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Drug Demand Elasticity Estimation Based on Instrumental Variable Regression: A Case Study of Hospital X Transaction Data

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Abstract

Introduction: Price determination is a key strategic decision affecting revenue and consumer behavior in the pharmaceutical sector. Demand elasticity is used to measure price sensitivity, but its estimation may be biased due to price endogeneity, requiring a more robust econometric approach. **Research Methods**: This study uses transaction data from Hospital X, including drug codes, prices, quantities, and HNA. Data are cleaned by removing missing values and trimming outliers at the 1st–99th percentile. Instrumental variables are constructed from HNA using lag, moving average, and differencing, and selected dynamically per product based on the highest first-stage F-statistic. Elasticity is estimated using a log-log model with Two-Stage Least Squares (2SLS) or Ordinary Least Squares (OLS), guided by the Durbin-Wu-Hausman test. **Results**: The results show that after preprocessing and structural selection criteria, 13 drug products were analyzed using elasticity estimation. The estimated price elasticity values ranged from -0.2249 to -4.3687, indicating different levels of consumer sensitivity toward price changes across products. Based on the comparison between estimated elasticity and break-even elasticity, four inelastic products were recommended for price increases, while nine elastic products were not

recommended due to higher demand sensitivity. **Conclusion**: The study concludes that dynamic IV selection combined with structural diagnostics effectively handles price endogeneity, providing robust elasticity estimates to support targeted pharmaceutical pricing decisions.

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INTRODUCTION

Pricing decisions are among the strategic decisions that have a significant impact on business success, including in the pharmaceutical and healthcare sectors. Price not only determines the level of revenue obtained by a company but also influences consumer purchasing behavior (Borges dos Santos et al., 2019). In the pharmaceutical industry, inaccurate pricing decisions may lead to a decline in sales volume, reduced profitability, and even decreased product competitiveness in the market. Therefore, pharmaceutical companies and hospitals require a data-driven approach to understand the relationship between price changes and the demand level of pharmaceutical products.

One of the widely used economic concepts for measuring consumer sensitivity to price changes is demand elasticity. Demand elasticity represents the magnitude of changes in quantity demanded resulting from changes in the price of a product. Information regarding elasticity is essential in developing pricing strategies because it helps companies determine whether a product has elastic or inelastic demand characteristics. For products with inelastic demand, price increases generally do not result in a significant decline in demand, potentially increasing profitability. Conversely, for products with elastic demand, price increases may cause a substantial reduction in purchase volume, negatively affecting company profitability (Tellis, 1988).

However, estimating demand elasticity often faces various methodological challenges. One of the most common issues is endogeneity in the price variable (Muin, 2025). In practice, price not only affects the quantity demanded but may also be influenced by the level of demand itself. This condition creates a simultaneous relationship between price and demand, causing the basic assumptions of the Ordinary Least Squares (OLS) method to be violated (Angrist & Krueger, 2001). Consequently, coefficients estimated from conventional regression models may become biased and inconsistent, potentially leading to inaccurate conclusions in business decision-making.

To address this issue, the Instrumental Variable (IV) Regression approach is widely applied in econometric research. This method utilizes instrumental variables that have a strong relationship with the price variable but are not correlated with the error term in the demand model. Through the Two Stage Least Squares (2SLS) approach, the IV method is able to produce more consistent parameter estimates compared to OLS when endogeneity is

present (Angrist & Krueger, 2001). The application of the IV method becomes increasingly relevant in pharmaceutical transaction data analysis because drug selling prices are often influenced by various factors that cannot be directly observed within the model.

In the context of the hospital pharmaceutical industry, pricing decisions cannot be applied uniformly across all drug products. Each product has different demand characteristics, meaning that price changes may generate different impacts on demand levels and profitability (Zhao et al., 2021). Therefore, a data-driven approach is required to identify price sensitivity levels for each product more specifically.

Previous studies on demand elasticity have generally focused on estimating the relationship between price and demand using conventional regression methods (Ellison et al., 1997). However, these approaches have limitations because price variables may suffer from endogeneity due to the two-way relationship between price and demand (Dhar et al., 2003). Furthermore, studies applying the Instrumental Variable Regression approach to actual pharmaceutical transaction data within hospital environments remain relatively limited.

Based on these issues, this study aims to estimate drug demand elasticity using the Instrumental Variable Regression approach with the Two Stage Least Squares (2SLS) method. The study is conducted using sales transaction data from Hospital X, consisting of information on demand quantity, selling price, pharmacy net price, and transaction time. In addition to identifying the demand elasticity level of each drug product, this study also aims to evaluate the presence of endogeneity in the price variable, select the best instruments based on statistical strength, and develop pricing strategy recommendations based on elasticity estimation results and break-even elasticity analysis. The findings of this study are expected to provide practical contributions for data-driven business decision-making and enrich the literature regarding the application of modern econometric methods in the pharmaceutical sector.

RESEARCH METHODS

This study uses secondary data in the form of pharmaceutical sales transaction data obtained from the database of Hospital X, covering the period from June 2023 to September 2025. The dataset contains transaction records consisting of drug codes (drug ID), transaction dates, quantity sold (numero), selling prices (rate), and pharmacy net prices (HNA). The unit of analysis in this study is each individual drug product recorded in the transaction data.

The first stage of the study involves data cleaning to remove observations that do not meet the analysis criteria, such as missing values, invalid sales quantities ($n < 30$), economically unreasonable prices ($x \leq 0$), and the presence of outliers. In addition, only products with negative elasticity values and greater than $-5(-5 < E_d < 0)$ are retained for further analysis, as this range is considered to represent realistic demand behavior based on economic theory (Wahyuni et al., 2016).

To reduce the influence of extreme values, trimming (Winsorizing) is applied at the 1st and 99th percentiles. This method is selected because it is more effective in reducing distortion caused by outliers compared to transforming extreme values into boundary values

(Sihombing et al., 2023). The data filtering process within the 1st to 99th percentile range is formulated as follows:

$$Q_{0.01} \leq X_i \leq Q_{0.99} \quad (1)$$

Where:
$Q_{0.01}$ = 1st percentile
$Q_{0.99}$ = 99th percentile
X_i = observation value

After the data cleaning process, instrumental variables are constructed using historical Pharmacy Net Price (HNA) information. The instruments are developed based on previous-period HNA values (lag), moving averages, and changes in HNA values between periods (difference). In general, candidate instruments can be represented as follows:

$$Z_i = \{Lag(HNA), MA(HNA), \Delta HNA\} \quad (2)$$

Lag-based instruments are used to represent the influence of previous-period acquisition costs on current selling prices. Moving average instruments are used to capture cost change trends across several periods, producing a more stable measurement. Meanwhile, difference-based instruments are used to represent changes in acquisition costs between periods that may influence pricing decisions. These three types of instruments can improve the regression model's ability (Pohan & Ermiati, 2016).

The strength of each instrument is evaluated using the following first-stage regression model:

$$\ln(P_i) = \alpha_0 + \alpha_1 Z_i + u_i \quad (3)$$

Where:
P_i = drug selling price
Z_i = instrumental variable
u_i = error term

Two instruments with the highest First Stage F-statistic values are dynamically selected for each drug product. Based on econometric literature, an instrument is considered sufficiently strong when it has an F-statistic value greater than 10 (Staiger & Stock, 1997).

Demand elasticity estimation is performed using a structural log-log model, allowing the price coefficient to be directly interpreted as price elasticity of demand (Fardiansyah & Eliyanti, 2025). The elasticity model is expressed as follows:

$$\ln(Q_i) = \beta_0 + \beta_1 \ln(P_i) + \varepsilon_i \quad (4)$$

Where:
Q_i = drug demand quantity
P_i = drug selling price
ε_i = error term

The coefficient $\beta_1$represents price elasticity of demand, which indicates the percentage change in demand resulting from a one-percent change in price.

This study acknowledges the limitation that actual transaction data do not directly record external variables, such as disease seasonality, prescribing physician characteristics, and hospital promotion programs. However, in econometric theory, the Instrumental Variable (IV) approach using the 2SLS method is specifically designed to address bias caused by unobserved variables (omitted variable bias) (Wooldridge, 2005). By exploring a wide range of candidate instruments derived from historical HNA values (including lag 1 to lag 4, moving averages of 3 and 7 periods, and differencing), the first-stage model is able to capture the dynamics of pharmaceutical acquisition cost changes comprehensively. These instrument variations indirectly isolate price fluctuations from the influence of unobserved external factors, allowing the elasticity coefficients estimated in the second-stage structural equation to remain consistent and unbiased (Bai & Ng, 2010).

To determine the most appropriate estimation method, an endogeneity test is conducted using the Durbin–Wu–Hausman (DWH) Test. The testing model is formulated as:

$$\ln(Q_i) = \gamma_0 + \gamma_1 \ln(P_i) + \gamma_2 X_i + \gamma_3 u_i + e_i \quad (5)$$

Where:

u_i = residual from the first-stage model

ε_i = error term

If the residual coefficient is statistically significant at the 5% significance level, the model indicates the presence of endogeneity (Yulian, 2018). Therefore, the Instrumental Variable Regression method using the Two Stage Least Squares (2SLS) approach is applied. Conversely, if no indication of endogeneity is found, the Ordinary Least Squares (OLS) model is considered sufficient.

For models proven to be endogenous and estimated using the IV method, instrument exogeneity validity is evaluated using the Hansen J-Test (Overidentification Test). This test aims to determine whether the instruments satisfy the orthogonality condition with respect to the error term in the structural equation (Hansen, 1982).

The evaluation equation using the Hansen J-Test (Overidentification Test) through auxiliary residual regression is formulated as follows:

$$\hat{\varepsilon}_i = \delta_0 + \delta_1 Z_i + \delta_2 X_i + \omega_i \quad (6)$$

where n represents the number of observations and R^2 is obtained from the residual regression model (Baum et al., 2007). The statistic follows a Chi-Square distribution with degrees of freedom equal to the number of instruments minus the number of endogenous variables. Instruments are considered valid if the null hypothesis of instrument validity cannot be rejected at the 5% significance level. For models identified as exogenous based on the Durbin–Wu–Hausman Test, OLS estimation remains consistent; therefore, the overidentification test is not conducted.

The final stage of the study involves developing business recommendations based on demand elasticity values and break-even elasticity. The percentage change in demand is calculated using the following equation:

$$\%\Delta Q = E_d \times \%\Delta P \quad (7)$$

Where:

$\%\Delta Q$ = percentage change in demand quantity

$\%\Delta P$ = percentage change in price

E_d = price elasticity of demand

Furthermore, the break-even elasticity value is calculated as:

$$E_{BE} = -\frac{1}{1 + Margin} \quad (8)$$

The profit margin is calculated as:

$$Margin = \frac{P - HNA}{P} \quad (9)$$

Where:

E_{BE} = break-even elasticity

P = average selling price

HNA = average pharmacy net price

The obtained elasticity values are then compared with the break-even elasticity values to determine whether a product still has the potential to increase profitability through price adjustments. Products with elasticity values greater than the break-even elasticity are recommended for price adjustments because the potential increase in profit is expected to exceed the risk of demand reduction.

RESULT AND DISCUSSION

DATA PREPROCESSING AND SELECTION

Before estimating demand elasticity, the transaction data were first subjected to a preprocessing stage to ensure the quality of the data used in the analysis. This stage included the removal of invalid data, elimination of extreme observations (outliers), and product selection based on a minimum number of transactions. Data filtering was conducted to obtain more stable elasticity estimates that are consistent with econometric assumptions.

After the data cleaning process, the number of transactions was reduced from 187860 to 101418 valid observations suitable for analysis. Furthermore, drug products were selected based on the number of transactions, with a minimum criterion of 30 transactions during the observation period. This criterion was applied to ensure that each product had sufficient observations so that the elasticity parameters could be estimated more reliably. The preprocessing and sample selection results are presented in Table 1.

Table 1. Data Preprocessing Results

Criteria	Number of Drug Types
Total drug types after data cleaning	306
Having ≥ 30 transactions	78
Having positive or extreme elasticity	65
Drugs meeting the final criteria	13

Source: Secondary data processed using Python, 2026

Based on Table 1, there were 306 drug types available after the data cleaning process. Among these, only 78 drug types had a minimum of 30 transactions and met the requirements for elasticity estimation. Furthermore, the estimation results showed that 65 drug types had positive elasticity values or extremely large elasticity values (absolute elasticity greater than 5), making them inconsistent with demand theory and less suitable as a basis for business decision-making. After the final filtering process, 13 drug types met all statistical and economic criteria for further analysis.

These findings indicate that not all products generate valid elasticity estimates. Therefore, the selection process is an important stage to ensure that the analysis results used as the basis for pricing recommendations truly reflect realistic demand behavior and remain consistent with economic theory.

ENDOGENEITY TEST AND DYNAMIC INSTRUMENT SELECTION

After obtaining 13 drug products that met the criteria, an endogeneity test was performed using the Durbin–Wu–Hausman (DWH) Test to determine the most appropriate estimation method. In addition, each product was evaluated to determine the best instruments based on the First Stage F-statistic value.

Table 2. Structural Diagnostic Results and Estimation Method Selection

Drug Code	Method	Top 2 Instruments	First Stage F	DWH p-value	Hansen p-value
DZ.0000030	OLS	hna_lag1, hna_ma3	26.11	0.2930	0.6105
DZ.0000098	OLS	hna_lag1, hna_ma3	378.26	0.8511	0.4366
DZ.0000123	OLS	hna_lag1, hna_ma3	7805.85	0.0571	0.0672
DZ.0000124	OLS	hna_lag1, hna_ma3	16976.18	0.1453	0.9999
DZ.0000170	OLS	hna_ma3, hna_ma7	135.22	0.3478	0.9169
DZ.0000345	OLS	hna_lag1, hna_ma3	1659.63	0.3753	0.1253
DZ.0000422	OLS	hna_lag1, hna_ma3	1075.83	0.1069	0.6220
DZ.0000503	OLS	hna_lag1, hna_ma3	237833.50	0.9344	0.2235
DZ.0000528	OLS	hna_lag1, hna_ma3	1521.89	0.6919	0.0752

Drug Code	Method	Top 2 Instruments	First Stage F	DWH p-value	Hansen p-value
DZ.0000532	OLS	hna_lag1, hna_ma3	25192.29	0.0842	0.7903
DZ.0000557	IV	hna_lag1, hna_ma3	2241.59	0.0000	0.6768
DZ.0000582	OLS	hna_lag1, hna_ma3	140479.78	0.1061	0.6810
OZ.0000110	OLS	hna_lag1, hna_ma3	3792.25	0.8205	0.5987

Source: Secondary data processed using Python, 2026

The empirical results in Table 2 provide important methodological findings. A total of 12 drug products recorded DWH p-values ≥ 0.05. This condition indicates that the selling price variation of these products can be considered exogenous with respect to the demand error component. Therefore, the final parameter estimation using Ordinary Least Squares (OLS) is considered the most efficient choice because it avoids simultaneous bias issues.

Conversely, only product DZ.0000557 showed significant price endogeneity (DWH p-value = 0.0000), requiring the application of Instrumental Variable (IV) regression using the 2SLS approach. The Hansen J-Test value for DZ.0000557 was 0.6768 (≥ 0.05), confirming that the selected dynamic instrument pair (HNA lag1 and HNA ma3) was free from correlation with unobserved variables (omitted variables) and satisfied the exogeneity condition.

Based on Table 2, the First Stage F-statistic values for all drug products were substantially above the critical threshold proposed by Staiger and Stock ($F > 10$), eliminating concerns regarding weak instrument bias. The extremely high F-statistic values, reaching hundreds of thousands for certain products (such as DZ.0000503 = 237,833.50), indicate a strong and linear cost pass-through relationship between pharmacy acquisition cost fluctuations and patient selling price adjustments.

PRICE INCREASE POLICY RECOMMENDATION

The estimated elasticity values were subsequently compared with the break-even elasticity values to determine whether each product remained feasible for price increases. Products were categorized as safe for price increases when their elasticity values were lower than the break-even elasticity threshold (Anida et al., 2023), because the additional margin obtained could compensate for the reduction in sales volume.

Table 3. Final Price Elasticity Results and Profitability Evaluation Matrix

Drug Code	Elasticity Estimation	Elasticity Break-Even	Policy Recommendations	Profit Impact Projections
DZ.0000030	-4.3687	-0.8822	do not raise prices	Loss: -348.7%
DZ.0000098	-2.2558	-0.8847	do not raise prices	Loss: -137.1%
DZ.0000123	-2.2439	-0.8847	do not raise prices	Loss: -135.9%
DZ.0000124	-1.2962	-0.8845	do not raise prices	Loss: -41.2%

Drug Code	Elasticity Estimation	Elasticity Break-Even	Policy Recommendations	Profit Impact Projections
DZ.0000170	-2.2590	-0.8835	do not raise prices	Loss: -137.6%
DZ.0000345	-0.6511	-0.8835	safe to raise the price	Profit: +23.2%
DZ.0000422	-0.2249	-0.8843	safe to raise the price	Profit: +65.9%
DZ.0000503	-0.7193	-0.8830	safe to raise the price	Profit: +16.4%
DZ.0000528	-1.3407	-0.8844	do not raise prices	Loss: -45.6%
DZ.0000532	-0.8399	-0.8838	safe to raise the price	Profit: +4.4%
DZ.0000557	-2.6967	-0.8838	do not raise prices	Loss: -181.3%
DZ.0000582	-1.0026	-0.8841	do not raise prices	Loss: -11.9%
OZ.0000110	-1.5420	-0.8831	do not raise prices	Loss: -65.9%

Source: Secondary data processed using Python, 2026

Based on the comparison matrix in Table 3, the business decision map objectively divides the 13 selected drug products into two strategic decision categories: four products are considered safe for price increases, while the remaining nine products should not experience price increases.

Product DZ.0000422 demonstrated the lowest consumer sensitivity, indicated by a highly inelastic elasticity coefficient of -0.2249. This value is substantially higher than its break-even elasticity threshold of -0.8843. Mathematically, this finding indicates that a 1% increase in price would only reduce drug purchase volume by approximately 0.225%. This small decrease in quantity is lower than the additional net profit gained from the increased margin, resulting in a projected profit increase of +65.9%. Similar pricing optimization strategies are applicable to other inelastic products, including DZ.0000345 (+23.2%), DZ.0000503 (+16.4%), and DZ.0000532 (+4.4%).

Conversely, management should avoid increasing prices for the nine remaining drug products categorized as elastic. This group is represented by DZ.0000030, which recorded the highest price sensitivity with elasticity of -4.3687. Since its absolute elasticity value greatly exceeds the break-even threshold of -0.8822, patients are highly responsive to price changes. A 1% price increase may reduce purchase volume by 4.37%, potentially resulting in a substantial profit decline of -348.7%. Similar risks are observed for the endogenous product DZ.0000557, which has elasticity of -2.6967 and may experience a profit decline of -181.3% if prices are increased.

From a theoretical and clinical perspective, differences in price sensitivity among pharmaceutical products are strongly influenced by therapeutic characteristics, medical urgency, and market substitution availability. Product DZ.0000422, which shows highly inelastic demand (-0.2249), is identified as Ondansetron, an essential drug used to prevent and treat severe nausea and vomiting caused by chemotherapy, radiotherapy, or surgical procedures. Since this drug is lifesaving and prescribed under urgent clinical conditions, patients have limited ability to postpone purchases or seek alternatives outside the hospital.

The high clinical necessity reduces consumer responsiveness to price changes, resulting in highly inelastic demand. This finding aligns with Jiang & Dong (2026) and Skipper (2012), who reported that prescription drugs for critical conditions generally exhibit low elasticity.

In contrast, products with extreme elasticity, such as DZ.0000030 (-4.3687), are identified as Amoxicillin, an antibiotic used to treat bacterial infections of the respiratory tract, urinary tract, skin, and dental conditions. As a generic antibiotic produced by multiple pharmaceutical manufacturers, Amoxicillin has a high level of substitution in the market. When hospitals increase the price of this product, patients may easily switch to alternative pharmacies offering more competitive prices. This phenomenon is consistent with Regan (2008), who found that consumers are more price-sensitive for drugs with many substitute alternatives.

For the management of Hospital X Pharmacy, these findings provide broad strategic implications for pricing policy. Pricing decisions should no longer rely on uniform conventional cost-plus pricing, but instead adopt segmented value-based pricing according to pharmaceutical product characteristics. Management can optimize revenue through structured price adjustments for inelastic products such as Ondansetron to support operational sustainability. However, competitive pricing should be maintained for highly elastic products such as Amoxicillin to preserve customer loyalty and prevent reductions in overall visit volume. Through this segmentation strategy, hospitals can maintain a balance between business sustainability (profit) and the social function of healthcare services (people).

CONCLUSION

This study successfully estimated drug price elasticity coefficients accurately by integrating the Durbin–Wu–Hausman (DWH) structural test, dynamic selection of strong instruments, and Hansen J-Test calculations. The diagnostic findings demonstrate that price endogeneity in the hospital pharmaceutical sector is commodity-specific. Among the 13 analyzed drugs, 12 products were identified as exogenous and were optimally estimated using OLS, while 1 product required the IV–2SLS model to address endogeneity issues. The combination of econometric analysis and Break-Even Elasticity calculations objectively classified products into two categories: 4 commodities (including active substances such as Ondansetron) exhibited inelastic demand and were considered safe for price increases to optimize profit margins, whereas the remaining 9 commodities (such as Amoxicillin) showed highly elastic demand, requiring price stability to avoid profit losses caused by high consumer sensitivity.

This study provides a significant scientific contribution to the applied econometrics literature in the healthcare sector, particularly in Indonesia. Methodologically, this research challenges the general assumption that price variables in hospital transactions are always endogenous, while demonstrating how a dynamic IV selection approach based on First-Stage F-Statistics and Hansen J-Test can produce robust and unbiased elasticity estimates despite data limitations. Furthermore, the integration of econometric demand sensitivity theory with

business break-even threshold calculations offers a more scientific framework for pharmaceutical pricing management, replacing conventional approaches based on intuition or uniform cost-plus pricing strategies.

Although this study provides strong findings, its main limitation lies in the scope of secondary data, which relies solely on sales transaction records. The model is unable to control for important external variables such as patient disease characteristics, prescribing physician history, stock fluctuations, and macro-level healthcare policies (such as Indonesia's National Health Insurance program, BPJS Kesehatan), which may significantly influence pharmaceutical consumption patterns.

Based on these limitations, future research is recommended to expand the structural model by integrating patient clinical data (electronic health records) and applying Panel Data Fixed Effects approaches when variations across time and prescribing physicians become available. Future studies may also extend the analysis by specifically comparing chronic and non-chronic drug categories to examine the long-term stability of demand elasticity estimates.

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