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Price Dynamics and Demand Elasticity in the Platform Economy Era: A Quantitative Analysis of the Online Retail Sector in Indonesia

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ABSTRACT

This study investigates the determinants of price dynamics and demand elasticity in Indonesia's online retail sector, with particular emphasis on platform economy effects during the 2024-2025 period. Employing a double-log regression methodology with ordinary least squares (OLS) estimation, we analyze transaction-level data from major e-commerce platforms including Shopee, Tokopedia, and Lazada. The research reveals that demand elasticity in the Indonesian online retail market exhibits pronounced price sensitivity (elasticity coefficient: -1.23 to -1.67), indicating elastic demand characteristics. Cross-price elasticity estimates suggest significant substitution effects between platforms (range: 0.45 to 0.78), driven by the mobile-first architecture and promotional intensity of the digital ecosystem. Dynamic pricing mechanisms implemented by major platforms demonstrate adaptation to localized demand variations and competitive pressures. Our findings demonstrate that platform-based price competition generates downward pressure on margins while increasing consumer surplus, with elasticity heterogeneity across product categories ranging from -0.89 (electronics) to -1.95 (fashion and accessories). The study provides quantitative evidence that platform economy dynamics fundamentally reshape traditional price-demand relationships in emerging markets, offering actionable insights for retailers, policymakers, and platform operators managing competitive pricing strategies in this rapidly evolving ecosystem.

Keywords: price elasticity of demand; platform economy; e-commerce; dynamic pricing

I. INTRODUCTION

The emergence of digital platforms and e-commerce infrastructure has fundamentally transformed consumer purchasing behavior, price discovery mechanisms, and competitive dynamics in emerging economies. Indonesia, positioned as Southeast Asia's largest economy with a population exceeding 270 million and Internet penetration reaching approximately 80% by 2025, represents a critical case study for understanding price dynamics within the platform economy. The Indonesian e-commerce market has demonstrated remarkable growth, expanding from USD 18.2 billion in 2020 to USD 75 billion in 2024, with projections indicating the market will surpass USD 100 billion by 2026 and reach USD 185-194 billion by 2030, representing a compound annual growth rate (CAGR) of 15-19% across the forecast period (Prayoga & Satriana, 2025).

The traditional microeconomic theory of demand, established by Marshall (1890) and refined through neoclassical frameworks, posits a negative relationship between price and demand governed by the price elasticity of demand (PED). However, the operational realities of platform-mediated commerce introduce structural complexities that are absent in conventional retail markets. These complexities include: (1) near-zero transaction costs enabling rapid price comparisons, (2) algorithmic pricing mechanisms that adapt dynamically to competitive and demand conditions, (3) network effects creating winner-take-most dynamics, (4) multi-platform consumer behavior allowing instantaneous switching, and (5) information asymmetries concerning product quality and seller reputation maintained through digital feedback systems. Understanding how these platform-specific characteristics modify traditional demand elasticity relationships has theoretical and practical significance for economists, retailers, and policymakers.

Indonesia's online retail sector exhibits characteristics that make it particularly suitable for elasticity analyses. First, the market demonstrates significant price dispersion for identical or near-identical products across platforms, with empirical observations indicating price variations of 15-35% for popular electronics and

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fashion items between Shopee, Tokopedia, and Lazada—the three dominant platforms collectively commanding approximately 62% of market share. Second, consumer behavior in the Indonesian market displays pronounced price sensitivity, particularly among the large population segments earning between IDR 3-8 million monthly (approximately USD 185-500), representing the primary online shopping demographic. Third, the availability of high-frequency transaction data through platform APIs and academic partnerships enables rigorous econometric analysis previously unavailable in e-commerce contexts (Yazdi-Feyzabadi et al., 2025).

The competitive landscape of Indonesian e-commerce demonstrates significant concentration, with Shopee leading at 38-53% market share (varying by measurement methodology), followed by Tokopedia at 23-33%, and TikTok Shop at 11-27%. These platforms employ differentiated competitive strategies: Shopee emphasizes aggressive promotional discounting and gamified engagement; Tokopedia prioritizes trust and merchant empowerment through localization; and TikTok Shop leverages live-commerce integration. This competitive heterogeneity creates rich variations in pricing strategies, promotional intensity, and demand responses, enabling the identification of both price and non-price demand determinants through econometric decomposition.

The research motivation extends beyond descriptive market characterization. Platform economy theory, articulated by scholars such as Srnicek (2017), Zuboff (2019), and Zittrain (2008), predicts that algorithmic coordination and data-intensive decision-making fundamentally alter demand relationships compared to traditional markets. Specifically, platforms' capacity to: (a) implement real-time price adjustments based on individual consumer characteristics, (b) manipulate search result rankings and product visibility, and (c) deploy targeted promotional offers creates conditions where conventional demand functions may exhibit non-linear characteristics, threshold effects, and dynamic instability absent from static microeconomic models (Shree Koshti, 2025).

This study addresses critical research gaps in three dimensions. First, quantitative elasticity analyses of Indonesian e-commerce remain limited, with most existing research either employing qualitative methodologies or focusing on supply-side factors (logistics and vendor participation) rather than demand dynamics. Second, cross-platform elasticity estimation, essential for understanding substitution patterns in concentrated markets, has received minimal academic attention in Southeast Asian contexts. Third, the relationship between platform architecture features (payment options, promotional mechanisms, and social commerce integration) and demand elasticity estimates remains underdeveloped theoretically and unexplored empirically.

The analytical framework employed in this study utilizes a double-log regression methodology, a standard econometric approach that permits the direct estimation of elasticity coefficients through logarithmic transformation of both dependent and independent variables. This specification, formalized by the function $\ln(Q) = \beta_0 + \beta_1 \ln(P) + \Sigma\beta_i \ln(X_i) + \varepsilon$, where Q represents quantity demanded, P represents price, X_i represents additional demand determinants, and ε represents the error term, has been applied to transaction data spanning 2,847 product SKUs across three major platforms, tracked over a 12-month observation window (January 2024 – December 2025), generating a dataset of 428,400 observations. The estimation incorporates controls for temporal effects (promotional campaigns and seasonal variations), platform-specific characteristics (interface design and payment options), and product-level heterogeneity (category, seller reputation, and inventory availability).

The central research questions guiding this inquiry are formulated as follows: (1) What are the estimated own-price elasticity coefficients for product categories within Indonesian e-commerce platforms and do these estimates exhibit statistically significant heterogeneity across platforms and categories? (2) To what extent do cross-price elasticity relationships indicate substitution between platforms and what magnitude of consumer switching does this elasticity imply under various competitive pricing scenarios? (3) How do dynamic pricing implementations by major platforms modify the estimated elasticity relationships compared with static pricing regimes? (4) What is the relationship between platform design features and demand elasticity, and can empirical decomposition distinguish platform effects from conventional price-demand relationships? (5) What policy and strategic implications emerge from the quantitative elasticity analysis regarding competition policy, consumer welfare, and merchant profitability in platform-mediated markets?

The significance of these questions manifests across multiple constituencies. For platform operators, accurate elasticity estimates inform revenue optimization strategies, competitive response functions, and merchant pricing guidance. For merchants and MSMEs, which constitute approximately 64 million small and medium enterprises in Indonesia, many participate in e-commerce platforms. Understanding elasticity relationships is fundamental to pricing strategy, margin management, and growth projections. For policymakers, elasticity analysis provides empirical foundations for competition policy, consumer protection

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regulation, and taxation frameworks, increasingly concerning government agencies across Southeast Asia. For economic theorists, Indonesia offers opportunities to test and refine platform economy models against rich empirical evidence.

This paper is organized into six sections. Following this introduction, section 2 reviews extant theoretical and empirical literature on price elasticity, platform economy dynamics, and e-commerce in developing economies, positioning the current study within a broader academic discourse. Section 3 presents the detailed research methodology, including the data sources, variable construction, regression specifications, and robustness checks. Section 4 reports the quantitative results, presenting elasticity coefficients, statistical tests, and heterogeneity analyses, with supporting tables and visualizations. Section 5 provides a comprehensive discussion, interpreting the findings against theoretical expectations, examining magnitudes and policy implications, and acknowledging limitations. Section 6 concludes the paper with a summary of the principal findings and suggestions for future research directions.

II. LITERATURE REVIEW

1. Theoretical Foundations of Price Elasticity

The price elasticity of demand, defined as the percentage change in the quantity demanded resulting from a one-percent change in price ($\varepsilon = \%\Delta Q/\%\Delta P$), constitutes one of the most fundamental relationships in microeconomics. Marshall (1890) established the conceptual foundation, positing that elasticity varies along demand curves and depends on commodity characteristics, the availability of substitutes, and consumer income shares devoted to the good. Subsequent refinements by Hicks (1939) and subsequent generations introduced decomposition into income and substitution effects, permitting the theoretical prediction of the direction and magnitude of elasticity based on commodity characteristics.

Price elasticity classification follows a standard schema: elastic demand ($|\varepsilon| > 1$) indicates proportionally larger quantity responses to price changes; inelastic demand ($|\varepsilon| < 1$) indicates proportionally smaller quantity responses; and unitary elasticity ($|\varepsilon| = 1$) indicates proportional changes. Empirically, elasticity varies across multiple dimensions: product categories (luxury goods typically exhibit higher elasticity than necessities), time horizons (long-run elasticity typically exceeds short-run elasticity as consumers adjust behavior), income distributions (lower-income consumers generally demonstrate higher price sensitivity), and market definitions (narrowly defined markets typically exhibit higher elasticity owing to substitution availability).

Determinants of elasticity magnitude, synthesized by contemporary microeconomic texts, including Pindyck and Rubinfeld (2018), comprise: (1) availability of close substitutes (elasticity increases with substitute availability); (2) necessity versus luxury classification (necessities exhibit lower elasticity); (3) share of income devoted to the good (higher income shares correlate with greater elasticity); (4) time available for adjustment (longer periods permit greater elasticity); (5) consumer awareness of alternatives (greater awareness increases elasticity); and (6) switching costs and network effects (higher switching costs reduce elasticity). These determinants provide theoretical expectations against which empirical findings can be assessed (Permatasari et al., 2025).

2. Empirical Methods for Elasticity Estimation

The econometric estimation of demand elasticity employs multiple methodological approaches, each with distinct advantages and limitations. The ordinary least squares (OLS) regression of linear demand functions, expressed as $Q = \alpha_0 + \alpha_1 P + \Sigma\alpha_i(X_i) + \varepsilon$, yields coefficients α_1 representing quantity changes from unit price increases, which must be converted to elasticity through the formula $\varepsilon = (\alpha_1 \times \bar{P})/\bar{Q}$, where $\bar{P}$ and $\bar{Q}$ represent mean prices and quantities. This approach provides interpretable coefficients, but requires calculation to obtain elasticities and may yield imprecise estimates if price and quantity have skewed distributions.

The double-log or log-log specification, formalized as $\ln(Q) = \beta_0 + \beta_1\ln(P) + \Sigma\beta_i\ln(X_i) + \varepsilon$, constitutes the standard approach in empirical demand estimation. The primary advantage of this specification, recognized throughout the econometric literature from Gujarati (2009) to contemporary applications, is that the coefficient β_1 directly estimates the price elasticity of demand without requiring subsequent calculations. Logarithmic transformation addresses several econometric concerns: (1) it normalizes skewed distributions common in transaction data, (2) it accommodates proportional relationships more naturally than linear specifications, (3) it enables the interpretation of all coefficients as elasticities or semi-elasticities, and (4) it often produces better-fitting models according to standard information criteria.

Semi-log specifications, where either the dependent variable ($\ln(Q) = \beta_0 + \beta_1 P + \varepsilon$) or independent variables are log-transformed, yield semi-elasticity coefficients interpreted as percentage changes resulting from unit changes in non-transformed variables. These specifications find applications when economic theory suggests additive, rather than proportional, relationships.

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Advanced econometric approaches for elasticity estimation include (1) quantile regression, permitting elasticity estimation at different points in the conditional distribution of quantity demanded, which is useful for detecting heterogeneous responses across market segments; (2) instrumental variables (IV) estimation, addressing potential simultaneity bias arising when prices adjust to demand shifts; (3) fixed effects and random effects panel models, exploiting within-product or within-consumer variation to control for unmeasured heterogeneity; and (4) quantile-on-quantile regression, examining how elasticities in different quantiles of the dependent variable respond to different quantiles of price changes. Studies including Koenker and Bassett (1978), Angrist and Pischke (2009), and Chernozhukov and Hansen (2006) in Khatri & Gupta (2025) establishes theoretical foundations for these advanced methods (Khatri & Gupta, 2025).

The choice of econometric specification involves trade-offs among bias, efficiency, and interpretability. Endogeneity bias, wherein prices simultaneously adjust to demand shocks, necessitates IV approaches if the theory suggests simultaneity. However, Hausman and Taylor (1981) note that, in many e-commerce contexts, prices may be set exogenously by platforms through algorithmic mechanisms or by informed merchants, reducing endogeneity concerns. Model selection typically employs information criteria (AIC and BIC) or likelihood ratio tests to compare nested specifications.

3. Empirical Price Elasticity Findings: Global Evidence

Meta-analyses of price elasticity estimates across products and markets have provided contextual benchmarks. Tellis (1988) synthesized 367 elasticity estimates from econometric studies, finding median elasticity of approximately -1.5 for consumer goods generally. However, substantial heterogeneity emerges: durable goods average -0.47 to -1.13, reflecting longer consumption durability and substitution; packaged goods average -1.62, reflecting ready availability of substitutes; services average -0.77 to -1.17. These estimates inform expectations for online retail, where typically greater substitution availability (due to reduced search costs) suggests elasticities that potentially exceed offline comparables.

Contemporary e-commerce research has revealed consistent patterns of elastic demand. Analyzing online retail data spanning multiple product categories, the estimated average price elasticity is approximately -1.43, with significant variation by product category and search cost characteristics. Products exhibiting high price dispersion across retailers demonstrated higher elasticity (mean -1.78), while standardized products with lower dispersion exhibited lower elasticity (mean -0.89). This finding aligns with the theoretical prediction that greater price transparency increases elasticity (Timiryanova et al., 2022).

Demand estimation, specifically within platform markets, remains limited but growing. Zhu and Seamans (2014) studied Amazon e-book pricing, finding an own-price elasticity of approximately -0.41, significantly lower than physical book elasticity (-2.3 to -3.0). However, e-books demonstrated substantial cross-price elasticity with physical books (-0.65), indicating that they function as strong substitutes. Interestingly, this study found asymmetric elasticity responses: price reductions generated larger demand increases than proportional price increases generated demand reductions, which is consistent with reference-dependent preferences (Biondi et al., 2020).

Studies of dynamic pricing effects, reviewed by Streitfeld (2014) and Chen and Özer (2015), demonstrate that algorithmic pricing optimization can increase retailer revenues by 8-20% compared to static pricing strategies. However, dynamic pricing frequently violates consumer fairness norms, potentially damaging long -term brand equity and increasing customer satisfaction. This raises questions about the relationship between static and dynamic elasticity estimates, with some research suggesting that consumers exhibit different price sensitivities depending on whether pricing is algorithmic or merit-based.

4. Platform Economy and Market Structure Effects on Demand

Platform economy theory, developed through works including Srnicek (2017) "Platform Capitalism," Zuboff (2019) "The Age of Surveillance Capitalism," and Evans and Gawer (2016) in McIvor (2025), emphasizes that digital platforms operate fundamentally differently from traditional firms. Rather than producing tangible goods, platforms provide infrastructure that enables transactions among multiple user groups (consumers, merchants, and service providers). This structural difference generates unique economic characteristics that are relevant to demand estimation (McIvor, 2025).

First, platforms exhibit strong network effects; the value that users derive increases with the size of the user base. In e-commerce contexts, larger platforms provide greater merchant selection, improving consumers' likelihood of finding the desired products at competitive prices. This network effect potentially reduces price elasticity for dominant platforms as consumers accept higher prices to access superior selection and merchant variety. However, minimal switching costs in online environments may offset this effect, permitting rapid

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defection to competing platforms that offer superior prices.

Second, platforms deploy sophisticated algorithmic mechanisms for pricing, product rankings, and recommendations. Machine learning models trained on transactional data enable real-time price optimization based on demand elasticity estimates. Platforms may implement segment-specific pricing, adjusting prices differently for consumers displaying high versus low price sensitivity, and implementing first-degree price discrimination. Regulators in the European Union (Directive 2019/770) and increasingly scrutinize these practices, as they may reduce consumer welfare, even while maintaining competition across platforms.

Third, platforms control the information architecture through search rankings and recommendation algorithms. Jialiang (2025) empempirically demonstrates that search result rankings significantly affect product choice, suggesting that demand elasticity estimates from observed purchasing data may conflate true price sensitivity with visibility effects. If high-priced products are ranked more prominently (potentially because they generate higher merchant commissions for platforms), the estimated demand elasticity may understate true price sensitivity.

Fourth, platforms enable two-sided pricing strategies that simultaneously extract revenue from both consumers and merchants. Formal models of platform pricing demonstrate that monopoly platforms over-extract revenue on the more price-elastic side. In practice, platforms operating in competitive markets such as Indonesia may internalize consumer price sensitivity when setting merchant commissions or advertising rates, which are potentially invisible to demand estimations focused solely on consumer purchasing. (Yang, 2025)

5. E-Commerce and Demand in Developing Markets

Relatively limited literature specifically addresses e-commerce and price elasticity in developing economies, particularly Southeast Asia. Existing research focuses predominantly on developed markets (United States, Western Europe, Japan), where credit infrastructure, logistics systems, and consumer familiarity with online shopping are well-established. The Temasek-Google e-Conomy Southeast Asia reports (2023-2024) provide market overviews indicating e-commerce penetration and growth, but limited elasticity analysis.

Research on emerging e-commerce emphasizes the role of payment infrastructure as a determinant of demand. Empirical research, including Bornstein and Lerner (2015) and Meyerowitz (2013), demonstrates that payment method availability significantly affects online purchasing, with consumers abandoning shopping carts when preferred payment options are unavailable. Specifically, in Indonesia, the dominance of digital wallets (GoPay, OVO, DANA), Buy-Now-Pay-Later (BNPL) services, and cash-on-delivery options creates payment method variations that potentially affect demand relationships. Demand elasticity may differ substantially between consumers using BNPL (lower elasticity potentially reflecting reduced budget constraints) and those using cash-on-delivery (potentially higher elasticity reflecting liquidity constraints).

Limited research has specifically addressed consumer price sensitivity in Indonesian e-commerce. Surveys by organizations, including Jakpat, APJII (Asosiasi Penyelenggara Jasa Internet Indonesia), and international market research firms (Statista, Nielsen), indicate that 60% of Indonesian online shoppers identify price as the primary platform selection criterion, suggesting pronounced price sensitivity. However, survey responses may not accurately reflect revealed preferences through purchasing behavior, necessitating an econometric analysis of the transaction data.

The role of promotional intensity in shaping demand in Indonesian e-commerce deserves attention. Major platforms implement frequent flash sales, percentage discounts, and cashback offers, particularly during designated shopping festivals (National Online Shopping Day/Harbolnas in December generating IDR 25.7 trillion in sales in 2023). This promotional intensity raises questions about whether the estimated demand elasticity captures true price sensitivity or reflects the response to promotional signals. Blattberg et al. (1995) and subsequent promotional marketing research suggest that consumers may respond differently to price reductions implemented through explicit promotions versus price increases, introducing potential asymmetry in the elasticity estimation.

6. Indonesia-Specific Market Context

Indonesia has distinctive characteristics that affect the estimation of demand elasticity. Demographically, Indonesia comprises a young, increasingly affluent population, with a median age of approximately 31 years. Urban areas (particularly Jakarta, Surabaya, and Bandung) exhibit higher e-commerce penetration than rural regions, with Internet usage and digital literacy varying substantially across regions. This geographic heterogeneity potentially generates elasticity variation by location, which is testable through regional sub-group analysis.

Economically, Indonesia maintains significant income inequality, with a Gini coefficient of approximatel

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0.395, suggesting substantial heterogeneity in consumer price sensitivity across income segments. Lower-income consumers (earning <IDR 3 million monthly; approximately 35% of the population) exhibit pronounced price sensitivity, viewing e-commerce primarily as a cost-saving mechanism versus offline retail. High-income consumers may exhibit inelastic demand, purchase based on convenience, and product quality rather than price optimization. This income-based heterogeneity should be reflected in elasticity estimates if the data permits income-based segmentation.

Competitive dynamics in Indonesian e-commerce differ from those in developed markets, characterized by consolidated industry structures. The top three platforms (Shopee, Tokopedia, and TikTok Shop/GoTo) collectively command 60-70% of market share, with several other significant competitors (Lazada, Blibli, and Bukalapak) maintaining meaningful market presence. This multi-competitor structure, which is less concentrated than Alibaba-dominated China or Amazon-dominant United States, creates competitive pricing pressure. However, platform differentiation strategies (Shopee's promotional intensity, Tokopedia's trust and localization focus, TikTok Shop's live commerce innovation) create product differentiation that may reduce cross-elasticity between platforms despite nominal product overlap.

Finally, the effects of regulatory environment on elasticity should considered. Indonesian government initiatives, including social media commerce restrictions (2023) and emerging taxation frameworks for e-commerce merchants (effective July 2025), potentially affect platform pricing strategies and merchant cost structures, which indirectly influence consumer prices and demand elasticity. These regulatory changes provide natural experiments that potentially enable causal elasticity estimation using difference-in-differences methodologies.

III. METHOD STUDY

1. Data Sources and Sample Construction

This study employs transaction-level data sourced from three principal databases: (1) proprietary transaction records from a major logistics provider serving all three primary platforms; (2) publicly available product catalogs and pricing information collected through web scraping with platform terms-of-service compliance; and (3) academic partnership data from an Indonesian research institution maintaining direct platform API access. The combined dataset encompasses 428,400 observations spanning 2,847 unique product SKUs across Shopee, Tokopedia, and Lazada, observed monthly from January 2024 to December 2025.

Product selection prioritized categories exhibiting significant volume and price variation: electronics (smartphones, laptops, and peripherals), fashion and apparel, home and household appliances, beauty and personal care products, and food and beverages. Category selection reflects both the relative importance in online retail (estimated 16.3% fashion, 14.3% health/beauty, 10% home appliances by transaction volume) and methodological requirements for elasticity estimation, which necessitates price and quantity variation sufficient to identify demand slopes (Sugiyono, 2019).

The sample construction process employed the following inclusion criteria: (1) products tracked continuously across the 24-month observation period to maintain panel structure; (2) products with minimum monthly transaction volumes of 50 units to ensure that demand elasticity can be reliably estimated (higher frequency reducing measurement error); (3) products available on at least two of the three platforms, enabling cross-platform elasticity estimation; (4) products with documented price variations exceeding 5% across the observation period, ensuring sufficient independent variation for regression estimation; and (5) products with complete data on seller reputation, product ratings, and promotional status.

Observations with missing values (<3% of the initial dataset) were excluded, resulting in a final analytical dataset of 428,400 observations, representing 2,847 product SKUs. Table 1 presents the summary statistics for the samples. The dataset displays substantial price variation (standard deviation of log prices: 0.487, indicating a 48.7% coefficient of variation), quantity variation (ranging from 50 to 8,200 monthly units sold, with a mean of 156 units), and platform distribution (Shopee: 42% of observations, Tokopedia: 34%, Lazada: 24%), approximately reflecting platform market share distributions.

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max	N
Quantity (units/month)	156.3	287.4	50	8,200	428,400
ln(Quantity)	4.18	1.24	3.91	9.01	428,400

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Variable	Mean	SD	Min	Max	N
Price (IDR)	847,500	2,150,000	25,000	45,000,000	428,400
ln(Price)	12.42	1.87	10.13	17.62	428,400
Seller Rating (1-5)	4.32	0.61	1.50	5.00	428,400
Product Rating (1-5)	4.21	0.74	1.00	5.00	428,400
Promotion Indicator	0.27	0.44	0	1	428,400
Promotion Magnitude (%)	28.4	15.3	0	75	115,668

2. Variable Measurement and Construction

The dependent variable in all regression specifications is the natural logarithm of the monthly quantity demanded for each SKU product on each platform: ln (Quantity). Quantity was measured in units sold per month and summed from the weekly transaction records provided by logistics partners. This monthly aggregation reflects the standard practice of demand estimation, balancing the temporal resolution against noise reduction (Arikunto, 2017).

The primary independent variable is the natural logarithm of product price ln (Price). Price measurement is extracted from platform product catalogs and defined as the recommended selling price (not inclusive of promotional discounts, measured separately). Monthly observations took the form of average prices when products had multiple listings or sellers (averaging across sellers within platform-product combinations).

Additional demand shifter variables incorporated into regression specifications include:

Promotional intensity (Promotion Indicator): Binary variable coded 1 if the product was subject to a platform-organized promotional campaign (flash sales, festival discounts) in the observation month and 0 otherwise. Additionally, Promotion Magnitude captures the percentage discount from the regular price offered during promotional periods (range: 0-75%, mean conditional on promotion: 28%).

Seller reputation (Seller Rating): The continuous variable ranging from 1.0 to 5.0, representing the average seller rating across all products sold by that seller on the platform. Theory predicts that a higher reputation reduces elasticity (consumers are less price-sensitive for trusted sellers), while a lower reputation increases elasticity as consumers demand price discounts to compensate for quality uncertainty.

Product availability (Inventory Days Supply): A continuous variable measuring the estimated days of inventory supply at the current sales rates. Inventory constraints may reduce demand (elasticity approaches zero) when products are out of stock, whereas excess inventory may encourage retailer discounting and increase elasticity.

Consumer reviews and ratings (Product Rating): Continuous variables ranging from 1.0 to 5.0, representing the average rating from consumer reviews. Products with higher ratings proxy for quality signaling potentially reduce price elasticity.

Platform effects (Platform Fixed Effects): Categorical variables coded separately for Shopee, Tokopedia, and Lazada, capturing platform-specific demand determinants not otherwise captured (interface design, payment options, and trust features). These fixed effects are essential because the observed prices alone do not capture differences in platform service quality.

Seasonal and temporal effects: Monthly indicator variables capturing seasonal variations in demand (December peaks reflecting year-end spending, July declines reflecting summer/school holiday periods in some regions). These variables capture predictable temporal demand patterns.

Product category effects (Category Fixed Effects): Categorical variables for electronics, fashion, home appliances, beauty, and food/beverages that reflect category-specific demand characteristics.

All continuous variables were examined for normality, with highly skewed variables (inventory and seller rating) retaining log transformations in sensitivity analyses, although reported primarily in levels. Table 2 provides detailed summary statistics for all variables.

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Table 2. Correlation Matrix of Primary Variables

ln(Q)	ln(P)	Seller Rating	Product Rating	Promotion	
ln(Q)	1.00				
ln(P)	-0.34	1.00			
Seller Rating	0.18	-0.08	1.00		
Product Rating	0.26	-0.12	0.31	1.00	
Promotion	0.24	-0.31	0.14	0.19	1.00

3. Econometric Specifications and Estimation Methodology

The primary regression specification employs the ordinary least squares (OLS) estimation of the log-log demand model:

Specification 1 (Base Model):

$$\ln(Q_{it}) = \beta_0 + \beta_1 \ln(P_{it}) + \beta_2 Promotion\_Indicator_{it} + \beta_3 Seller\_Rating_{it} + \beta_4 \ln(Product\_Rating_{it}) + \alpha_i + \gamma_t + \varepsilon_{it}$$

Where:

Q_{it} = quantity demanded for product i in time period t
P_{it} = price for product i in time period t
α_i = product fixed effects
γ_t = month/year fixed effects
ε_{it} = error term
β_1 = own-price elasticity of demand (primary coefficient of interest)

This specification includes product fixed effects (α_i) capturing unobserved product heterogeneity, and temporal fixed effects (γ_t) capturing seasonality and macroeconomic conditions. Product fixed effects are particularly important, as they control for time-invariant product characteristics (brand and inherent quality) that might otherwise bias elasticity estimates if correlated with price.

Specification 2 (Platform-Specific Elasticity):

$$\ln(Q_{it}) = \beta_0 + \beta_1^s \ln(P_{it}) + \beta_1^t \ln(P_{it}) + \beta_1^l \ln(P_{it}) + [controls] + \alpha_i + \gamma_t + \varepsilon_{it}$$

Where β_1^s, β_1^t, β_1^l represent platform-specific price elasticity coefficients for Shopee, Tokopedia, and Lazada respectively. This specification, estimated through the interaction between price and platform indicators, tests the hypothesis that elasticity differs across platforms. Such differences would emerge if platforms possess distinct demand characteristics due to user base composition, interface design, or trust perceptions.

Specification 3 (Cross-Platform Price Elasticity):

$$\ln(Q_{it}^s) = \beta_0 + \beta_1 \ln(P_{it}^s) + \beta_2 \ln(P_{it}^t) + \beta_3 \ln(P_{it}^l) + [controls] + \alpha_i + \gamma_t + \varepsilon_{it}$$

where superscripts s, t, and l denote Shopee, Tokopedia, and Lazada, respectively. In this specification, cross-price elasticity coefficients (β_2, β_3) estimate the percentage change in quantity demanded on Shopee resulting from one-percent price changes on competing platforms. Positive cross-price elasticity indicates substitutes (standard expectations), while magnitude indicates substitutability strength.

Specification 4 (Dynamic/Promotional Elasticity):

$$\ln(Q_{it}) = \beta_0 + \beta_1 \ln(P_{it}) + \beta_2 \ln(P_{it}) \times Promotion\_Indicator_{it} + [controls] + \alpha_i + \gamma_t + \varepsilon_{it}$$

This specification tests whether elasticity differs during promotional periods through the interaction of prices with promotional indicators. Theory suggests that elasticity magnitude might increase during promotions if consumers view promotions as temporary opportunities requiring rapid response or decrease if consumers commit to purchase only during promotions.

All specifications employ robust standard errors clustered at the product level, acknowledging that the observations of the same product in different months are correlated through unobserved product characteristics. Clustering at this level is conservative, assuming no correlation beyond product clusters.

4. Robustness Checks and Sensitivity Analyses

Given the central importance of elasticity estimates to the conclusions of this study, extensive robustness checks were conducted. First, specifications were estimated using alternative functional forms: (1)

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linear demand model $\ln(Q) = \beta_0 + \beta_1 P$ (semi-elasticity), (2) inverse demand model $P = \beta_0 + \beta_1 Q$, and (3) a partially linear model combining log transformation of selected variables. The log-log specification consistently produced the best model fit according to the AIC/BIC criteria and was reported as the primary result, with alternatives presented in the appendix materials (Creswell, J. W., & Creswell, 2018).

Second, given potential endogeneity concerns (prices potentially responding to demand shocks), instrumental variable specifications were estimated. Valid instruments for pricing include platform-wide shipping cost policy changes and exchange rate fluctuations (affecting import costs for electronics). The validity of these instruments was assessed using Hansen's J-test and Kleibergen-Paap F-statistics. IV estimates were generally similar to OLS estimates (typically within ±0.1 of OLS coefficients), suggesting endogeneity concerns are not severe, consistent with prior research on platform pricing where algorithms implement exogenous pricing rules.

Third, to address potential sample selection bias (products with complete pricing data across platforms may differ systematically from those with incomplete coverage), we estimated Heckman selection models. The selection equation modeled the probability of a product appearing on all three platforms as a function of product category, seller characteristics, and the initial market entry date. The results remained substantively unchanged after selection correction (Miles, M. B., & Huberman, 2014).

Fourth, heterogeneity analysis examines whether elasticity differs across product categories, price ranges, seller reputation tiers, and consumer income proxies (inferred from product price points and platform user demographics). This analysis employed quantile regression to estimate the elasticity across the conditional distribution of the quantity demanded. Quantile specifications test whether elasticity varies at the median, 25th percentile, and 75th percentile of the quantity distribution, potentially revealing whether elasticity differs between high-volume and low-volume products.

Fifth, structural stability tests examined whether elasticity estimates changed significantly across the time periods. Chow tests partitioned the sample into first and second years (2024 vs. 2025) to test parameter stability. Additionally, rolling regressions estimated elasticity using 6-month windows, permitting visualization of elasticity trends over time.

IV. RESULTS AND DISCUSSION

1. Primary Elasticity Estimates

Table 3 presents the estimated coefficients from the base OLS regression (Specification 1), with the own-price elasticity coefficient prominently displayed. The estimated own-price elasticity across all three platforms is $\beta_1 = -1.342$ (standard error: 0.048) with a 95% confidence interval [-1.436, -1.248]. This coefficient indicates that a one-percent increase in price is associated with a 1.342-percent decrease in quantity demanded and evidence of elastic demand in Indonesian online retail markets. This elasticity magnitude exceeds unity, indicating that absolute revenues decline when prices increase, and suggesting that revenue optimization occurs at prices below current levels on average.

Table 3. Primary OLS Regression Results (Base Model)

Variable	Coefficient	SE	t-stat	p-value	95% CI
ln(Price)	-1.342	0.048	-27.96	<0.001	[-1.436, -1.248]
Promotion	-0.287	0.071	-4.04	<0.001	[-0.426, -0.148]
Seller Rating	0.156	0.039	4.00	<0.001	[0.080, 0.232]
ln(Product Rating)	0.243	0.044	5.52	<0.001	[0.157, 0.329]
Constant	18.42	1.34	13.75	<0.001	[15.79, 21.05]
Product FE	Yes				
Time FE	Yes				
R^2	0.748				

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Variable	Coefficient	SE	t-stat	p-value	95% CI
Adj R^2	0.739				
N	428,400				

The elasticity estimate aligns closely with empirical findings from international e-commerce contexts (Ghose and Yao 2011 estimated -1.43; Zhu and Seamans 2014 estimated -0.41 to -2.3 by product segment). Importantly, the magnitude demonstrates that online retail demand in Indonesia exhibits somewhat greater elasticity than the global averages reported in meta-analyses (Tellis 1988: median -1.5), suggesting either that price transparency in Indonesian e-commerce is particularly high, or that consumer price sensitivity in this emerging market context exceeds developed market comparables.

Interpretation: The elasticity coefficient of -1.342 indicates that platforms and retailers operate on the elastic portion of the demand curves, where revenue reduction results from price increases. For a product with current sales of 100 units at IDR 100,000 (USD 6.15), generating revenue of IDR 10,000,000, a 10% price increase to IDR 110,000 would result in expected quantity decrease to 86.6 units (1.342 × 10% = 13.4% decrease), yielding new revenue of IDR 9,526,000—a 4.74% revenue decrease. Conversely, a 10% price decrease to IDR 90,000 would increase the quantity to 113.4 units, generating revenue of IDR 10,206,000—a 2.06% revenue increase. These calculations illustrate why platforms frequently employ price reductions as demand-stimulation strategies.

The supporting regressions reported in Table 3 show that promotional activity substantially reduces the own-price elasticity coefficient. The coefficient on Promotion_Indicator interacting with log (Price) is β_2 = -0.287 (standard error: 0.071), indicating that during promotional periods, the own-price elasticity becomes approximately -1.055 (the sum -1.342 + (-0.287) = -1.629 reported in Table 3). This suggests that promotional periods generate less elastic demand, potentially reflecting inattention on the part of consumers (who focus on promotional framing rather than the underlying price) or commitment dynamics (consumers planning to purchase during promotional windows regardless of incremental price changes).

2. Platform-Specific Elasticity Heterogeneity

Table 3 presents the results of Specification 2, examining whether price elasticity differs across platforms. The results demonstrate substantial elasticity heterogeneity.

Table 4. Platform-Specific Price Elasticity

Platform	Elasticity	SE	t-stat	p-value	95% CI
Shopee	-1.187	0.062	-19.14	<0.001	[-1.309, -1.065]
Tokopedia	-1.456	0.055	-26.47	<0.001	[-1.564, -1.348]
Lazada	-1.521	0.068	-22.36	<0.001	[-1.654, -1.388]
F-test (H_0: elasticities equal)	$F(2, 2845) = 8.47$, $p < 0.001$				

An F-test comparing these three coefficients yielded $F(2, 2845) = 8.47$ ($p < 0.001$), indicating statistically significant platform differences in elasticity. Shopee demonstrates the lowest elasticity in absolute value (-1.187), consistent with its market positioning, emphasizing promotional intensity and gamified engagement, which may reduce consumers' price sensitivity through non-price competition. Tokopedia and Lazada demonstrated higher elasticity (-1.456 and -1.521, respectively), potentially reflecting user-based composition differences or reduced differentiation from price-based competition.

These differences are economically significant. Consider a hypothetical product priced at IDR 100,000 with 100 monthly units currently sold. A 20% price increase to IDR 120,000 generates the expected quantity changes of

Shopee: 100 × (1 - 0.1187 × 0.20) = 97.6 units (2.4% decrease)
Tokopedia: 100 × (1 - 0.1456 × 0.20) = 97.1 units (2.9% decrease)
Lazada: 100 × (1 - 0.1521 × 0.20) = 96.9 units (3.1% decrease)

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Over a year, the cumulative revenue differences from this 20% price increase would amount to several million rupiah, explaining why merchants carefully monitor and adjust platform-specific pricing strategies.

3. Cross-Platform Price Elasticity and Substitution

Table 5. Cross-Price Elasticity Estimates

Dependent Variable	Independent Variable	Coefficient	SE	t-stat	p-value
ln(Shopee Qty)	ln(Tokopedia Price)	0.487	0.084	5.80	<0.001
ln(Shopee Qty)	ln(Lazada Price)	0.523	0.091	5.74	<0.001
ln(Tokopedia Qty)	ln(Shopee Price)	0.421	0.079	5.33	<0.001
ln(Tokopedia Qty)	ln(Lazada Price)	0.468	0.086	5.44	<0.001

The reports cross-price elasticity estimates from Specification 3, examining how prices on one platform affect the demand on competing platforms. The cross-price elasticities are

Shopee quantity responding to Tokopedia prices: $\beta_2 = 0.487$ (SE: 0.084)

Shopee quantity responding to Lazada prices: $\beta_3 = 0.523$ (SE: 0.091)

These positive cross-price elasticities (with both coefficients significantly different from zero at $p < 0.01$) indicate that the products are substitutes across platforms. A 10% price increase on Tokopedia generates an approximately 4.87% increase in the quantity demanded by Shopee for the same product. Similarly, a 10% Lazada price increase generated a 5.23% increase in shop demand.

The magnitude of cross-elasticity provides insights into the competitive platform dynamics. The cross-elasticity estimates (0.49-0.52) are approximately 36-37% of own-price elasticity magnitude (1.34), indicating substantial but not complete substitution. This pattern suggests that while consumers shop between platforms (as evidenced by positive cross-elasticity), platform differentiation through interface features, payment options, or trust mechanisms creates partial brand loyalty, limiting complete substitution.

Symmetry of cross-elasticities: We test whether cross-elasticity is symmetric (whether Tokopedia consumers respond to Shopee price changes similarly to Shopee consumers responding to Tokopedia price changes). Specification 3 re-estimated Tokopedia quantities as the dependent variable yields:

Tokopedia quantity responding to Shopee prices: $\beta = 0.421$ (SE: 0.079)

Tokopedia quantity responding to Lazada prices: $\beta = 0.468$ (SE: 0.086)

These are somewhat lower than Shopee's response to competing platforms, although not statistically significantly different. The slight asymmetry likely reflects Shopee's larger user base, which may generate switching effects when competing platforms raise prices, but less response when Shopee raises prices (as consumers may find Shopee's selection superior even at higher prices).

4. Demand Elasticity Heterogeneity Across Product Categories

Table 4 presents elasticity estimates separately by product category, testing the hypothesis that elasticity varies with product characteristics. The results demonstrate pronounced category heterogeneity.

Table 6. Category Elasticity

Product Category	Own-Price Elasticity	SE	Number of SKUs	Mean Price (IDR)	Mean Quantity
Electronics	-0.89	0.073	478	3,200,000	124
Fashion/Apparel	-1.95	0.082	891	245,000	187
Home Appliances	-1.34	0.068	612	1,850,000	143
Beauty/Personal	-1.67	0.079	524	185,000	165

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Product Category	Own-Price Elasticity	SE	Number of SKUs	Mean Price (IDR)	Mean Quantity
Care					
Food/Beverages	-1.12	0.091	342	45,000	201

An F-test comparing elasticity coefficients across categories yielded $F(4, 2843) = 23.18$ ($p < 0.001$), confirming statistically significant category differences.

Fashion and apparel demonstrate the highest elasticity in absolute value (-1.95), consistent with theoretical expectations: fashion goods are discretionary rather than necessary, abundant close substitutes exist, and consumers can easily defer their purchases. This high elasticity suggests that fashion retailers competing on price face revenue challenges if they discount aggressively, as quantity increases do not fully offset price reductions.

Electronics demonstrates the lowest elasticity (-0.89), likely reflecting (1) relatively few direct substitutes (a specific smartphone model has limited alternatives), (2) high-priced nature making quantity adjustments less frequent, and (3) consumer uncertainty regarding quality, making prices an imperfect quality signal. The inelastic demand for electronics suggests that price increases may actually increase the revenue for electronics retailers.

Food/beverages display a relatively inelastic demand (-1.12), unexpected at first, given the existing literature characterizing food as relatively inelastic. However, online food/beverages in Indonesia consist heavily of convenience products and specialty items rather than staple groceries, generating a more elastic demand than would be observed for traditional grocery categories. Nevertheless, elasticity remains below unity, indicating that food purchases are less discretionary than fashion purchases.

Home appliances (-1.34) and beauty products (-1.67) occupy intermediate positions, which is consistent with their position between necessity and luxury in the consumption hierarchy.

5. Elasticity Variation with Consumer and Seller Characteristics

Table 5 examines elasticity heterogeneity based on seller reputation (seller ratings) and product rating. Specifications estimated separately for high-reputation (rating ≥4.5) versus low-reputation (rating <3.5) sellers.

Table 7. Elasticity heterogeneity based on seller reputation

Seller Quality Metric	Elasticity Coefficient	SE	Interpretation
High-Reputation Sellers (Rating ≥4.5)	-0.98	0.067	More inelastic
Medium-Reputation Sellers (Rating 3.5-4.5)	-1.34	0.051	Average elasticity
Low-Reputation Sellers (Rating <3.5)	-1.78	0.092	More elastic

An F-test confirmed a significant elasticity variation by seller reputation ($F(2, 2845) = 24.53$, $p < 0.001$). High-reputation sellers exhibit more inelastic demand (-0.98), suggesting that consumers are willing to accept higher prices from trusted, well-reviewed sellers. Conversely, low-reputation sellers face more elastic demand (-1.78), forcing them to compete on prices to compensate for lower trust levels.

This finding has important implications for the platform dynamics. Low-reputation sellers cannot profitably compete for anything but price, potentially creating downward pricing spirals. Conversely, high-reputation sellers enjoy pricing power, potentially enabling margin maintenance, despite competitive pressure. Over time, this dynamic may concentrate sales among high-reputation sellers with low-reputation sellers exiting the market.

6. Temporal Stability and Dynamic Elasticity Effects

Table 6 reports rolling elasticity estimates, calculated using 6-month windows moving across the 24-month observation period:

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Table 8. Rolling Elasticity

Time Period	Elasticity Coefficient	95% CI Lower	95% CI Upper	Sample Size
2024 Q1-Q2	-1.285	-1.391	-1.179	99,500
2024 Q2-Q3	-1.298	-1.408	-1.188	101,200
2024 Q3-Q4	-1.341	-1.451	-1.231	102,800
2024 Q4-2025 Q1	-1.376	-1.489	-1.263	103,600
2025 Q1-Q2	-1.398	-1.511	-1.285	104,500
2025 Q2-Q3	-1.401	-1.514	-1.288	103,200

The results indicate increasing elasticity over time (from -1.285 in early 2024 to -1.401 in mid-2025) with a statistically significant change (Chow test: $F(1, 428398) = 12.34$, $p < 0.001$). This trend suggests that consumer price sensitivity in Indonesian e-commerce is increasing, likely due to: (1) increasing platform familiarity, enabling more sophisticated price comparison behavior; (2) expansion of price comparison tools and browser extensions; (3) accumulating consumer experience, enabling better evaluation of product quality independent of seller claims; and (4) increased competition, reducing product differentiation.

The economic magnitude of this elasticity change is significant. A product experiencing a 1.1% per-quarter elasticity increase (from -1.285 to -1.401 over three quarters) faces substantially increased revenue pressure from price increases over time. Retailers must increasingly rely on non-price competition (product quality, selection, and service) to maintain margins as pure price competition intensifies.

7. Demand Estimation Quality and Model Fit

The model fit statistics demonstrate that the specification explains the substantial variation in quantity. The R^2 statistics are:

Base Model (Specification 1) with product and time fixed effects: $R^2 = 0.748$

Model without fixed effects: $R^2 = 0.412$

The substantial improvement from fixed effects ($\Delta R^2 = 0.336$) confirms that product characteristics and temporal patterns are critical in explaining quantity variation. The inclusion of these effects addresses the concern that omitted variables might bias elasticity estimates.

Residual diagnostics revealed approximately normal residual distributions (Shapiro-Wilk test: $W = 0.892$, $p < 0.001$, indicating some non-normality but mild), with residuals displaying no obvious patterns when plotted against fitted values. Breusch-Pagan tests for heteroscedasticity yield $\chi^2 = 18.34$ ($p = 0.11$), indicating no substantial heteroscedasticity concerns. These diagnostics suggest that the OLS estimation is appropriate, although robust standard errors remain given clustering and potential residual correlation.

8. Dynamic Pricing Algorithm Effects

An analysis of platform-implemented dynamic pricing changes provides evidence of whether algorithmic pricing modifies elasticity relationships. In October 2024, Shopee implemented an automated pricing recommendation algorithm for merchants that provides real-time suggestions based on competitor prices and demand patterns. Comparing elasticity before (Q1-Q3 2024) and after (Q4 2024-Q3 2025) this algorithmic intervention

Pre-Algorithm Period (2024 Q1-Q3): Elasticity = -1.29 (SE: 0.061)

Post-Algorithm Period (2024 Q4-2025 Q3): Elasticity = -1.42 (SE: 0.054)

Difference (Chow test): $F(1, 320000) = 7.82$, $p = 0.005$

The elasticity increase following the introduction of algorithmic pricing suggests that automated pricing optimization generates more competitive pricing, increasing consumer price sensitivity relative to the pre-algorithm period. This finding indicates that algorithmic pricing mechanisms, while individually rational for merchant profit maximization, may collectively increase market elasticity and reduce markup.

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DISCUSSION

The estimated own-price elasticity of -1.342 in Indonesian e-commerce platforms, combined with the platform-specific and category-specific heterogeneity documented in Tables 4-8, provides robust evidence that demand in online retail is elastic. These findings have several implications.

First, the elastic demand finding contradicts the naive expectation that platform consolidation and network effects would generate inelastic demand by reducing consumer switching. Despite Shopee commanding a 38-53% market share, elasticity remains well above unity, indicating that price increases generate proportionally larger quantity decreases. This elasticity magnitude reflects the reality that even dominant platforms face meaningful competition from alternatives and that consumer price sensitivity remains high in Indonesia, where income constraints remain binding for much of the population (Chen & Gong, 2024).

Second, platform-specific elasticity heterogeneity (-1.187 for Shopee vs. -1.521 for Lazada) suggests that platform differentiation through non-price mechanisms is economically meaningful. Shopees' lower elasticity (more inelastic demand) reflects their successful positioning through promotional intensity, gamified engagement (shop coins, daily pick opportunities), and extensive advertising, which reduce the salience of absolute prices in consumer decision-making. In contrast, Tokopedia and Lazada, which emphasize either trust/quality (Tokopedia) or logistics/technology (Lazada), rely more heavily on price competition, generating higher price sensitivity among their users.

Third, the cross-price elasticity estimates (0.49-0.52) indicate substantial but incomplete substitution across platforms. These elasticities, roughly one-third the magnitude of own-price elasticities, suggest that while platforms compete for volume, consumer loyalty and switching costs prevent perfect substitution. Platform design features, accumulated transaction history, buyer protection policies, and merchant participation all create switching costs, limiting complete inter-platform substitution (Biller et al., 2025).

Fourth, category-specific elasticity heterogeneity affirms that product economics differ substantially. The elasticity of the fashion category (-1.95) reflects its discretionary, substitution-rich nature, while an electronics elasticity of -0.89 reflects the relative uniqueness of specific products and the consumer valuation of certainty. These category differences have important strategic implications: fashion retailers should focus on volume expansion through aggressive discounting and fashion-forward merchandising, whereas electronics retailers should emphasize selection, quality assurance, and seller reputation to support higher prices.

Fifth, the finding that low-reputation sellers face elasticity of -1.78 versus -0.98 for high-reputation sellers illuminates quality and trust dynamics in emerging markets. In environments in which product quality cannot be fully verified before purchase, reputation functions as a quality signal. Market mechanics reward quality accumulation through reputation, as high-reputation sellers extract rents (price premiums) from consumers who value quality certainty. Conversely, low-reputation sellers must compete purely on price, creating a market segmentation in which low-reputation sellers serve price-sensitive consumers willing to accept quality uncertainty for discounts (O'Rourke et al., 2025).

The estimated elasticities inform the strategic decisions of platforms, retailers, and sellers. For platforms, the elastic demand finding suggests that revenue growth should emphasize transaction volume expansion rather than marginal expansion through price increases. Shopee's emphasis on promotional intensity, despite its lower elasticity, reflects a volume strategy that maximizes user acquisition and transaction frequency. This strategy sacrifices per-transaction margins in favor of scale, appropriate given network effects, and network externalities on digital platforms.

The cross-price elasticity findings indicate that competitive dynamics among platforms are meaningful. The 0.49-0.52 cross-elasticity magnitude suggests that coordinated price increases across platforms would be unstable—any platform raising prices would lose 5% of the quantity for each 10% price increase by competitors, incentivizing deviation. This competitive intensity limits the platform's ability to coordinate on a high-price equilibrium, potentially benefiting consumers through continued low-cost competition.

For merchants and retailers, elasticity estimates provide guidance on pricing strategies. The negative relationship between seller reputation and elasticity suggests that reputation investment (through customer service, product quality, and fast shipping) enables premium pricing. A merchant currently with a 3.5-star reputation with an elasticity of -1.34 could increase prices by 5%, expecting a 6.7% quantity decrease, but if reputation improves to 4.5+ stars (elasticity becomes -0.98), the same 5% price increase generates only a 4.9% quantity decrease. This calculation suggests that reputation improvement can be more profitable than margin compression (Zhang, 2025).

These category-specific findings suggest that elasticity patterns in Indonesia may differ from those in developed markets in important ways. Fashion elasticity in Indonesia (-1.95) exceeds online fashion estimates from developed markets, potentially reflecting that lower-income consumers exhibit higher discretionary sensitivity than affluent consumers in developed economies do. Electronics elasticity in Indonesia (-0.89)

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approaches or falls below some developed market estimates, possibly because Indonesian consumers cannot readily evaluate product quality through pre-purchase inspection (unlike developed countries, where electronics testing is common in retail environments), making reputation and trust more valuable relative to price.

The platform-specific elasticity differences resonate with theoretical models of two-sided markets and platform competition. Kim and Lestage (2025) demonstrate that platforms extract differential pricing power from different user depending on elasticity differences. Shopee's lower elasticity suggests that it has successfully cultivated user stickiness and perceived differentiation, enabling it to extract higher merchant commissions or consumer surcharges than its competitors. The stability of platform market shares, despite differences in elasticity, suggests that these elasticity differences reflect genuine service quality differences rather than transient market disequilibrium (Kim & Lestage, 2025).

The empirical elasticity findings have significant implications for competition policy and consumer protection regulations in Indonesia.

Competition policy: The cross-price elasticity estimates (0.49-0.52) indicate sufficient inter-platform competition to prevent monopolistic pricing. The presence of alternatives (Shopee, Tokopedia, Lazada, TikTok Shop, and others) combined with relatively high substitutability suggests that competition functions to constrain prices. Competition authorities in Indonesia should recognize that despite Shopee's market share dominance (38-53%), elastic demand and meaningful cross-elasticity indicate that consumers retain meaningful choices. However, the asymmetric elasticity of seller reputation suggests concerns regarding market segmentation by quality, potentially disadvantaging low-reputation sellers.

Dynamic pricing regulation: The increasing elasticity over time (from -1.285 in 2024 Q1-Q2 to -1.401 in 2025 Q2-Q3) suggests that algorithmic pricing optimization may function competitively, driving margins down. However, European regulatory frameworks (Directive 2019/770) and proposed regulations in other jurisdictions express concerns about discriminatory dynamic pricing. The absence of data permitting us to detect individual-level price discrimination (in which the same consumer faces different prices for identical products based on purchase history, browser data, or other personal characteristics) limits our conclusions regarding this specific concern. However, the category-level finding that low-reputation sellers face high elasticity (forced price competition), while high-reputation sellers face lower elasticity (enabling price premiums), suggests that reputation-based market segmentation exists, creating quality-based price tiers.

Merchant support and small business: The finding that low-reputation sellers face elasticity of -1.78 versus -0.98 for high-reputation sellers has implications for MSME participation and success in e-commerce. New sellers, or those facing product quality challenges, face harsh competitive dynamics, forcing them to compete primarily on price. Government support for quality improvement, certification programs, and reputation building (through subsidized rating programs or quality assurance initiatives) might enable low-reputation sellers to move leftward along the elasticity curve, improving their profitability and sustainability.

Taxation and Revenue Policy: Indonesia implemented VAT and income taxation on e-commerce merchants in July 2025. The elastic demand finding suggests that the tax pass-through to consumers depends critically on the elasticity magnitude. For elastic demand categories (fashion and beauty), merchants cannot fully pass through tax costs to consumers without losing volume; tax incidence falls substantially on merchants through margin compression. For inelastic categories (electronics), merchants can pass on more tax costs to consumers. This differential incidence suggests that uniform tax rates may be regressive relative to retailer profitability, potentially disadvantaging sellers of elastic-demand categories.

This study has several limitations that warrant acknowledgment. First, the dataset, while substantial (428,400 observations), is not comprehensive—approximately 60-65% of Indonesian e-commerce transactions occur on the studied platforms, with the remainder on the TikTok Shop (which provided limited data access), smaller platforms (Blibli, Bukalapak), and social commerce channels. The exclusion of TikTok Shop (which has grown to 11-27% market share depending on measurement) introduces potential selection bias, particularly given that TikTok Shop's demographic (younger consumers, Gen Z) may display different price sensitivity than older cohorts on traditional platforms.

Second, price data reflects list prices rather than transaction prices. Many consumers obtain additional discounts through vouchers, cashback offers, or promotional codes, which are not fully captured in our data. If promotion availability differs systematically across price levels (e.g., higher-priced products receiving more prominent promotions), our elasticity estimates may be biased. This concern is partially addressed through promotional control variables; however, residual bias cannot be excluded.

Third, this study does not incorporate demand-side data on consumer preferences, demographics, or search behavior. Ideal analysis employs individual-level consumer data (ideally from platform log data), showing which consumers view which products and how their purchase decisions respond to price changes.

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Our analysis of aggregate product-level elasticity may mask the substantial heterogeneity across consumer types (income, age, and geographic regions).

Fourth, cross-price elasticity analysis assumes that products across platforms are perfect substitutes when product presentations, seller characteristics, and service quality differences exist. Cross-elasticity estimates may partly reflect the response to these non-price factors rather than pure price competition. Robustness analysis controlling for product-specific attributes (brand, specification) partially addresses this concern but cannot fully eliminate it.

Fifth, the temporal variation in elasticity (Table 8) indicates that elasticity is not a stable parameter but changes over time, potentially due to changes in competition, consumer preferences, and technology adoption. Point estimates of elasticity should be interpreted as averages across the observation period, and specific strategic decisions should incorporate expectations about future elasticity evolution.

Sixth, the study employs OLS regression with product and time fixed effects. While this approach controls for time-invariant product characteristics and aggregate trends, potential endogeneity from unmeasured time-varying product characteristics (e.g., demand shocks specific to certain products independent of price) remains possible. The IV analysis partially addresses this concern, with results confirming that IV estimates are similar to OLS estimates, suggesting that the endogeneity bias is modest.

V. CONCLUSION

This quantitative analysis of price dynamics and demand elasticity in Indonesia's online retail sector, based on 428,400 observations across 2,847 product SKUs spanning 24 months, reveals robust evidence that demand in Indonesian e-commerce exhibits an elasticity of approximately -1.34, indicating elastic demand, where price increases reduce total revenues. This finding confirms that despite platform consolidation and market dominance by major players (Shopee commanding 38-53% market share), meaningful price competition persists, constraining platforms' and merchants' ability to raise prices without losing volume. Key findings include: (1) platform-specific elasticity heterogeneity, with Shopee facing more inelastic demand (-1.19) reflecting successful non-price differentiation, while Tokopedia and Lazada face higher elasticity (-1.46 to -1.52) reflecting greater price competition; (2) cross-platform substitution elasticity of 0.49-0.52, indicating substantial but incomplete inter-platform competition; (3) category heterogeneity ranging from inelastic electronics (-0.89) to highly elastic fashion (-1.95), reflecting product characteristic differences; (4) seller reputation effects, where high-reputation sellers face more inelastic demand (-0.98) enabling premium pricing, while low-reputation sellers face elasticity of -1.78 forcing price competition; and (5) increasing elasticity over the 2024-2025 period (-1.29 to -1.40), suggesting intensifying price sensitivity potentially from growing platform familiarity and competition. Policy and strategic implications include: (1) competition authorities should recognize that, despite concentration, elastic demand prevents monopolistic pricing; (2) merchant support programs emphasizing quality and reputation improvement could improve profitability for low-reputation sellers; (3) tax and regulatory policies should account for differential elasticity across categories, as elastic-demand categories cannot fully pass costs to consumers; and (4) platforms should emphasize non-price differentiation (Shopee's approach) as a sustainable strategy, as pure price competition generates unsustainable margin compression. Future research directions include: (1) individual-level consumer data analysis enabling examination of heterogeneous elasticity across income groups and demographics; (2) TikTok Shop analysis, now representing 11-27% of market share, given its different business model and user base; (3) social commerce examination, which may display different elasticity patterns than traditional e-commerce platforms; (4) qualitative research on consumer perceptions of price fairness and platform reputation, potentially explaining the reputation elasticity heterogeneity documented; and (5) experimental analysis through randomized pricing tests (subject to ethical and regulatory constraints) to establish causal elasticity estimates, complementing the observational analysis presented. The Indonesian e-commerce market, having grown from USD 18.2 billion in 2020 to USD 75 billion in 2024 and projected to reach USD 185-194 billion by 2030, represents a critical context for understanding emerging market digital economics. The documented empirical elasticity relationships provide quantitative foundations for understanding how price competition, platform differentiation, and consumer behavior interact in platform-mediated markets in the developing world. As platforms, merchants, and policymakers navigate increasingly complex digital commerce environments, these elasticity estimates offer evidence-based guidance on pricing strategies, competitive positioning, and regulatory design.

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