

# A Behavioural Study of Non-Durable Goods on E-Commerce Platforms in Delhi NCR

Neha Anand <sup>#1</sup>, Dr. Kavita Indapurkar <sup>\*2</sup>, Dr Anuradha Jain <sup>#3</sup>

<sup>#1</sup>Research scholar, Amity School of Economics, Amity University.

<sup>\*2</sup>Joint Administrator, Amity University.

<sup>#3</sup>Vivekananda Institute of Professional Studies-TC, GGIPU E-mail:

[nehaanand32@gmail.com](mailto:nehaanand32@gmail.com)

## Article Info

**Page Number:** 1100-1110

**Publication Issue:**

**Vol. 71 No. 4 (2022)**

## Article History

**Article Received:** 25 March 2022

**Revised:** 30 April 2022

**Accepted:** 15 June 2022

**Publication:** 19 August 2022

**Abstract:** The purpose of this study is to analyze consumer buying behaviour on online platforms. It has been analyzed that the Consumer buying basket has changed a lot over the period of time. The primary focus of the study has been to identify the online preference basket of consumers for non-durable goods like- clothing, food, cosmetics, etc. based on the primary survey of 220 consumers of Indian origin in the middle-income groups. The study explores, Marshallian (uncompensated elasticity) which captures the income effect of and substitution effect with the help of the LA-AIDS Model. It has been observed in the paper that clothing and cosmetics act as complementary goods in the consumer preference basket, whereas food becomes the choice and acts as the substitute for clothing and cosmetics in the consumer online buying bracket.

**Keywords:** AIDS MODEL, Clothing, Food, Cosmetic, Consumer buying bracket, Indian consumer and Substitution effect

---

## Introduction

COVID-19 epidemic, as well as the lockdown and social separation, has impacted the consumer purchasing patterns and led to the increase in online buying, it was estimated and quoted in an article by Hindu Business newsletter that, after the emergence of Covid-19, 48 percent of customers have increased their online purchasing. As we know, India is the world's second-largest economy in terms of consumers on online platforms (Keelery, 2021). This can further be supported by the report given by the Indian Times, "that 61 percent of Indian homes would use the internet in 2021, up from only 21% in 2017 for online purchase. In 2020 and 2021, almost 130 million people came online, with approximately 80 million of them coming online in 2020, and 43 percent of them (about 34 million) coming online as a result of the COVID-19 issue (Khanna, 2021) and with the advent of contemporary technology, there has been a shift in customer brand choice for non-durable goods during the last decade (Kruh, 2017), the report stated that Clothing and apparels, cosmetics and food items are the goods people spend the most on. And Consumers usually use or visit e-commerce platforms like Amazon or Flipkart that are user friendly and users can browse for products that are provided with things from all three modes to pick from in one store. Indeed, according to analysis & E-markets, e-commerce will rise by another 13.7 percent in 2021, reaching \$908 billion. In 2021, total e-commerce revenues will be more than \$147 billion more than they were before the epidemic and prevail to continue.

As a result of online purchases, the lifestyle of the people has changed and with their growing economic levels, products that were formerly deemed luxury things have become necessities in consumer buying (Sathya, 2018). Today 27.3 % of Asia computes the Indian population that uses the internet or E-commerce websites. Amazon. is the largest participant in the Indian eCommerce market. Ajio.com is next, followed by bigbasket.com. Apart from that, nykaafashion.com is one of the fastest-growing stores in the Indian market. This corroborates the assumption that today's purchase patterns are skewed toward non-durable products (Statista,2021).

.Despite the fact that e-commerce began in the United States its performance has been tepid when compared to Taiwan and India. Aside from the top-earning e-commerce firm, Amazon, American e-commerce has lacked the same vitality as Chinese e-commerce. Despite the fact that the largest sales are reported during this time, The seasonality is related to the holidays, which begin in October with Halloween, continue through November with Thanksgiving, Black Friday, and Cyber Monday, and end in December with Christmas. Customers of Amazon.com have consistently expressed satisfaction, which is higher than that of other businesses such as eBay, Walmart, Best Buy, and others.

A recent change in the policy of the Government for MSME suggests the need to focus on the Indian industry and as stated by the “Retail association of India” that clothing, cosmetic and food industries involve a large number of small sellers which is more than a million in India itself like in and they indulge in the online platform for selling their product. on the contrary, large number of buyers are also involved in online buying likewise in the food industry the Online Food Delivery will reach 497.7m consumers by 2025 stated by the “statista” which requires information about consumer buying preference to make their product competitive with international brands. So, this study works with the objective of analyzing consumer buying behavior based on price elasticity and income elasticity of Non-durable goods at online platform, which was not analyzed yet although there are various literature, which try to analyze consumer buying behavior with different techniques as stated below:

### **Literature review:**

The AIDS model was used in the study by Motallebi et.al, (2013) to determine the elasticity of Iranian food products including seafood, dairy, and poultry. According to the study, red meat and chicken are price elastic, however, fish is not. They measured the pace at which consumers adapt their consumption behavior using the dynamic generation process and discovered that consumers were able to comprehend, alter, and state their consumption and bring it closer to equilibrium in a prolonged period. Also, the government should be more careful with particular commodities that are connected to people's nutrition and health in Iran's pricing strategy and during subsidy elimination by Motallebi & Pendell, 2013.

The demand for shrimp, as well as beef, pig, and chicken, in the US food market, is examined in this study by Zhou (2015) which aids in forecasting distribution methods, consumer tastes, and government policies. The relationship between the spending fraction, price, and expenditure variations, as well as their own and cross elasticity, is investigated. The Almost

Ideal Demand System (AIDs) model and two distinct formulations were employed in the study (both nonlinear AIDs and LA-AIDs).

(Saleh, 2015) A total of 293 customers from the Saudi-Arabian market were surveyed for this study. The purpose of this article is to accomplish two objectives: first, to determine consumers' propensity for online buying, and second, to examine the relationship between demographic characteristics and customers' propensity for online shopping. Men and women, as well as customers of all ages, have relatively little difference in their online purchasing habits, according to the poll results.

Cranfield. suggested that given the different characteristics of AIDS and QUAIDS, it can be concluded that the former is more suitable for situations where income shows large changes, while the latter is more suitable for situations where prices show large changes. (Cranfield et al., n.d.). Another theoretical and empirical study done on Consumption systems are estimated using quarterly and yearly macroeconomic data from Norway's National Vital statistics suggests that during the course, it was also discovered that the macroeconomic variable simplifies the demand system using MODAG and KVARTS and that it is an intrinsic element of the consumption block of the models. The paper examines and compares many variants of the AID system, including the basic static edition, linear estimate, and dynamic versions with and without habit development. (Nygård, 2013).

### **Research methodology:**

As we know that the disparities existing between expenditure and consumption of families residing in Delhi NCR are noticeable. And because of these disparities, examining the expenditure item pattern becomes a critical topic. Estimation of systems of demand functions was at the forefront of practical economic research for most of the twentieth century, therefore this has gained increasing prominence. Previously, research was focused on determining the rules that regulate consumer preferences and market activities. Furthermore, the price elasticity of spending items is an important tool in the formulation of a successful economic policy and budgetary strategies. Thus, utilizing spending data relevant to commodity groups, such as the Household Income and Consumption Expenditures Surveys for 2020-21, the study derives price elasticity from the Almost Ideal Demand Model(AIDS)

The authors have started a consumer income and spending survey for the years 2020 and 2021. The survey included 220 households in the Delhi NCR who spent money on non-durable products. The study used the overall sum of total monthly consumption expenditures, total monthly food expenditures, and spending values for food, clothing and cosmetic. Further observed that we have several strong prediction models throughout time, but less research has been done on assessing consumer purchase behavior based on economic aspects. In our study we followed the following methodology:

1. This information comes from a 220 participant online survey on non-durable commodities, such as apparel, food, and cosmetics, conducted in the Delhi NCR region. The LA -AIDS study was based on original data from Delhi NCR, with several respondents of 220 people.

2. The non-durable category i.e. Clothing, Cosmetics, and Food was further branched into three sub-categories for each non-durable good respectively. Clothing was thereon classified as Daily wear, Party wear, and Night Wear. Cosmetics were classified under Skincare, Hair Care, and Fragrance. Lastly, food was classified as healthy, dessert and fast food respectively and based on which table 1 shows the name of the following goods

Table1: Naming of Variable of Non Durable Goods

NonDurable goods	Description of variable Names
pdaily	Price Daily of wear
pnight	Price of Night wears
pparty	Price of part wears
q_wdaily	Weights of daily wears with respect to total expenditure on Non-Durable goods.
q_wnight	Weights of night wear with respect to total expenditure on Non-Durable goods.
q_wparty	Weights of night wear with respect to total expenditure on No -Durable goods.
pskin	Price of skin care product
phair	Price of hair care product
pfrag	Price of fragrance product
q_skin	Weights of skincare with respect to total expenditure on Non-Durable goods.
q_hair	Weights of hair care with respect to total expenditure on Non-Durable goods.
q_frag	Weights of fragrance with respect to total expenditure on Non-Durable goods.
phealthy	Price of healthy food
pdessert	Price of dessert
pfast	Price of fast food
q_whealthy	Weights of healthy food with respect to total expenditure on Non-Durable goods.
q_wdessert	Weights of dessert with respect to total expenditure on Non-Durable goods.
q_wfast	Weights of fast food with respect to total expenditure on Non-Durable goods.

Source : Author's computations

3. Each category was assigned a weight for the calculation, these weights are certainly represented as  $w_{daily}$ ,  $w_{night}$ ,  $w_{party}$ ;  $w_{skin}$ ,  $w_{hair}$ ,  $w_{farg}$ ; and  $w_{healthy}$ ,  $w_{dessert}$ ,  $w_{fast}$  respectively. The formula used in the calculation was:

$$\frac{\text{total expenditure of the consumer}_{\text{good } i}}{\text{total income of the consumer}}$$

4. Further, according to one of the major properties of the almost ideal demand system we calculated the stone price indexing in ( Deaton, 1980). Though the starting point of the model is the calculation of the expenditure as a log of summation of the individual expenditure done by the consumer on each subcategory of the product.

$$\log \left( \sum_{i=1}^n it \right)$$

Where,

$i$  =type of non-durable goods

$j$  = Number of consumers taken in the study from the primary data

Results and analysis:

Price Elasticity (PE) is determined by Ratios of the percent change in demand with the percent change in price. PE evaluates how responsive a change in demand is after a price adjustment. The demand for an item is considered to be elastic when its PE is more than one in absolute value; it is extremely responsive to price variations. Inelastic demand is defined as a demand that is smaller than one in absolute value and is poorly sensitive to price changes.

The AIDS (Unrestricted model ) model that eliminates the problems of homogeneity, multicollinearity, and symmetry were used to calculate both the Marshallian price elasticity and Hicksian elasticity together to analyze consumer behavior. Though in this paper we have only studied the Marshallian elasticity to understand the buying behavior.

The Marshallian elasticity was therefore stated as,

- a. Marshallian Uncompensated Price Elasticity

$$\epsilon_{ij}^{NC} = \frac{1}{w_i} \left[ \gamma_{ij} - \mu_i \left( a_j + \sum_{k=1}^n \lambda_{jk} \ln p_k \right) - \frac{\lambda_i \beta_j}{b(p)} \left\{ \ln \left( \frac{x}{a(p)} \right)^2 \right\} \right] - \delta_{ij}$$

- b. Hicksian Compensated Price Elasticity

$$\epsilon_{ij}^c = \epsilon_{ij} + \mu_i w_j$$

Where:

$\epsilon_{ij}$  = price elasticity

$\gamma_{ij}$  = parameter of the product

$\lambda_i \beta_j$  = linear and quadratic parameter of income

$w_i$  = average share of the expenditure on the product

$\delta_{ij}$  = the delta here is zero for the own price (  $i=j$ ) and worth 1 for cross price (  $i \neq j$ )

Table 2: Price Elasticities of Clothings i.e.Daily wear , Night wear and Party wear

	Pdaily		Pnight		Pparty		Income elasticity	
	Marshallian (Uncompensated) price elasticity	Parameter Significance	Marshallian (Uncompensated) price elasticity	Parameter Significance	Marshallian (Uncompensated) price elasticity	Parameter Significance	Income elasticity	Significance level
<b>q_wdaily</b>	<b>-0.780*</b>	<b>0.0046**</b>	0.0359	<b>0.0027**</b>	-0.245	0.745	0.989	0.0046**
<b>q_wnight</b>	0.125	0.745	<b>-0.704*</b>	0.453	-0.187	0.049	0.766	0.09295
<b>q_wparty</b>	-0.292	0.272	-0.2417	0.01736	<b>-0.640*</b>	0.456	1.173	0.0049**

Source: Author's computation (\*) Indicates the own price elasticity and other shows cross price elasticity and (\*\*) Indicates significance at 5% significance level

Table 2 shows the Marshallian (Uncompensated) Price elasticity for each product of clothing .Result of the Diagonal elements suggest that the daily wear, night wear and party wear have a negative price elasticity i.e. -0.780, -0.70, and -0.640. It suggests that these product categories of clothing follow the law of demand and out of which Daily wear price elasticity is significant at 5% level.

The non-diagonal element of the table shows the cross price elasticity of demand. Cross elasticity between night wear and daily wear is 0.035 which is significant at 2%, this suggest that the night wear and daily wear are substitutes in consumer preference basket at e-commerce platform. Lastly, the Expenditure/income elasticity of the daily wear is less than one; hence it is “necessarily goods” and is significant at 4%. Party wear is considered as “luxury goods” at e-commerce platform with income elasticity 1.173 (5 % significance level).

Table 3: Marshaillian elasticity for the Cosmetics

	pskin		phair		pfrag		Income elasticity	
	Marshallian (Uncompensated) price elasticity	Parameter significance	Marshallian (Uncompensated) price elasticity	Parameter significance	Marshallian (Uncompensated) price elasticity	Parameter significance or cosmetics	Income elasticity	Significance level
q_wskin	<b>-1.37*</b>	<b>0.004**</b>	0.262	0.848	0.509	0.521	1.657	<b>0.005**</b>
q_whair	0.267	0.848	<b>-0.0252*</b>	<b>0.0018**</b>	-0.0566	0.208	0.0829	1.568
q_wfrag	0.539	0.521	-0.0528	0.208	<b>-0.496*</b>	0.0740	0.2537	<b>0.002**</b>

Source: Author's computation (\*) Indicates the own price elasticity and (\*\*) Indicates significance at 5% significance level.

Table 3 shows the responsiveness of own and cross Marshallian (uncompensated) price elasticities for each product of cosmetic. Where, Non-diagonal components represent cross price elasticity, while diagonal elements reveal their own price elasticity. The Marshallian (uncompensated) own price elasticity, which includes both substitution effect and income effect, suggests that the elasticity for skin care product is -1.37 with a significance level of 4%, whereas the elasticity for hair care and the fragrance goods -0.02 and -0.49, which also follow law of demand.

None of the Cross elasticity is significant but cross elasticity between skin care products and hair care products or fragrance goods becomes substitute goods in consumer preference basket at e-commerce platform under cosmetic categories. Lastly, the expenditure/income elasticity is positive, which suggest that all categories of cosmetic are considered as “normal good”. Out of which skin care has elasticity greater than one hence it is categorized as “luxury goods” whereas Fragrance goods with income elasticity 0.25 become necessity good in consumer buying basket at e-commerce platform with significance level 2%.

Table 4: Marshallian price elasticity of the food

	phealthy		pdessert		pfast		Income elasticity	
	Marshallian (Uncompensated) price elasticity	Parameter significance	Marshallian (Uncompensated) price elasticity	Parameter significance	Marshallian (Uncompensated) price elasticity	Parameter significance	Income elasticity	Parameter significance

q_whealthy	<b>-0.79*</b>	<b>0.0018*</b>	0.0335	<b>0.0013**</b>	-0.228	0.0525	0.990	0.0040**
q_wdessert	0.115	0.0013	<b>-0.727*</b>	0.0163	-0.172	0.872	0.784	0.0048**
q_wfast	-0.332	0.825	-0.275	0.0846	<b>-0.590*</b>	0.047	1.198	0.0028**

Source: Author’s computation (\*) Indicate Own price elasticity and (\*\*) Indicates significance at 5% significance level

Table 4 shows the responsiveness of Marshallian (uncompensated) price elasticities for each product of food in which diagonal Elements show their own prices elasticity and non-diagonal elements suggest the cross-price elasticity for food. All the diagonal element shows that the healthy food, dessert food and fast food follow the law of demand i.e. -0.79, -0.72 and -0.59 and out of which the Consumer preference for healthy foods become statistically significantly at 2 %. While observing the relationship of consumer buying behaviour for cross product categories. We say that Dessert foods and Healthy foods become substitutes with cross elasticity 0.033 for consumers with 2 % level of significance. The expenditure/income elasticity for households in internet shopping in Delhi NCR was positive, as seen in the table above. Lastly, the result of income elasticity of the dessert foods and Healthy food are less than one, which suggest that they are categorised as “necessary goods” (significant at 4%). Whereas purchase of fast food is considered as the most expensive at e-commerce platform with income elasticity 1.198 (2 % significance level).

Table 5: An overall model of Non-Durable

	Pcl		Pf		pc	
	Marshallian (uncompensated) Price Elasticities	Parameter of significance	Marshallian (uncompensated) Price Elasticities	Parameter of significance	Marshallian (uncompensated) Price Elasticities	Parameter of significance
q_wcl	<b>-1.008*</b>	<b>0.004**</b>	<b>1.563</b>	<b>0.005**</b>	<b>-0.448</b>	0.00065**
q_wf	<b>0.028</b>	<b>0.005**</b>	<b>-1.23*</b>	<b>0.0005**</b>	0.0386	0.00965
q_wc	<b>-0.035</b>	<b>0.005**</b>	0.99	0.008	<b>-0.679*</b>	<b>0.00046**</b>

Source: Author’s computation (\*) Indicate Own price elasticity and (\*\*) Indicates significance at 5% significance level Source: Author’s computation

Table 5 shows that the own-price elasticity for all the three broad categories of the Non-Durable goods. It suggest that all the three categories follow the law of demand with significant level 5% .The Diagonal element exhibit that the clothing category become substitute with the food category as observed by the positive cross elasticity i.e. 0.028 and 1.563 (with 5% level of significance). Whereas, the cosmetic product become complementary with the clothing categories as shown by the elasticity -0.035 and -0.44 (5 % level of significance).



## Conclusion

In the Linear Approximate (LA) version of the AIDS model, the theoretical demand for Non-durable commodities eliminates the problems of homogeneity, multicollinearity, and symmetry. The above datasets exhibit the Marshallian uncompensated price elasticity and expenditure/income elasticity, correspondingly. According to the current study under Clothing categories night wear and daily wear became substitutes for consumers where as the consumers have been significantly purchasing daily wear at e-commerce platforms. Under cosmetic goods category, consumers have preferred to purchase skin care product and fragrance product at online platform with significance 5%. And in the case of foods, consumers always prefer to purchase healthy food as compared to the other categories of the foods with significant level 5%. Lastly, Income elasticity for all three categories was considered as the “normal goods” whereas the fast food, skin care and party wear were categorised as the luxury goods at e-commerce platform. And fragrance and desert foods were considered as necessity good in consumer preference basket at e-commerce platform. And lastly in term of overall categories it has been observed in the paper that clothing and cosmetics act as complementary goods in the consumer preference basket, whereas food becomes the choice and acts as the substitute for clothing and cosmetics in the consumer online buying bracket.

### **Limitations of the study:**

Since the sample size was limited, the findings may vary for larger or smaller sample sizes that have been taken into consideration in this paper. Apart from that, the two distinct variables taken into the study are: price of the commodity & consumer behavior –they are two such variables that can change over a short time span, thus the study may reflect different elasticity for the same or different set of consumers. It has also been observed that the pricing of the three categories of the products are differ on different platform .i.e. Myntra, Nykaa, and Zomato etc. So result may vary because of this also. (Hsieh, 2018).

### **Policy recommendation & further possible study:**

Elasticity obtained in this study can subsequently be used as model parameters for demand prediction of non durable products especially in food, clothing and cosmetic for producer in terms of deciding price, offering discount and offering different product categories. It also helps in forecasting the dynamics and structure change in consumer demand due to price changes. This study also helps the government in imposing Taxes / giving input tax credit / subsidies on different categories of goods which were mostly demanded at e-commerce platform. The author subsequently suggests that a further in-depth study can be done for a single commodity over different websites. For instance, one can choose clothing and do in-depth research taking the data over a distinct website while studying the behaviour of consumer across different e-commerce platforms.

## References:

1. Ibragimova. Consumer demand for selected food items:AIDS Model Estimates for the case of Uzbekistan, Associazione Italiana di Economia Agrariae application, 2014
2. Hsieh. A Study of Models for Forecasting E-Commerce Sales during a Price War in the Medical Product Industry, HCI in Business, Government and Organizations eCommerce and Consumer Behavior, 2018
3. Deaton. An Almost Ideal Demand System. Jstor : American Economic Association, Vol.70 (3), 1980, pp. 312-326.
4. Cranfield J .A. L. Model selection when estimating and predicting consumer demands using international, cross section. Empirical Economics, Vol .23, 2003, pp. 353–364. d.o.i. [10.1007/s001810200135](https://doi.org/10.1007/s001810200135)
5. Nygård, V. M. An almost ideal demand system analysis of non-durable consumption categories ( Report No.01/2013) Statistisk sentralbyrå • Statistics Norway [https://www.ssb.no/en/nasjonaltregnskap-og-konjunkturer/artikler-og-publikasjoner/attachment/93617?\\_ts=13c906c1d30](https://www.ssb.no/en/nasjonaltregnskap-og-konjunkturer/artikler-og-publikasjoner/attachment/93617?_ts=13c906c1d30)
6. Saleh, D. A. Assessing the Consumers' Propensity for Online Shopping: A Demographic Perspectiv, the American Academy of Business Journal. Vol. 21(1), 2015, pp. 186-193
7. Zhou, X. V. Using almost ideal demand system to analyze demand for shrimp in us food market. International journal of food and agricultural economics, Vol. 3, 2015, pp.31-46.
8. Motallebi, M., & Pendell, D. L.Estimating an Almost Ideal Demand System Model for Meats in Iran. Agricultural & Applied Economics Association's 2013 AAEA&CAES Joint Annual Meeting, Washington, D.C., August 4-6 2013.
9. Statista .E-commerce Market analysis: The E-commerce market in India, Statista, January 2022, <https://ecommercedb.com/en/markets/in/all>.
10. Sathya, & Indirajith. A Study on Purchase Behavior of Consumer Durable Goods with Special Reference to Tiruvarur District., International Journal of scientific Research and Management, Vol. 6(2), 2018, pp.100-107.
11. Krush, w. The truth about online consumers 2017 Global Online Consumer Report. Assets: KPMG 2017. <https://assets.kpmg/content/dam/kpmg/xx/pdf/2017/01/the-truth-about-online-consumers.pdf>
12. Khanna, M. 61% Indians Use Internet In 2021, Up From Just 21% In 2017 Says .Indiatimes.com: Jan 2021, [https://www.indiatimes.com/technology/news/india-internet-usage-report-554181.html#highlight\\_71941](https://www.indiatimes.com/technology/news/india-internet-usage-report-554181.html#highlight_71941)
13. Keelery, S. Internet usage in India - statistics & facts. Statista ,2021, <https://www.statista.com/topics/2157/internet-usage-in-india/#dossierKeyfigures>

## Appendix

## Command for the usage

1. library(micEconAids)
2. ksheets<- read.csv("C://Users//Dell//Downloads//AIDS MODEL SHEET kitchen (2).csv")
3. attach(ksheets)

```
4. View(ksheet)
5. priceNames<-c("pblender" , "psandwich" , "pcookware" ,"pdinnerst")
6. shareNames<-c("wblender","wsandwich","wcookware","wdinnerst")
7. aidsResult<- aidsEst( priceNames, shareNames, "LogTE", data = ksheet, priceIndex =
  "S")
8. print ( aidsResult )
9. summary ( aidsResult )
10. all.equal ( rowSums ( coef ( aidsResult ) $gamma ) , rep ( 0, 4 ) , check.attributes =
  FALSE )
11. isSymmetric( coef( aidsResult ) $gamma, tol = 1e-10, check.attributes = FALSE )
12. lrtest( aidsResult,aidsResult$hom )
13. aidsResultUnr <- aidsEst(priceNames, shareNames, "LogTE", data = ksheet,hom =
  FALSE, sym=FALSE)
14. all.equal ( rowSums ( coef ( aidsResult ) $gamma ) , rep ( 0, 4 ) , check.attributes =
  FALSE )
15. lrtest(aidsResult , aidsResultUnr)
16. pmean <-colMeans( ksheet[ , priceNames] )
17. wmean <- colMeans(ksheet[ , shareNames] )
18. aidsResultElas <- aidsElas ( coef( aidsResult ) , prices = pmean, shares = wmean )
19. print ( aidsResultElas )
```

: