

## Seminar component

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**Title of paper:** Calculating decile inflation in Iran by using online prices data and fuzzy clustering method.

### Abstract

Differences in expenditure patterns may weaken the ability of the price index to proxy the experiences of all households. To deal with this problem, calculating the price index for different group of revenue could be a good option. In this paper, we try to use fuzzy method to assign different price to different groups of revenue. Besides, we try to use online data by web scrapping which could be replace with conducting survey. In this case we show the operational limitation arising in using web scrapping data. Different households experience different inflation rates. This paper finds that these differences is significant in different income groups during the period 2016-2019. The results show that Foods inflation rates are more than nonfoods inflation rates in all groups of different revenue. This is more significant in second decile. Finally, the rate of inflation rates in lower income are more than higher income during the period of study.

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## I. Introduction

The abnormal rising in the general level of prices as a result of the exchange rate fluctuations in Iran, increased the public and the media attention to the monthly CPI announcements. The claims of individuals across the income distribution are that the rates of inflation that they experience are significantly different to (higher than) the official consumer inflation statistics. Differences in expenditure patterns, may weaken the ability of the price index to proxy the experiences of all households. (Oosthuizen, 2007) To deal with this problem, calculating the price index of deciles could be a good option. This indicator has been producing and disseminating in Iran since 2016. Hence, the weights calculated in the index are only divided into deciles; one of the most important challenges in this case is how we could consider demographic and locational factors. (e.g. different markets has different price) Furthermore, conducting survey is known as a costly method and replacing it with other modern such as using online data is recommended by statistical officials. Therefore, in this paper, while considering the issue of using modern methods of collecting information, fuzzy clustering method is applying in order to consider locational factors effects on calculating CPI. Our empirical approach improves upon the existing literature in several important ways: First, calculating the inflation of different deciles in different groups of goods and services based on COICOP. Second, utilizing new methods of data collection (web scraping) for some items and also use existing data of CPI survey to reduce cost of operation. Finally, applying fuzzy clustering method in order to assign prices from representative shops to a particular subgroup.

The paper is organized as follow: in section 2, we provide some empirical investigations on price inflation and web scraping. Section 3 dedicates to theoretical framework (formula of price index and web-scraping methods. Advantages& disadvantages). Section 4 contains methodology of fuzzy clustering method and data. Section 5 we demonstrate the process of calculations and results. Finally, section 6 concludes.

## II. Body of text

### A. The literature review

The world is enjoying the fruits of modern technology in many ways which are based on the quality of statistics for economic sector. Statistical center of Iran (SCI) has been moving towards a modern NSO, since late 2014. In first step, SCI focused on the statistics which are necessary for policy making both macroeconomic and microeconomic. Rebased Consumer price index (2015=100), inflation rate calculated for urban, rural and whole country.

Irrespective of how the 'representative outlet' is determined, it is clear that households may face different inflation due to both different spending patterns and differences in the price changes of various goods and services.(Hait & Janský,2014).It could weaken the ability of the price index to proxy the experiences of all households. This is, to some extent, borne out by the claims of individuals across the income distribution that the rates of inflation that they experience are significantly different to the official consumer inflation statistics. (Oosthuizen, 2007). Calculating price index in deciles could be a beneficial way to deal with this point. This indicator has been producing and disseminating in I.R. of Iran since 2016. The strength of this index is to calculate the inflation rate based on the consumption pattern of households, broken down by income deciles. According to incompatible markets in whole country, yet it is necessary to pay attention to pattern of changing in different prices for different goods & services.

Empirically, there are many articles investigating group-specific price indices. For example Idson and Miller (1999) consider how different expenditure patterns cause in differing inflation rates for US families with and without children. Moulton & Stewart (1999) discussed that the number of households in a subgroup and total effect on the calculation of subgroup inflation rates. They also pointed that the data on prices from representative shops of the whole population might not be applicable to a particular subgroup. Hait and Janský (2014) compared the democratic and plutocratic average inflation rates recommended democratic average for analysis of inflation differentials for subgroups. Oosthuizen (2007) shows plutocratic weights does not differ substantially over longer periods of time from the democratically weighted inflation rate unlike in short run.

Bertolotto and Diego Aparicio(2016) forecast the CPI inflation by using goods' prices collected online through web scraping retailer's websites in multiple countries including the US , the UK, France, Germany, and Netherlands. Its advantage is releasing the non-negligible delay in the official CPI release. This paper recommends that simple autoregressive models augmented especially equal-weighted pooled forecasts as the best performing online models. Alberto Cavallo and Roberto Rigobon (2016) show that online prices can be successfully used as an alternative source of information for constructing consumer price indexes. They describe their work with online data at the Billion Prices Project at MIT and discuss key lessons

for both inflation measurement and some fundamental research questions in macro and international economics. In particular, they show how online prices can be used to construct daily price indices in multiple countries. Cavallo (2012) uses online prices to study how online indices match up with official statistics in five Latin American countries. The finds that while in some country such as Brazil, Chile, Columbia, and Venezuela online price indices approximate both the level and the main dynamics of official inflation others like Argentina 's web inflation was nearly three times higher than official statistics. Yukhymenko & others (2018) test the association between online price indices and official statistics. They find that online inflation is generally consistent with official estimates, but the matching capability varies across sub-indexes. Although they find that online prices may indeed represent new information that is not captured by official statistics.

## B. Theoretical frame work

### 1. Price index in deciles

CPI inflation approximates increases in the cost of living, and it is the final cost of consumer goods and services that matters for many contracts. Any overall price index is a weighted average of its constituent parts. (Oosthuizen, 2007) The effect of inflation on the consumption patterns of consumers should consider like the effect of income on consumer expenditure.(Nyamekye&Poku, 2017) There are four basic decisions to be made in order to calculate CPI in deciles:

1. Which items could be a good representative to show mutation in the price of all commodities and consumer products?
2. What is the method of data collection?
3. How the weight of each group of commodities is calculated in deciles?
4. To specify of the primary and secondary formulas for calculating the price index.

As it is determined in formula,  $S_{i,k}^0$  represents the weight of  $k_{th}$  goods or services in the decile  $i$  and  $\frac{P_{i,k}^t}{P_{i,k}^0}$  is the relative price being calculated in one of Carly, Detot, or Jones's methods.

$$I_{i,k} = \sum_{i=1}^N \left( \frac{P_{i,k}^t}{P_{i,k}^0} \right) * S_{i,k}^0$$

By using data of HIC<sub>s</sub> survey,  $S_{i,k}^0$  is calculated for different expediters' deciles.  $K$  is all goods and services which nominated in based basket of CPI (2015==100). We could calculate the index by using CPI data exclusive of this fact that households may face different inflation due to differences in the price changes of various goods and services. (Hait & Janský, 2014).

## 2. Online data

Alternative sources of data have the potential to greatly improve the quality and efficiency of consumer price indices. One such data source is point of *sale scanner data*. (Breton & others, 2015) In addition, a large and growing share of retail prices are posted *online* all over the world. Retailers show these prices either to sell online or to advertise prices to potential offline customers. This source of data provides an important opportunity for economists who want to study price dynamics, yet it has been largely untapped because the information is widely across thousands of web pages and retailers. Furthermore, there is no historical record of these prices, so they must be continually collected over time. (Cavallo, 2018)

Web scraping is data scraping used for extracting data from websites. (Boeing & Waddell, 2016)

The term typically refers to automated processes implemented using a bot or web crawler. It is a form of copying, in which specific data is gathered and copied from the web, typically into a central local data base or spreadsheet, for later retrieval or analysis. **Web scraping** is used for contact scraping, and as a component of applications used for web indexing, web mining and specially for online price change monitoring and price comparison. Web scraping offers many benefits. It could provide an opportunity for us to *automate* some aspects of price collection. Web scraping also has potential for use in other areas, such as the collection of attribute information for the quality adjustment of technological items, also known as *hedonics*.

Price and attribute collection procedures place a heavy burden on official resources. Web scraping has the potential to offer savings in these areas. However, these savings need to be considered alongside potentially high maintenance costs. Web scraping also provides an opportunity to improve *quality* by increasing the number of price quotes feeding into the index, and to produce indices on a more frequent basis. Perhaps most importantly, it gives us the opportunity to explore *big datasets* and develop methodologies that are appropriate for the volume of data. These experiences will be invaluable should other sources of big data (e.g. point of sale scanner data) be introduced into consumer price statistics. (Breton & others)

The scraping methodology has three steps. First, at a fixed time each day, a software program downloads a selected list of public web pages where product and price information are shown. These pages are individually retrieved using the same web address (URL) every day. Second, the underlying code is analyzed to locate each piece of relevant information. This is done by using special characters in the code that identify the start and end of each variable, which have been placed by the page programmers to give the website a particular look and feel. For example, prices may be shown with a dollar sign in front of them and enclosed within and tags. Third, the software stores the scraped information in a database that contains one record per product per day. These variables include the product's price, the date, and category information. (Cavallo, 2018)

**Scraped data** have some important *advantages*. First, these data sets contain posted daily prices that are free from unit values, time averaging, and more imputations. The daily data are also useful to better identify sales and other price changes that might be missed with monthly data. Second, detailed information can be obtained for all products sold by the sampled retailers instead of a few (as in CPI data) or selected categories (as in scanner data). Third, there are no censored or imputed price spells in scraped data. Prices are recorded from the first day they are offered to consumers until the day they are discontinued from the store. In CPI, by contrast, there are frequent imputations and forced substitutions when the agent surveying prices cannot find the item. Fourth, scraped data can be collected remotely in any country where price information can be found online. Fifth, scraped data sets are comparable across countries, with prices that can be collected for the same to perform simultaneous cross-country analyses. Finally, Scraped data are available in real time, without any delays in accessing and processing the information. Eventually this could be used by central banks to obtain real-time estimates of stickiness and related statistics.

There are, have ever, some *disadvantages* with scrape data: First, they typically cover a much smaller set of product categories than CPI prices. While this is enough to demonstrate the effect of measurement errors on pricing statistics, the quantitative findings on stickiness and size of changes shown here should not be viewed as representative of services and other sectors that cannot yet be covered with online data. Second, the data come only from large multichannel retailers that sell both online and offline. Currently the vast majority of retail sales take place in this type of retailer, but in principle, this may represent a form of sampling bias compared to the CPI (though not due to the online nature of the data. Finally, a major disadvantage of scraped data is the lack of information on quantities sold. In measuring stickiness, quantities are useful in obtaining detailed expenditure weights for narrowly defined categories. (Cavallo, 2018)

### C. Methodology & data:

#### 1. Collecting data:

Given the advantages and disadvantage of online data mentioned in previous section, we use both online data and survey data. First, goods and services are chosen which have these characteristics:

- It is possible to buy them online nationwide.
- The specifications impacting on their price could be classified.
- Their online prices are the same as the real market.

So online data limited to electronic devises items and we use the survey data for others. Using data of website named Digikala<sup>1</sup>, the price of electronic products was

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<sup>1</sup><https://www.digikala.com/>Digikala is the most widely-used website in online shopping of electronic products in Iran

extracted from website based on their specified characteristics by web scraping method and Scrappy and BeautifulSoup packages in Python on low website traffic hours. For example, we collected price upon: Brand, CPU Brand, RAM Capacity, RAM type, Hard Disk Capacity, GPU Brand, GPU RAM, Display Size, Operating System for Laptop; Storage Capacity, USB Type for flash Disk.

Since there is a variety of goods and services in household basket it is impossible to collect of one website. Meanwhile it is hard to have geographic coverage for all goods; each website has its own theme to build its HTML webpage. That is, it needs to design Software separately which is costly and further of this paper. So in second step, we used fuzzy method in survey data in order to considering locational factor effects on inflation rate.

## 2. Fuzzy method:

Cluster analysis is a way of “slicing and dicing” data to allow the grouping together of similar entities and the separation of dissimilar ones. Issues arise due to the existence of a diverse number of clustering algorithms, each with different techniques and inputs, and with no universally optimal methodology. Thus, a framework for cluster analysis and validation methods are needed. Our approach is to use cluster ensembles from a diverse set of algorithms.

Fuzzy C-Means (FCM) is a soft clustering algorithm proposed by Bezdek (1974; 1981). Unlike K-means algorithm in which each data object is the member of only one cluster, a data object is the member of all clusters with varying degrees of fuzzy membership between 0 and 1 in FCM. Hence, the data objects closer to the centers of clusters have higher degrees of membership than objects scattered in the borders of clusters.

It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m \|x_i - c_j\|^2, \quad 1 \leq m \leq \infty$$

where  $m$  is any real number greater than 1,  $u_{ij}$  is the degree of membership of  $x_i$  in the cluster  $j$ ,  $x_i$  is the  $i$ th of  $d$ -dimensional measured data,  $c_j$  is the  $d$ -dimension center of the cluster, and  $\|*\|$  is any norm expressing the similarity between any measured data and the center.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership  $u_{ij}$  and the cluster centers  $c_j$  by:

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}, \quad c_j = \frac{\sum_{i=1}^N u_{ij}^m \cdot x_i}{\sum_{i=1}^N u_{ij}^m}$$



This iteration will stop when  $\max_{ij} \{|u_{ij}^{(k+1)} - u_{ij}^{(k)}|\} < \varepsilon$ ,  $\varepsilon$  where is a termination criterion between 0 and 1, whereas  $k$  are the iteration steps. This procedure converges to a local minimum or a saddle point of  $Jm$ .  
the algorithm is composed of the following steps:

First, it needs to Preparation and pre-processing of data in order to use fuzzy method. This section consists of 2steps:

- Step 1: Removing Incomplete, poor quality and confused data. This step removed some records have missing information or were not consistent with other information.
- Step 2: Extract data and create a database. The purpose of this step is to create an integrated database of urban price of consumer goods and services. A database is a repository of collected data from various sources that have been stored and structured in different shapes.

Second, after collecting urban prices of goods and services of consumption and preparing them, Fuzzy clustering is used to assign a price to each cost decile. For this purpose, R software has been used. R software is a powerful software in the field of data mining and modern statistical methods. Clustering in R software is performed by various packages. In the present study, the package "*ppclust*" and the "*fcm*" function for data clustering have been used. In order to cluster with high quality and accuracy has been used the price information of the previous period and the spatial location of the province related to current price information of each goods and services. And also, for clustering of prices online data has been used the determined special specifications.

Then, Relative Price should be generated:

Step 1: The average prices for each consumer goods and services in the each cluster is calculated.

Step 2: Then, these averages are arranged ascending and assigned to each cost decile. So that, the lowest average price assigned to first decile and the highest mean for assigned to 10<sup>th</sup> decile. As previously mentioned, to assign average prices of goods to each deciles ascending is based on the fact that higher-priced goods will be purchased by high-income people or a privileged location.

Step 3: Use the Dutot method to generate a relative price. Therefore, the relative price is obtained by dividing the average price of each goods in each decile in the current period to the average price of the same goods in the corresponding decade in the past period.

Finally, price index of decile is generated.

Laspieres formula is used to generate price index for each decile.

Figure 1 presents a simplified flow diagram of the current system. Fuzzy Cluster Decile Detection step is discussed in more detail in the following sections.

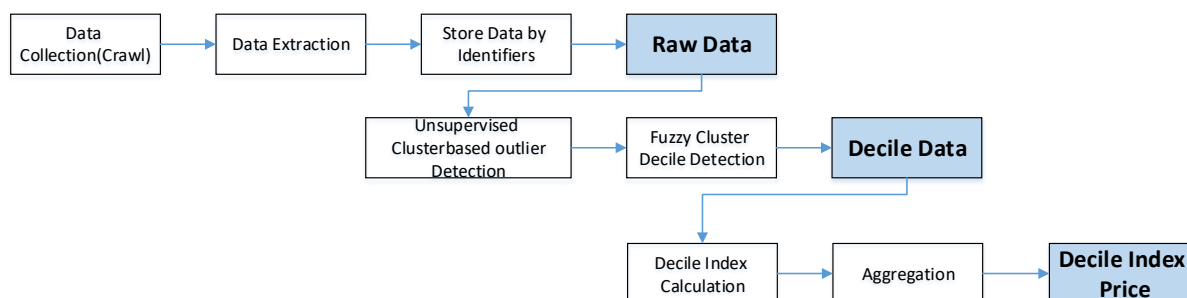


Figure 1: process of generating price index for each decile

#### D. Empirical results

The Table 1 reports the results of price indices in deciles monthly and yearly from March 2016 to February 2019. The inflation rate is also shown in table 2 for the same period. The results show that inflation rate are higher for first and second deciles in most the time. Evidently, the most fluctuations belong to second decile. At a higher rate of inflation, it is more severe. Obviously, these results seem to be consistent with economic theory. Goods and services with price elasticity less than 1, named essential commodities, which have a higher weight in household basket with lower revenue, face more changes in fluctuations of price. Nonfood inflation rate is also higher than food inflation rates for all deciles. It is more severe for lower revenue group.

In this study, we shouldn't compare these results with the results of traditional methods (survey of CPI). The difference of sample size, methods of calculating index (jevens and dutot) and differences in basket of items (fruits are omitted for their seasonal fluctuations) may be important. But, one of the most important reason which is the advantages of this method, is assigning different price to different groups of revenue that is unavailability in traditional methods. In other words, in traditional way, the only weights of the goods and services are different. While in the fuzzy method, different prices and weights are used for each deciles. Despite, the sample size of traditional method is not optimum for fuzzy method and if we use data of CPI survey, we should increase the size of sample several times that is costly. Therefore, the results of this study are definitely accompanied by a sampling error that should be considered.

However, if we want to consider the results of the two ways at least in aggregation, we got some significant points that is better to pay attention in future. According to the table 1, 2, 3 and 4, the highest inflation rate is related to the lower deciles of the community most the time in new method which is quite the opposite of the traditional way. For instance, in Feb 2019, quantity of CPI index in fuzzy method is absolutely higher than traditional CPI index. Furthermore, traditional CPI index is completely smooth while new CPI (fuzzy method) has fluctuations. Major differences is between second and 10th deciles. (Graph 1)

### III. Conclusion

In this article, we try to propose a new qualitative method to calculate price index in deciles. Fuzzy method is a beneficial method to consider the effect of location factor and different price on different groups of revenue. Although, using this method needs a large sample size. We also try to use online data. Also, these data is limited for some CPI's goods and services in each time, but using web scraping method may be a good method to substitute with conducting survey and sampling method. However, we need to investigate more in this case.

We can classify some points of the research results as bellow:

#### 1. Accuracy

using web scraping techniques will increase the number of price quotation per item more than traditional method (sample survey which has its limitations) and it causes using the cluster method improvement which needs more records.

#### 2. Cost (advantage)

Using web scraping techniques will be beneficial to reduce cost of Collecting information about some items, such as electronic items, due to the many features that affect the price, such as brand, size, color, memory capacity, etc.

#### 3. Cost (disadvantage)

Providing new and higher-tech software for collecting, clearing and classifying information, Software maintenance and redevelopment following changes in the source sites have their charge

#### 4. Opportunities

Ability to use other features along with prices like descriptions and Possibility to produce price index in newer groups.

#### 5. Risk

- Copyright: having permission of the site trustee to use data

- Training the staff: Using intelligent data cleaning and pricing clustering requires the use of newer and more sophisticated tools.

- Time: according to the volume of information, the time of collection and processing of information will be further increased. it depends on the volume of market transition and also to Site Capacity

- Traffic of site: The probability of increasing the traffic load on the source site, which is collected daily or in a few days and data center limitation

6. We could not compare the result of tradition CPI because the sample size is different and in clustering method you use both different price and weight for different decices while in traditional CPI we just use different weight.

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## Appendix

Table 1: price indices in deciles monthly and yearly from March 2016 to February 2019

	Dec1	Dec2	Dec3	Dec4	Dec5	Dec6	Dec7	Dec8	Dec9	Dec10
1395	100	100	100	100	100	100	100	100	100	100
1395-01	86	79	85	86	85	84	83	83	83	85
1395-02	85	83	88	88	87	87	86	86	87	89
1395-03	88	86	90	91	90	90	89	89	90	92
1395-04	93	90	94	94	93	94	93	93	93	94
1395-05	95	94	96	96	96	96	96	96	96	97
1395-06	98	96	98	99	99	98	99	99	99	99
1395-07	99	98	99	101	101	100	101	102	101	101
1395-08	103	106	103	104	103	102	104	103	104	104
1395-09	108	109	106	105	106	106	107	107	106	107
1395-10	110	112	109	109	109	110	111	111	109	108
1395-11	117	121	114	111	113	114	113	114	114	111
1395-12	119	126	119	116	118	118	117	118	119	114
1396	156	185	162	153	151	158	154	155	158	145
1396-01	126	133	126	124	126	125	123	124	124	118
1396-02	131	139	130	126	127	130	128	129	127	121
1396-03	141	146	137	132	131	135	132	133	132	127
1396-04	143	156	142	135	133	140	136	138	140	132
1396-05	151	163	146	140	139	147	144	146	148	138
1396-06	155	175	154	148	146	153	150	151	152	143
1396-07	160	183	161	154	151	158	155	157	158	146
1396-08	162	196	171	159	157	163	160	161	166	155
1396-09	168	213	181	167	166	175	171	169	178	159
1396-10	169	218	192	174	171	179	176	175	181	164
1396-11	175	243	201	185	178	188	185	184	193	169
1396-12	191	253	207	189	185	200	193	193	203	173
1397										
1397-01	201	281	225	205	197	210	208	207	218	178
1397-02	213	290	242	217	210	224	218	220	227	185
1397-03	234	326	268	240	225	244	233	232	238	197
1397-04	259	376	297	259	238	261	256	255	264	213
1397-05	284	419	330	292	257	284	283	278	293	236
1397-06	302	443	352	312	279	312	312	313	330	262
1397-07	358	533	395	355	307	342	352	348	370	288
1397-08	365	572	412	374	329	370	383	379	408	313
1397-09	383	593	438	405	358	413	414	415	429	326
1397-10	390	610	476	427	385	443	431	446	458	344
1397-11	398	655	519	455	415	477	457	478	492	361

Source: Research findings

Table 2: inflation rate in deciles monthly and yearly from March 2016 to February 2019

	Dec1	Dec2	Dec3	Dec4	Dec5	Dec6	Dec7	Dec8	Dec9	Dec10
1395										
1395-01										
1395-02	1.1-	4.5	3.4	1.9	1.2	2.1	2.6	3.2	5.0	5.3
1395-03	3.6	3.4	1.7	3.2	3.6	4.3	4.5	3.5	3.0	2.6
1395-04	6.3	5.3	4.8	2.9	4.1	4.0	4.7	4.9	3.4	2.1
1395-05	1.9	3.9	1.8	2.0	2.8	2.4	3.0	3.2	3.1	3.0
1395-06	3.5	2.7	2.3	3.5	2.6	1.7	2.5	3.0	3.0	1.7
1395-07	0.5	2.6	1.7	2.5	3.1	2.7	2.9	2.9	2.8	3.2

1395-08	4.5	7.5	3.6	2.6	1.4	2.3	2.5	1.6	2.2	2.9
1395-09	4.3	3.0	2.4	1.5	2.9	3.5	3.1	3.2	2.3	1.8
1395-10	2.2	2.8	3.3	2.8	2.9	3.2	3.2	3.2	2.6	1.2
1395-11	5.9	8.3	4.7	2.5	3.5	4.2	1.5	2.9	4.5	2.5
1395-12	1.7	3.0	3.7	3.3	3.7	2.6	3.5	3.4	3.6	2.5
1396	55.6	84.7	62.3	52.3	49.9	56.7	53.6	53.9	57.7	44.0
1396-01	5.5	6.0	6.0	7.0	6.7	6.1	5.0	4.4	4.5	3.3
1396-02	4.2	4.2	2.9	2.0	1.2	3.8	4.0	4.6	2.7	2.7
1396-03	7.9	5.0	5.5	4.3	2.5	3.5	2.9	2.9	3.4	4.9
1396-04	1.7	7.9	4.4	2.8	2.2	4.0	3.5	4.2	6.4	4.1
1396-05	5.7	4.5	2.9	4.0	4.9	5.4	6.3	5.8	5.8	4.4
1396-06	2.8	7.3	5.9	5.8	4.8	4.1	4.1	3.4	2.8	3.5
1396-07	3.3	4.8	4.3	4.3	3.7	3.6	3.3	3.8	4.3	2.0
1396-08	1.2	7.1	6.5	3.0	3.3	2.6	2.8	2.2	4.6	6.0
1396-09	3.1	7.8	5.2	4.2	5.7	7.5	7.0	5.4	7.2	2.9
1396-10	0.2	2.6	5.9	4.5	2.5	1.7	2.4	2.8	1.7	2.8
1396-11	3.4	11.0	4.7	5.9	4.5	5.2	5.5	5.3	7.0	3.2
1396-12	9.3	4.5	3.2	2.3	4.2	6.4	4.2	5.1	5.1	2.1
1397										
1397-01	5.4	11.5	9.1	8.3	6.3	5.1	7.6	7.7	7.5	3.2
1397-02	5.1	2.4	7.1	5.2	6.0	6.1	4.3	5.6	3.8	3.4
1397-03	8.7	11.6	9.9	8.6	5.6	7.2	5.8	4.5	4.3	6.0
1397-04	10.4	16.1	11.0	8.1	6.1	7.2	10.5	10.1	11.2	8.1
1397-05	9.9	11.9	11.5	13.6	8.5	9.4	10.7	9.2	10.7	10.5
1397-06	6.2	5.8	6.7	7.0	8.5	10.1	10.3	12.5	12.6	10.8
1397-07	20.0	21.0	12.8	14.5	11.0	10.1	13.5	11.8	12.6	10.2
1397-08	2.0	7.3	4.0	5.2	7.1	8.0	9.1	9.2	10.6	8.6
1397-09	4.5	3.2	6.3	7.4	8.6	10.8	7.5	8.9	5.1	4.2
1397-10	1.2	2.7	8.9	5.4	7.7	8.0	3.8	7.9	6.7	5.7
1397-11	2.0	6.6	8.7	6.4	7.6	7.1	5.7	6.9	7.2	4.8

Source: Research findings

Table 3 price indices in deciles monthly and yearly from March 2016 to February 2019(Calculated by traditional methods)

	Dec1	Dec2	Dec3	Dec4	Dec5	Dec6	Dec7	Dec8	Dec9	Dec10
1395	100	100	100	100	100	100	100	100	100	100
1395-01	96.5	96.4	96.4	96.5	96.5	96.5	96.6	96.7	96.7	97.0
1395-02	96.0	96.1	96.2	96.4	96.4	96.6	96.7	96.8	96.9	97.3
1395-03	96.9	97.0	97.1	97.2	97.2	97.3	97.4	97.4	97.5	97.7
1395-04	98.2	98.3	98.3	98.3	98.4	98.4	98.5	98.5	98.6	98.7
1395-05	99.8	99.7	99.7	99.6	99.6	99.6	99.6	99.5	99.5	99.4
1395-06	100.0	100.0	100.0	100.0	99.9	99.9	99.9	99.8	99.8	99.8

1395-07	100.1	100.2	100.2	100.3	100.3	100.3	100.3	100.3	100.4	100.4
1395-08	100.5	100.5	100.5	100.5	100.5	100.6	100.6	100.6	100.6	100.6
1395-09	101.7	101.6	101.6	101.5	101.5	101.4	101.4	101.4	101.3	101.2
1395-10	102.4	102.4	102.4	102.3	102.3	102.3	102.3	102.2	102.2	102.0
1395-11	102.9	103.0	102.9	102.9	102.9	102.8	102.8	102.8	102.7	102.5
1395-12	104.9	104.8	104.6	104.5	104.4	104.3	104.2	104.0	103.8	103.4
1396	109.0	108.9	108.8	108.8	108.7	108.6	108.5	108.3	108.2	107.7
1396-01	106.9	106.6	106.3	106.2	106.0	105.9	105.7	105.5	105.2	104.6
1396-02	106.6	106.3	106.1	106.0	105.8	105.7	105.5	105.4	105.1	104.6
1396-03	106.3	106.3	106.1	106.1	106.0	105.9	105.7	105.6	105.4	104.9
1396-04	107.5	107.3	107.2	107.2	107.0	107.0	106.8	106.7	106.5	106.0
1396-05	108.1	107.9	107.8	107.7	107.5	107.4	107.3	107.1	106.9	106.3
1396-06	107.6	107.5	107.5	107.5	107.4	107.4	107.2	107.1	107.0	106.6
1396-07	108.5	108.6	108.6	108.7	108.7	108.7	108.6	108.6	108.5	108.2
1396-08	110.1	110.0	110.0	110.0	109.9	109.9	109.8	109.7	109.5	109.1
1396-09	111.5	111.3	111.2	111.1	110.9	110.8	110.7	110.5	110.2	109.7
1396-10	111.5	111.5	111.4	111.4	111.3	111.2	111.1	111.0	110.8	110.4
1396-11	111.6	111.6	111.6	111.6	111.5	111.5	111.4	111.4	111.3	110.9
1396-12	111.5	111.7	111.7	111.7	111.6	111.6	111.7	111.6	111.6	111.3
1397										
1397-01	112.9	113.1	113.2	113.3	113.2	113.2	113.3	113.2	113.1	112.8
1397-02	113.8	114.3	114.4	114.5	114.5	114.6	114.7	114.6	114.6	114.3
1397-03	115.8	116.5	116.6	116.8	116.8	116.8	116.9	116.9	116.8	116.4
1397-04	120.6	121.4	121.6	121.8	121.8	121.9	122.1	122.2	122.1	121.9
1397-05	127.6	128.5	128.6	128.6	128.5	128.5	128.8	128.7	128.8	128.9
1397-06	133.4	134.6	134.8	134.9	134.8	134.9	135.6	135.8	136.6	138.2
1397-07	143.9	145.1	145.3	145.2	145.0	144.9	145.6	145.6	145.8	146.4
1397-08	147.7	149.1	149.2	149.1	149.0	148.9	149.6	149.5	149.6	150.0
1397-09	152.2	153.5	153.4	153.2	152.9	152.6	153.1	152.9	152.8	152.9
1397-10	155.1	156.5	156.5	156.3	156.1	155.7	156.2	156.0	155.9	156.0
1397-11	158.6	160.1	160.1	159.9	159.7	159.3	159.8	159.6	159.5	159.8

Source: Statistical Center Office of Iran

Table 4: inflation rate in deciles monthly and yearly from March 2016 to February 2019(Calculated by traditional method)

	Dec1	Dec2	Dec3	Dec4	Dec5	Dec6	Dec7	Dec8	Dec9	Dec10
1395										
1395-01	0.5-	0.3-	0.2-	0.1-	0.0	0.0	0.1	0.1	0.2	0.3
1395-02	1.0	0.9	0.9	0.8	0.8	0.8	0.7	0.7	0.6	0.5
1395-03	1.4	1.3	1.3	1.2	1.2	1.2	1.1	1.1	1.1	1.0
1395-04	1.6	1.5	1.4	1.3	1.3	1.2	1.1	1.0	0.9	0.7
1395-05	0.2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.4
1395-06	0.1	0.2	0.2	0.3	0.3	0.4	0.4	0.5	0.5	0.6
1395-07	0.4	0.3	0.3	0.3	0.3	0.3	0.2	0.2	0.2	0.2
1395-08	1.1	1.1	1.0	1.0	0.9	0.9	0.8	0.8	0.7	0.6
1395-09	0.7	0.8	0.8	0.8	0.8	0.8	0.9	0.9	0.8	0.8
1395-10	0.6	0.6	0.5	0.6	0.5	0.5	0.5	0.5	0.5	0.4
1395-11	2.0	1.8	1.6	1.5	1.5	1.4	1.3	1.2	1.1	0.9
1395-12	9.0	8.9	8.8	8.8	8.7	8.6	8.5	8.3	8.2	7.7
1396	1.9	1.7	1.7	1.7	1.6	1.5	1.5	1.4	1.3	1.2
1396-01	0.3-	0.3-	0.3-	0.2-	0.2-	0.2-	0.1-	0.1-	0.1-	0.0
1396-02	0.3-	0.0	0.1	0.1	0.1	0.2	0.2	0.2	0.3	0.3
1396-03	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

1396-04	0.6	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.4	0.3
1396-05	0.5-	0.4-	0.3-	0.2-	0.1-	0.1-	0.0	0.1	0.1	0.3
1396-06	0.9	1.0	1.1	1.1	1.2	1.2	1.3	1.3	1.4	1.5
1396-07	1.5	1.3	1.3	1.2	1.2	1.1	1.1	1.0	0.9	0.8
1396-08	1.3	1.1	1.0	1.0	0.9	0.9	0.8	0.8	0.7	0.6
1396-09	0.0	0.2	0.2	0.3	0.3	0.4	0.4	0.5	0.5	0.6
1396-10	0.1	0.1	0.1	0.2	0.2	0.2	0.3	0.3	0.4	0.5
1396-11	0.0	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.3	0.4
1396-12	25.9	26.9	27.1	27.1	27.1	27.1	27.7	27.8	28.1	28.9
1397										
1397-01	0.8	1.0	1.1	1.1	1.1	1.2	1.2	1.3	1.3	1.3
1397-02	1.8	2.0	1.9	2.0	1.9	1.9	2.0	1.9	1.9	1.9
1397-03	4.1	4.2	4.3	4.3	4.3	4.4	4.5	4.5	4.6	4.7
1397-04	5.9	5.9	5.7	5.6	5.5	5.4	5.4	5.4	5.4	5.7
1397-05	4.5	4.8	4.8	4.9	4.9	5.0	5.3	5.5	6.1	7.2
1397-06	7.9	7.8	7.8	7.6	7.5	7.4	7.4	7.2	6.7	5.9
1397-07	2.6	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.6	2.5
1397-08	3.1	2.9	2.8	2.7	2.6	2.5	2.4	2.3	2.2	2.0
1397-09	1.9	2.0	2.0	2.0	2.1	2.0	2.0	2.0	2.0	2.0
1397-10	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.3	2.5
1397-11	0.5-	0.3-	0.2-	0.1-	0.0	0.0	0.1	0.1	0.2	0.3

Source: Statistical Center Office of Iran

Graph 1: Feb 2019, Fuzzy and traditional CPI deciles

