Price Elasticity

Garima 14th May 2024

Contents

What is Price Elasticity of Demand(PED) ?

- **Definition:** The variation in demand in response to a variation in price is called price elasticity of demand. It may also be defined as the ratio of the percentage change in quantity demanded to the percentage change in price of commodity.

$$\text{PED}(\theta) = \frac{\Delta Q/Q}{\Delta P/P}$$

- The price elasticity of demand is ordinarily **negative** because quantity demanded falls when price rises, as described by the "***law of demand***" *

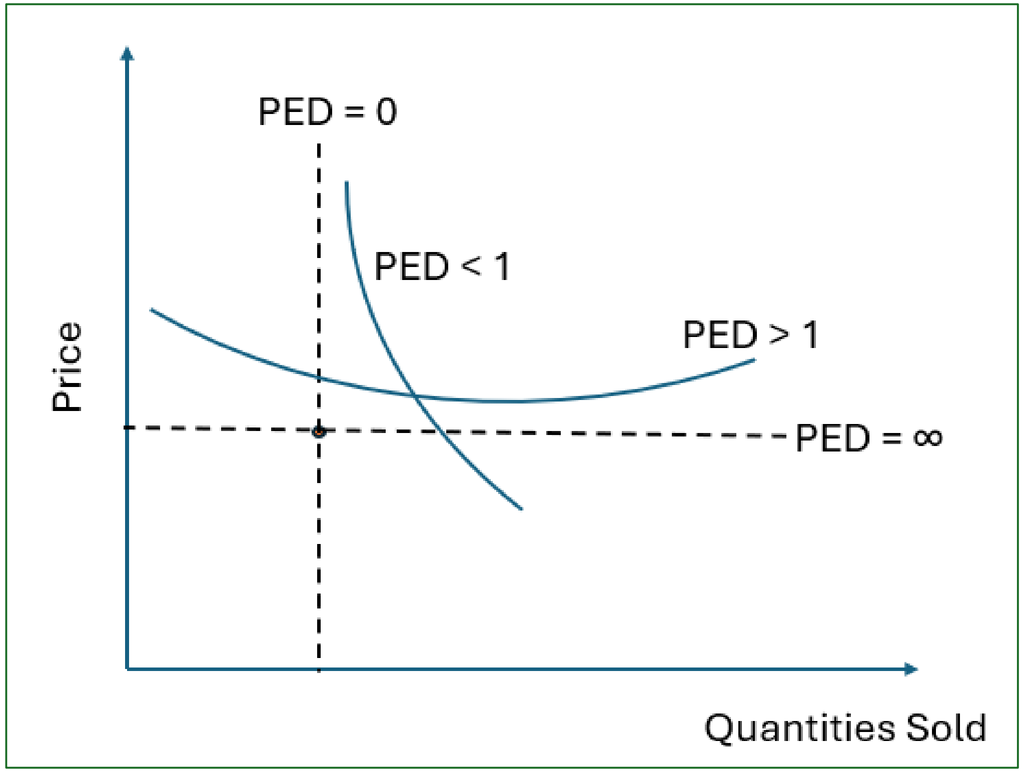
- Depending on its absolute value, a good is said to have elastic demand (> 1), inelastic demand (< 1), or unitary elastic demand (= 1).

  e.g. If PED = -2 , it means 1% rise in price decreases quantity demanded by 2%.

  & hence the demand here is elastic, the quantity demanded is very sensitive to price.

**Note :There are exceptions like luxury goods*

Understanding PED Mathematically and Graphically



Here we are referring to absolute values of Price Elasticity

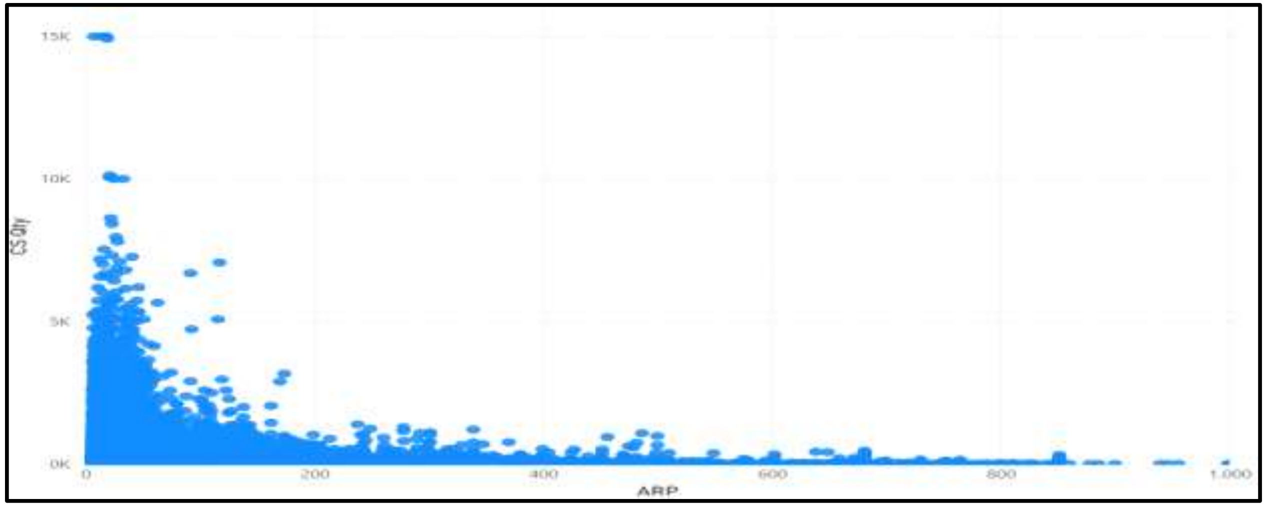
The graph on the left shows Quantities sold vs Price and depict how different price elasticity looks on graph.

One way to transform the above formulae into a continuous form so that we are not confused with which points should be Q2 , Q1 ,P2 ,P1 and improve consistency of the solution it to use derivative, to calculate the elasticity for an infinitesimal change in price and quantity at any given point on the demand curve

$$PED(\theta) = \frac{(Q_2-Q_1)/Q_1}{(P_2-P_1)/P_1} \longrightarrow \boxed{PED(\theta) = \frac{\partial Q/Q}{\partial P/P}}$$

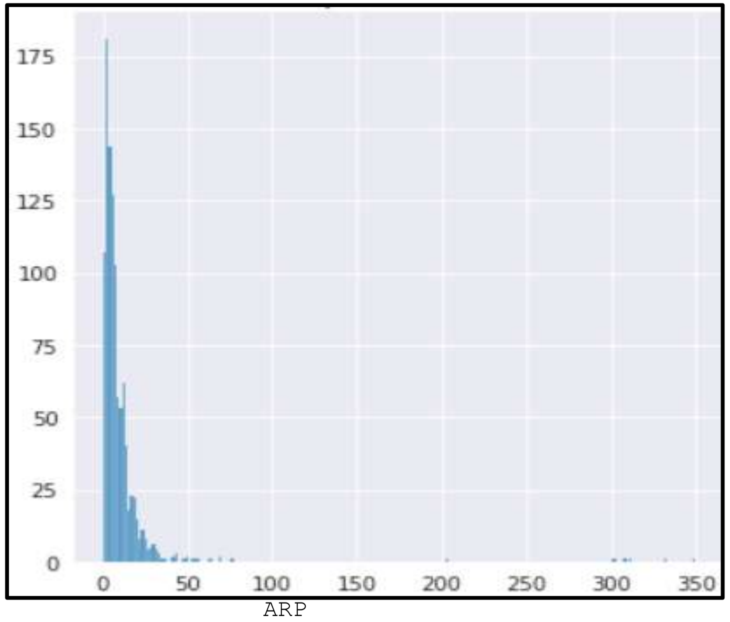
What data to use ?

CS Qty vs ARP



CS Qty vs Actual Retail Price(ARP) follows a typical Demand curve following the Law of Demand i.e., The quantity purchased varies inversely with prices.

Distribution of Std Dev in



The graph on the left shows Std Deviation of ARP. For identification of elasticity, we need variation in prices within products to differentiate price responses vs product preferences.
Hence, to measure true elasticity it is recommended to use ARP and not RRP(Recommended Retail Price)

Motivation of Double/Debiased Machine Learning?

Machine Learning vs Causal Inference

Machine Learning

- Aims to predict
- Traditional ML model fails to predict demand based on prices different from the pricing policy underlying the training data.(https://arxiv.org/abs/2205.01875)
- Machine Learning is prone to bias problem in causal inference settings(https://arxiv.org/pdf/1608.00060).
- However, ML can effectively manage overfitting.

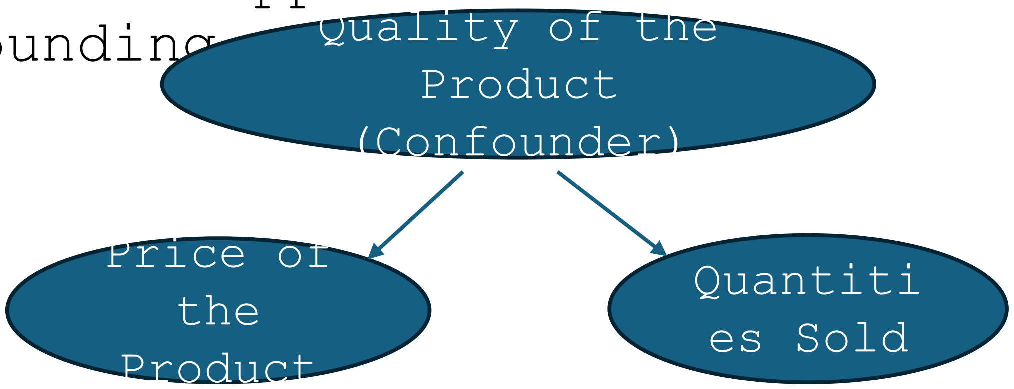
DML

Causal Inference

- Infer a treatment or causal relationship between variables.
- A/B testing is difficult in many scenario, where we only have observational data .
- There exists confounders that is not accounted.(i.e., $cov(T,\varepsilon)\neq 0$)
- Requires correct parametric assumption of data generating process.

Double Machine Learning

- Double Machine Learning tries to use best of both worlds :
  - **Non-parametric** approach for estimators to control for confounding



- Double Machine Learning, at its core, allows for the **residualization/orthogonalization** to reduce bias in the estimates.

Traditional vs. DML Approach

- **Traditional Approach using Causal Inference :**

$$\log(Q) = \text{Intercept} + \theta \log(P) + X$$

On differentiating

$$\boxed{\theta = \frac{\partial Q / Q}{\partial P / P}}$$

- **DML Approach :**

Step1. Predict Quantities (Effect), Q - *using some ML model*

Step2. Predict Price (Treatment), P- *using some ML model*

Step3. Residualizing Treatment(P) and Effect (Q)

$$\tilde{Q} = Q - \text{predicted}(Q)$$

$$\tilde{P} = P - \text{predicted}(P)$$

Step4. Infer elasticity as coefficient of linear regression by modelling residualized quantities and price :

$$\log \tilde{Q} \sim \theta \log \tilde{P} + \text{intercept}$$

Applications in Commercial Retail Industry

- To validate *downtrading* behavior of shoppers for business partners.
- Input to the Pricing team as a sense check of their pricing decisions.

MACRO ECONOMICS	Inflation
	Currency
	Economic Outlook
LOCAL LT INPUT	Cross Border Trading
	Retail Environment
	Market Insights
	Local Business Objectives
DATA ANALYSIS	LP/FMC Factor Development
	Price Sensitivity
	FMC Estimate

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