(stage\,3)} \times \eta_{i(stage\,3)} \times e_{five\ seasonings\,(stage\,2)}^{c}\right) \\ &+ \left(w_{j(stage\,3)} \times w_{five\ seasonings\,(stage\,2)} \times \eta_{i(stage\,3)} \times \eta_{five\ seasonings\,(stage\,2)} \times e_{food\,(stage\,1)}^{u}\right) \end{aligned}$$

(14) $$\begin{aligned} e_{ij}^{c(T)} &= e_{ij(stage\,3)}^{c} + \left(w_{j(stage\,3)} \times \eta_{i(stage\,3)} \times e_{five\ seasonings\,(stage\,2)}^{c}\right) \\ &+ \left(w_{j(stage\,3)} \times w_{five\ seasonings\,(stage\,2)} \times \eta_{i(stage\,3)} \times \eta_{five\ seasonings\,(stage\,2)} \times e_{food\,(stage\,1)}^{c}\right) \end{aligned}$$

where η_i^{T}, $e_{ij}^{u(T)}$, $e_{ij}^{c(T)}$ represent unconditional expenditure elasticity, unconditional uncompensated (Marshalian) price elasticity, and unconditional compensated (Hicksian) price elasticity, respectively.

5. Methods

5.1 Data and Model Estimation

This study examined 33 provinces in Indonesia from 2015 to 2022, excluding Kalimantan Utara and other newly established provinces. The data were primarily obtained from two types of surveys published by BPS-Statistics Indonesia. The first was a semiannual Socioeconomic Survey (SUSENAS) conducted in March and September that provided data on consumption. The second was a monthly consumer price survey conducted in multiple cities in each province, which provided information on commodity prices. Additional data were obtained from tables available online on the BPS-Statistics Indonesia website (www.bps.go.id).

For the model estimation, I employed the STATA command developed by Lecocq and Robin (2015). STATA offers a range of demand system modelling options, including Cobb-Douglas, basic linear expenditure, translog, generalized translog, almost ideal demand system (AIDS), generalized AIDS, quadratic AIDS, and generalized quadratic AIDS. While these models are predominantly static, recent developments have focused on dynamic demand system modelling, particularly for AIDS. Blanciforti and Green (1983) incorporated habit effects based on Pollak and Wales (1969) to develop a dynamic version of AIDS, which has been applied in subsequent research (Rathnayaka et al., 2019; Selvanathan et al., 2024). Nevertheless, endogeneity remains a significant concern among economic researchers. Therefore, this study employed a static LA/AIDS model and addressed the endogeneity issue in the analysis.

5.2 Handling Endogeneity

AIDS modelling faces endogeneity challenges arising from two primary sources. First, the total expenditure variable was constructed using budget shares as the dependent variable. Second, price variables may be determined simultaneously by supply-demand interactions. These factors are likely to result in a correlation between the error term (ε_{iht}) and both total expenditure (M_{ht}) and price (p_{jht}) variables. To address this issue and ensure robust results, I employ two instrumental variables (IVs) in the third stage.

The selection of instrumental variables for price and income was based on relevance and data availability. For the price instrument, I used data of quantity production for palm oil, red onions, garlic, red chili, and cayenne peppers. Ideally, the production quantity of cooking oil in each province would be more appropriate. However, given the data limitations, data productivity for palm oil was used here as a proxy. Similarly, data on stock quantity—for red onion, garlic, red chili, and cayenne pepper—is preferable rather than production data. This is primarily because stock levels are a more accurate representation of the supply side effects. Again, due to data limitations, production data were ultimately used here. For income, I then used GDP per capita as an instrumental variable. Furthermore, following the approach of Lecocq and Robin (2015), this study estimated the model parameters using the iterated linear least-squares method. This method successfully addresses potential endogeneity concerns while working within the constraints of the available data.

To evaluate the strength of the instrumental variables, there are several statistical measures that can be used. Following Stock & Watson (2020) and Sanderson et al. (2021), the F-statistic is commonly used as the rule of thumb.

An F-value greater than 10 indicates a strong instrumental variable, while a value less than 10 suggests a weak instrumental variable. However, Keane & Neal (2023) propose a higher standard for instrument strength in empirical practice. Therefore, in my analysis, I consider not only the F-statistic but also the adjusted R-squared and t-statistics for each type of instrumental variable to provide a more comprehensive evaluation.

Table 2 presents the validity test results for the six instrumental variables used in this study. Among these, four variables showed an F-statistic of 10 and above. However, only two variables—cooking oil and income—showed relatively high adjusted R-squared values. Further, the identification based on the t-statistic reveals that only palm oil production and GDP per capita are statistically significant instrumental variables. Therefore, I can conclude that out of the six instrumental variables used, two can be classified as strong instrumental variables while the remaining four can be considered as weak instrumental variables.

TABLE 2

CHECKING FOR INSTRUMENT STRENGTH

Endogenous variables	**F-stat**	**Adj. R-squared**	**Instrumental variables**	**t-stat**
Cooking oil	52.04***	0.452	Palm oil production	-3.81***
Red onion	10.61***	0.135	Red onion production	0.03
Garlic	8.89***	0.113	Garlic production	1.16
Red chili	10.00***	0.127	Curly chili production	0.28
Cayenne pepper	7.65***	0.097	Cayenne pepper production	-0.10
Income	37.08***	0.369	GDP per capita	5.21***

Source: Data processed.

Note: *, **, and *** refer to the significant level in 10%, 5%, and 1%, respectively.

6. Results

6.1 Descriptive Analysis

The data presented in Table 3 explain the consumption patterns of the five seasonings, focusing on the average expenditure, share of consumption, prices, and quantities consumed. Among these, cooking oil is the dominant commodity, accounting for about 39 percent of total consumption. Although the price of cooking oil is reported to be the lowest among other seasonings, the quantity consumed exceeds that of other seasonings by up to 4-7 times. As a result, the total value of consumption in monetary units remains high. By contrast, the remaining four seasonings demonstrate modest consumption shares, ranging from 12 to 20 percent.

TABLE 3
DESCRIPTIVE STATISTICS

Commodities	Expenditure (rupiah)	Share (percentage)	Price (rupiah)	Quantity
Cooking oil	13,449.320	38.871	14,585.660	0.998[a)]
	(3,791.632)	(6.553)	(2,528.881)	(0.156)
Red onion	6,751.234	19.195	32,631.940	0.233 [b)]
	(2,111.960)	(2.920)	(18,421.76)	(0.060)
Garlic	4,366.323	12.556	30,981.170	0.142 [b)]
	(1,767.403)	(3.882)	(9,289.332)	(0.043)
Red chili	5,250.842	13.244	38,913.840	0.163 [b)]
	(5,645.274)	(11.101)	(15,310.520)	(0.158)
Cayenne pepper	5,775.006	16.134	49,216.110	0.165 [b)]
	(3,254.201)	(6.644)	(23,111.740)	(0.078)

Source: Data processed.
Note: Quantity for each commodity defined as a) Liter, b) Kilogram.
(…) refers to standard deviation.

A comparison between similar commodities reveals a different pattern of consumption. The consumption of cayenne pepper was 1.2 times higher than that of red chili, while the consumption of red onion was 1.5 times higher than that of garlic. However, in terms of quantity, both types of chilies had relatively similar levels. In terms of price, red onion and garlic were relatively similar, whereas cayenne pepper was 20 percent more expensive than red chili. This price difference explains the higher consumption share of cayenne peppers compared to red chili, despite their similar quantitative consumption.

6.2 Elasticity Calculation

Table 4 presents the elasticity coefficients for each stage, including income elasticity and both Marshallian (uncompensated) and Hicksian (compensated) own-price elasticities. The analysis reveals the different responses of food and the five major consumption types of seasoning to changes in budget allocation. Food consumption is inelastic to budget allocation, indicating that an increase in budget allocation leads to a proportionally smaller increase in food consumption. Conversely, the consumption of the five major seasonings showed an elastic behaviour. This suggests that, as the food budget increases, the consumption of seasonings increases at a higher rate than the budget itself.

The analysis of uncompensated own-price elasticity reveals contrasting patterns between food and the five major seasoning types. Food consumption is elastic, with price increases resulting in substantial decreases in consumption. However, the data are not sufficiently specific to explain which food categories experienced a decline in consumption. By contrast, the five seasonings show price inelasticity, although they are still negative. This indicates that, while price increases in these commodities lead to reduced consumption, the magnitude of the reduction is proportionally smaller than the price increase. These findings highlight differential consumer responses to price changes across food and seasoning categories.

TABLE 4

ESTIMATION RESULTS FOR INCOME AND PRICE ELASTICITY

Elasticities at different stages	Income elasticity	Own-price elasticity (Marshalian)	Own-price elasticity (Hicksian)
A. Food expenditure with respect to total income (First stage—unconditional)	0.741***	-1.063***	-0.687***
	(0.020)	(0.081)	(0.077)
B. Five seasonings consumption with respect to food expenditure (Second stage—conditional)	1.117***	-0.495***	-0.426***
	(0.064)	(0.045)	(0.045)
C. Specific seasonings consumption with respect to five consumption seasonings (Third stage—conditional)			
Cooking oil	0.903***	-0.950***	6.607
	(0.028)	(0.072)	(34.456)
Red onion	0.892***	-0.939***	-3.705
	(0.038)	(0.291)	(19.916)
Garlic	0.899***	-0.999***	7.34
	(0.014)	(0.128)	(43.604)
Red chili	0.897***	-0.969***	-22.031
	(0.004)	(0.304)	(103.212)
Cayenne pepper	0.900***	-0.986***	7.945
	(0.015)	(0.077)	(44.737)

Source: Data processed.

Notes: *, **, and *** refer to the significant level in 10%, 5%, and 1%, respectively.
(…) refers to standard deviation.

The parameters for each commodity in Table 4 are conditional elasticities. Table 5 provides a comparative analysis of these results with the unconditional elasticities. In the previous table, all the compensated (Hicksian) elasticities were statistically insignificant, making it difficult to calculate the unconditional (Marshallian) elasticity. To address this issue, I use equation (11) to obtain significant values for compensated elasticity. Columns 2-4 of Table 5 present the conditional elasticities obtained from stage 3, while columns 5-7 present the unconditional elasticities that combine the estimation results from stages 1, 2, and 3.

TABLE 5

CONDITIONAL VS UNCONDITIONAL ELASTICITY

Commodities	**Conditional**			**Unconditional**		
	Income elasticity	Own-price (Marshalian)	Own-price (Hicksian)	Income elasticity	Own-price (Marshalian)	Own-price (Hicksian)
Cooking oil	0.903	-0.950	-0.599	0.747	-0.774	-0.765
Red onion	0.892	-0.939	-0.768	0.738	-0.853	-0.849
Garlic	0.899	-0.999	-0.886	0.744	-0.942	-0.940
Red chili	0.897	-0.969	-0.850	0.742	-0.910	-0.906
Cayenne pepper	0.900	-0.986	-0.841	0.745	-0.913	-0.910

Source: Data processed.
Notes: Own-price elasticity (Hicksian/compensated) are calculated using equation (11).

Unconditional elasticity is the primary coefficient employed in the interpretation and simulation of the consumption responses. A comparison between conditional and unconditional elasticities reveals that unconditional income elasticities are 0.1–0.2 points lower than conditional income elasticities, reflecting the parameter correction in the previous stage. Moreover, the analysis indicates that both Marshallian and Hicksian unconditional own-price elasticities yield similar results, suggesting that the substitution effect due to price changes is substantially higher than the income effect—Marshallian elasticity includes income and substitution effects, while Hicksian elasticity excludes the income effect. Furthermore, the same table shows that both income and price elasticity are inelastic. Income elasticities across the five commodities show similar patterns. However, the lowest level of own-price elasticity was observed for cooking oil among the commodities studied.

Additionally, this study examines the potential substitution-complement relationships among seasonings. In the third stage, both uncompensated and compensated cross-price elasticities were calculated. As Table 6 shows, the results indicate that none of the coefficients are statistically significant. Consequently, the presence of substitution or complementarity among the five seasoning commodities can be ignored.

TABLE 6

CONDITIONAL CROSS PRICE ELASTICITY IN STAGE THREE

Commodities	**Cooking oil**	**Red onion**	**Garlic**	**Red chili**	**Cayenne pepper**
		Marshalian/Uncompensated			
Cooking oil	-	0.024	-0.007	0.033	-0.003
	-	(0.054)	(0.163)	(0.300)	(0.150)
Red onion	0.028	-	-0.029	0.083	-0.035
	(0.190)	-	(0.325)	(0.627)	(0.374)
Garlic	0.021	0.034	-	0.045	0.000
	(0.197)	(0.095)	-	(0.357)	(0.137)
Red chili	0.032	0.029	0.000	-	0.010
	(0.146)	(0.075)	(0.135)	-	(0.099)
Cayenne pepper	0.024	0.036	-0.002	0.030	-
	(0.184)	(0.103)	(0.144)	(0.288)	-
		Hicksian/Compensated			
Cooking oil	-	-2.776	8.364	-21.153	8.959
	-	(19.710)	(43.675)	(103.263)	(44.849)
Red onion	7.493	-	8.240	-20.845	8.817
	(34.689)	-	(43.880)	(103.780)	(45.129)
Garlic	7.551	-2.756	-	-21.063	8.928
	(34.587)	(19.724)	-	(103.260)	(44.802)
Red chili	7.545	-2.755	8.322	-	8.918
	(34.540)	(19.690)	(43.608)	-	(44.763)
Cayenne pepper	7.555	-2.755	8.340	-21.085	-
	(34.577)	(19.737)	(43.625)	(103.193)	-

Source: Data processed.

Notes: *, **, and *** refer to the significant level in 10%, 5%, and 1%, respectively.
(…) refers to standard deviation.

6.3 Heterogeneity Analysis

I conducted a heterogeneity analysis by categorizing the sample based on three criteria: cuisine characteristics, COVID-19 pandemic period, and regional economic size. The first analysis focused on the common culinary profile in each province, with particular emphasis on the tendency towards spicy cuisine. This culinary profile was based on the findings of Wijaya (2020). From 33 provinces studied, 21 were classified as predominantly spicy foods, primarily in Sumatra, Sulawesi, Bali, and some parts of Java. The remaining provinces, including Kalimantan, Maluku, Papua, and other parts of Java, were classified as non-spicy cuisine regions.

Referring to Table 7, the results reveal that provinces characterized by spicy cuisines have higher income elasticity in the first and second stages. In the third stage—conditional elasticity—only the cooking oil and red onions showed higher elasticity in these regions. However, based on the unconditional elasticity—defined in equation (12)—income elasticity tends to be elevated in provinces associated with spicy cuisine. In terms of own-price elasticity, red onions, garlic, and red chili were found to increase significantly in provinces with spicy food preferences. Conversely, cooking oil and cayenne pepper showed lower elasticity than the non-spicy food provinces.

The second heterogeneity analysis compared the periods before and after the COVID-19 pandemic, with the pre-pandemic period defined as 2015h1–2019h2 and the post-pandemic period as 2020h1–2022h2. The results show that there is no significant variation between these two periods, with income and own-price elasticities remaining constant. This consistency suggests that consumer behavior towards these seasonings has remained largely unchanged, despite the pandemic. Moreover, these findings highlight the persistent importance of these five commodities in the Indonesian daily consumption landscape.

TABLE 7
HETEROGENEITY ANALYSIS

Category	Elasticity						
	First stage (Unconditional)	Second stage (Conditional)	Third stage (Conditional)				
			Cooking oil	Red onion	Garlic	Red chili	Cayenne pepper
Cuisines characteristic							
Spicy							
Income elasticity	0.788***	1.200***	0.923***	0.946***	0.908***	0.893***	0.916***
	(0.027)	(0.081)	(0.010)	(0.036)	(0.005)	(0.001)	(0.010)
Own-price (Marshalian)	-1.276***	-0.464***	-0.717***	-1.096***	-1.101***	-1.047***	-0.881***
	(0.106)	(0.054)	(0.169)	(0.179)	(0.128)	(0.039)	(0.078)
Own-price (Hicksian)	-0.875***	-0.388***	0.689	-0.710*	-0.052	-3.788***	0.018
	(0.102)	(0.054)	(0.457)	(0.394)	(0.511)	(0.499)	(0.529)
Other							
Income elasticity	0.641***	1.150***	0.918***	0.913***	0.915***	0.897***	0.939***
	(0.033)	(0.094)	(0.011)	(0.008)	(0.023)	(0.001)	(0.103)
Own-price (Marshalian)	-0.529***	-0.485***	-0.986***	-0.908***	-0.905***	-0.952***	-0.993***
	(0.141)	(0.069)	(0.041)	(0.046)	(0.202)	(0.065)	(0.252)
Own-price (Hicksian)	-0.202	-0.418***	1.063	0.449	-0.006	-4.621**	-0.630
	(0.131)	(0.070)	(1.118)	(0.753)	(1.149)	(1.919)	(0.787)
COVID-19 pandemic							
Before pandemic							
Income elasticity	0.753***	1.105***	0.911***	0.917***	0.914***	0.895***	0.920***
	(0.025)	(0.076)	(0.009)	(0.020)	(0.050)	(0.004)	(0.074)
Own-price (Marshalian)	-1.030***	-0.486***	-0.907***	-1.032***	-0.696	-1.018***	-0.614
	(0.109)	(0.057)	(0.055)	(0.127)	(1.350)	(0.089)	(1.559)
Own-price (Hicksian)	-0.647***	-0.423***	1.990	-0.063	-0.087	-5.173	0.066
	(0.104)	(0.057)	(1.924)	(1.135)	(0.717)	(3.539)	(0.843)

Category	Elasticity						
	First stage (Unconditional)	Second stage (Conditional)	Third stage (Conditional)				
			Cooking oil	Red onion	Garlic	Red chili	Cayenne pepper
During and after pandemic							
Income elasticity	0.684***	1.287***	0.923***	0.914***	0.902***	0.897***	0.904***
	(0.037)	(0.120)	(0.009)	(0.010)	(0.009)	(0.006)	(0.007)
Own-price (Marshalian)	-1.079***	-0.580***	-0.872***	-0.828***	-0.826**	-0.997***	-0.939***
	(0.127)	(0.074)	(0.064)	(0.264)	(0.383)	(0.038)	(0.072)
Own-price (Hicksian)	-0.748***	-0.500***	0.832	0.884	0.471	-6.230***	0.582
	(0.118)	(0.075)	(0.818)	(1.641)	(0.847)	(2.282)	(1.044)
Economy size							
Small economy							
Income elasticity	0.772***	1.252***	0.907***	1.345	1.064	0.892***	0.868***
	(0.027)	(0.071)	(0.013)	(18.939)	(6.106)	(0.015)	(0.252)
Own-price (Marshalian)	-1.158***	-0.497***	-0.872***	-1.893	-0.137	-1.116**	-1.731
	(0.096)	(0.050)	(0.070)	(39.089)	(34.375)	(0.465)	(4.908)
Own-price (Hicksian)	-0.765***	-0.418***	2.939	-1.834	-0.059	-3.592	-2.203***
	(0.093)	(0.050)	(3.738)	(40.744)	(31.951)	(4.407)	(0.720)
Large economy							
Income elasticity	0.634***	0.504***	0.919***	1.053	0.910***	0.899***	0.914***
	(0.019)	(0.100)	(0.010)	(1.150)	(0.011)	(0.003)	(0.018)
Own-price (Marshalian)	-0.553***	-0.597***	-0.921***	-0.192	-0.869***	-1.197***	-0.890***
	(0.104)	(0.066)	(0.055)	(6.106)	(0.189)	(0.188)	(0.066)
Own-price (Hicksian)	-0.226**	-0.564***	0.892	-0.052	0.775	-4.944	0.258
	(0.096)	(0.069)	(0.929)	(5.215)	(1.796)	(3.715)	(1.480)

Source: Data processed.
Notes: *, **, and *** refer to the significant level in 10%, 5%, and 1%, respectively.
(…) refers to standard deviation.

The third heterogeneity analysis categorizes provinces according to their economic size, which is determined by the share of regional GDP in the national GDP. Among the 33 provinces evaluated, eight were identified as having substantial economic shares: Sumatra Utara, Riau, Jakarta, Jawa Barat, Jawa Tengah, Jawa Timur, Banten, and Kalimantan Timur. These provinces were among the top 25 percent of the provinces with the highest GDP shares and met the minimum annual share threshold of 3 percent. The remaining provinces were classified as having small-to-medium-sized economies. The analysis revealed that although the third stage shows no significant difference in income and own-price elasticities, the first and second stages indicate that smaller provinces tend to have higher elasticities. This finding suggests that provinces with smaller economies are more responsive to income and price fluctuations than are those with larger economies.

6.4 Robustness Check

To verify the stability of the elasticity coefficients, a robustness check is conducted in the third stage. I use alternative data sources for the price variable while maintaining the existing model specifications. The benchmark model used price data from a consumer price survey, while the robustness check used price data from Socioeconomic Survey (SUSENAS). Price data were obtained by dividing the consumption values by quantity. Table 8 presents a comparison of the coefficients obtained from both data sources. The results demonstrate that income elasticity remains relatively consistent across data sources, with similar values and levels of significance. However, the uncompensated own-price elasticity shows different results for cooking oil and cayenne peppers. Specifically, the coefficients obtained in the robustness check for these two seasonings were not statistically significant. Notably, despite the lack of statistical significance, the results of the robustness check for cooking oil retained the same negative sign as the benchmark model.

TABLE 8
ROBUSTNESS CHECKS ON STAGE THREE
(CONDITIONAL ELASTICITY)

Commodities	Consumer Price Survey			Socioeconomic Survey (SUSENAS)		
	Income elasticity	Own-price (Marshalian)	Own-price (Hicksian)	Income elasticity	Own-price (Marshalian)	Own-price (Hicksian)
Cooking oil	0.903***	-0.950***	6.607	0.859***	-1.437	-2.285
	(0.028)	(0.072)	(34.456)	(0.318)	(2.993)	(4.160)
Red onion	0.892***	-0.939***	-3.705	0.910***	-0.921***	0.777
	(0.038)	(0.291)	(19.916)	(0.018)	(0.074)	(2.993)
Garlic	0.899***	-0.999***	7.340	0.902***	-0.928***	3.680
	(0.014)	(0.128)	(43.604)	(0.004)	(0.151)	(7.220)
Red chili	0.897***	-0.969***	-22.031	0.897***	-1.026***	-5.705
	(0.004)	(0.304)	(103.212)	(0.004)	(0.137)	(6.313)
Cayenne pepper	0.900***	-0.986***	7.945	0.970	0.615	0.837
	(0.015)	(0.077)	(44.737)	(2.058)	(49.063)	(43.105)

Source: Data processed.
Notes: *, **, and *** refer to the significant level in 10%, 5%, and 1%, respectively.
(…) refers to standard deviation.

6.4 Simulation Analysis

Using the coefficients from previous results, simulations were performed based on three different scenarios. The first scenario simulates a simultaneous 10 percent increase in both income and commodity prices. The second scenario simulates a 10 percent increase in income while holding the prices constant. The third scenario examines the impact of a 10 percent increase in prices with no change in income. For all three scenarios, I use the average per capita consumption data across all provinces for 2022 as the baseline. These simulations allow me to assess the potential impact of changes in income and prices on final consumption.

TABLE 9
CONSUMPTION RESPONSE SIMULATION

Commodities	At original price (consumption in 2022)	Scenario 1	Scenario 2	Scenario 3
Average expenditure per capita in rupiahs				
Cooking oil	19,464.700	19,412.411	20,919.512	17,957.599
Red onion	9,039.333	8,935.403	9,706.712	8,268.024
Garlic	5,607.288	5,496.046	6,024.526	5,078.807
Red chili	7,460.015	7,335.372	8,013.879	6,781.508
Cayenne pepper	8,278.803	8,139.407	8,895.514	7,522.697
Change in average expenditure (percentage)				
Cooking oil	-	-0.269	7.474	-7.743
Red onion	-	-1.150	7.383	-8.533
Garlic	-	-1.984	7.441	-9.425
Red chili	-	-1.671	7.424	-9.095
Cayenne pepper	-	-1.684	7.449	-9.133

Source: Data processed.
Notes: Scenario 1: income increase 10% and price increase 10%.
Scenario 2: income increase 10% and price constant.
Scenario 3: income constant and price increase 10%.
The price elasticity used is Marshalian (uncompensated).
We employed equation (11) to obtain the alternative parameter.

As illustrated in Table 9, the simulation displays changes in consumption in both real monetary units and percentages. The table results demonstrate that price elasticity exceeds income elasticity for all commodities. This relationship is particularly evident in Scenario 1, where a simultaneous increase in income and price results in a net decrease in total consumption. This outcome is attributed to the fact that the reduction in consumption due to price increases significantly outweighs the increase in consumption due to income increases. For instance, in Scenario 1, the red onion consumption decreased by 1.15 percent. Among the five commodities examined, cooking oil demonstrated the smallest percentage decrease at 0.3 percent, which was nearly negligible. In contrast, the remaining four commodities demonstrated more substantial declines in consumption, ranging from 1.15 to 1.98 percent.

7. Discussion And Policy Implication

Research on food consumption has extensively studied various commodities. However, seasoning consumption patterns remain largely unexplored. This study addresses this gap by conducting the first comprehensive investigation of seasoning consumption in Indonesia. Using the Linear Approximate Almost Ideal Demand System (LA/AIDS) model, this study provides significant findings on the elasticity of seasoning consumption with respect to income and price.

Five key seasonings play a central role in Indonesian cuisine: cooking oil, red onions, garlic, red chili, and cayenne pepper. These seasonings are essential components of daily culinary practices and significantly influence the cuisine flavour. Their ubiquity makes them irreplaceable items in the household grocery list. Moreover, the results of the LA/AIDS model indicate that the consumption of these seasonings is a necessity, as evidenced by their consumption elasticity with respect to income. As income rises, the consumption of these seasonings also increases, but at a lower rate than income growth itself. Thus, these results confirm that consumers respond predictably to the market signals. Therefore, although culturally important for daily consumption in Indonesia, demand showed an inelastic but not negligible response.

Among the five main seasonings in Indonesia, this study found that cooking oil is the most important for cuisine flavour, accounting for 39 percent of the total consumption. Red onions emerged as the second most important ingredient, accounting for 19 percent of the total consumption. These two commodities are essential ingredients in various cuisines that significantly enhance the final flavour. It is therefore not surprising that red onions in particular are consumed at a rate of 2.3 ounces per month per capita, almost double than garlic.

Chillies—particularly red chillies and cayenne peppers—are considered strategic commodities in Indonesia owing to their significant consumption share. The consumption share of each commodity exceeds 10 percent. Chili is an important ingredient in all regions, although the amount used may vary depending on local preferences. The importance of chili in the Indonesian diet is further emphasized by the high per capita consumption, which is 0.16 kg per month for each red chili and cayenne pepper. This high consumption rate makes it difficult to eliminate them from cuisine compositions, thus highlighting their role in Indonesian culinary culture (Wijaya et al., 2020).

While there are some similarities among the five commodities—between red onion and garlic, and between red chili and cayenne pepper—they do not reveal any substitution or complementarity relationships with each other. Each commodity plays a unique role in shaping the flavour landscape of Indonesian cuisine, as evidenced by the lack of significant cross-price elasticity coefficients. However, consumers respond to price increases in these seasonings by reducing consumption. For every 10 percent price increase, consumption falls by about 7.7 to 9.4 percent. Notably, this reduction in consumption persists even when income rises, suggesting that the negative effect of price increases on consumption outweighs the positive effect of income growth.

Further analysis of heterogeneity yielded another important result, especially when categorized by cuisine type. Regions characterized by spicy cuisine have higher elasticity coefficients, especially for the income elasticity and own-price elasticity of red onion, garlic, and red chili. Conversely, classifications based on economic size and COVID-19 pandemic periods did not cause significant variations in the elasticity coefficients. These results highlight the importance of regional culinary preferences in shaping seasoning consumption patterns.

As a policy implication, the government possesses various mechanisms to intervene in the market through its own authority. The main goal of these policies is to maintain purchasing power and the level of welfare. Currently, the government regulates the maximum retail prices of certain goods to prevent excessive price increases. Although this approach may seem effective, it can lead to market inefficiencies. Instead of imposing maximum retail prices, the government can stabilize prices by eliminating supply side frictions.

The government has three mechanisms to eliminate this friction. First, regional connectivity can be improved by providing adequate transportation facilities. So far, most of these seasonings have been imported locally from production centres in other provinces. For instance, statistical publications by BPS-Statistics Indonesia show that the main centres of frying oil production are concentrated in Sumatra, Java, and Kalimantan (BPS, 2024). Red onions are mainly produced in Jawa Tengah and Jawa Timur, and red chilies are mainly produced in Jawa Barat and Sumatra Utara (BPS, 2022a, 2022b). Therefore, connectivity and transportation remain crucial, as supported by Shively and Thapa (2017), who found that connectivity accounts for more than 50 percent of the volatility in agricultural commodity prices. Reducing transportation costs—through improved connectivity—can lead to lower food prices (Liu et al., 2025).

Second, the government must mitigate disruptions in the food supply chain caused by production delays among local farmers (Hommes et al., 2022). Anticipating crop failures due to pests, diseases, and natural disasters remains critical as they directly lead to shortages and price hikes in the market. Additionally, it is necessary to optimize the harvesting period by spreading out the harvest time and avoiding concentration during certain periods. This will prevent oversupply at certain times and minimize the risk of shortages at others. Third, when domestic agricultural production fails to meet market demand, the government should adopt flexible import policies (Shobur et al., 2025), including reducing import barriers through quotas and tariffs. This approach will help keep the supply of seasonings in the domestic market stable and minimize potential price fluctuations.

8. Concluding Remark

The empirical results confirm the existing demand theory and show inelastic demand elasticity for seasonings, with respect to both income and price. As expected, consumption rises with increasing income and falls as prices rise. Although seasonings seem to be essential goods for public consumption, consumer behaviour aligns with the market mechanisms. In particular, the results indicate that price increases have a more pronounced negative effect on reducing consumption quantity than the positive effect of rising income. Given the relatively inelastic demand for essential seasonings, policy responses should focus on promoting competitive supply conditions and minimizing market frictions rather than imposing direct price controls. This approach would preserve consumer welfare and minimize potential market distortions.

Furthermore, this study offers broader implications for managing food security in other countries. While this study limited the focus to certain seasonings, these commodities are still known to be essential for daily consumption. I realize that each country has its own consumption pattern, including which commodities are important to their people. Referring to my study, I found that although these commodities are still essential and frequently consumed, their consumption response still follows the market signals. Based on this, I suggest to other countries that are highly dependent on imports—such as those in Africa, the Middle East, and East Asia that rely on imports for their domestic food consumption—should identify which commodities remain important but vulnerable. These countries are often the most vulnerable to international food trade shocks. Therefore, it is necessary to mitigate resilience and food security earlier by creating a multiple food supply chain, possibly through domestic production, alternative trading partners, and substitution commodities.

Although my study successfully obtained unconditional elasticity estimates along with heterogeneity analysis, this study has certain limitations that should be addressed in the future. First and foremost, my reliance on macro-level data and the lack of access to micro-level datasets limit the ability to conduct an in-depth analysis. I recommend that future studies should examine the micro data level to gain a more nuanced understanding of consumption patterns across income levels—lower, middle, and upper classes. In addition, by using micro-level datasets, researchers can further explore the extent to which people will continue to increase their consumption of seasonings to enhance their food flavour. This approach will provide policymakers with sharper insights into the impact of price increases on overall consumption.

The second limitation relates to the use of static demand models. Although this study used instrumental variables to address endogeneity issues related to price and consumption variables, still it did not include dynamic LA/AIDS models. The use of a dynamic model would allow researchers to decompose the elasticity into short-run and long-run effects. However, obtaining these coefficients in STATA is challenging due to the current unavailability of appropriate commands. Future research could make a significant contribution by developing a STATA command—potentially published in The STATA Journal—that simultaneously addresses three key aspects: implementing instrumental variables, accounting for new product entry, and estimating both short- and long-run parameters. Such an approach would provide unbiased estimates and would better reflect the real-world conditions.

The third limitation concerns the threshold for seasoning consumption. While seasonings are essential in cuisines and have become a basic necessity, there are likely lower and upper limits on per capita consumption. These limits are influenced by individual dietary patterns and the ideal measurements of cuisine recipes. This suggests that the excessive consumption of seasonings is not possible. Conversely, even in the context of high seasoning prices, it is unlikely that consumption will be completely eliminated or significantly reduced—instead, it is likely to remain at the baseline level. Again, it was not possible in my study to determine the upper and lower thresholds for the consumption level. Therefore, future studies using experimental methods are needed to accurately determine these thresholds.

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