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Price Setting in Pakistan: Evidence from Micro SPI Dataset

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Abstract: An accredited fact in macroeconomics states that prices of commodities as well as services do not essentially change instantaneously in response to economic shocks, rather, evident an interval of unadjusted period. For the presence of such inflexibility, numerous facts and reasons are identified in the literature. The paper thus aims to investigate the price change mechanism inthe case of Pakistan.A widely used technique recognized as Duration Analysis is employed in the study.A Non-parametric estimation methodknown as the Kaplan-Meier estimator is used for estimating Survivorship function and hazard function.The study found that processed food and perishable food items have the shortest duration of spells. Staple food items and cooking oil & ghee are characterized as having spells of intermediate durations. While clothing & footwear, cigarettes, and cooked food reveal long-standing spells. Results show that on the aggregated level, the hazard rate is highest at the shorter duration of spells.Literature exploring the pricing mechanism started in developed countries since the evolution of the issue.Thevast literature for developed countries proves that the issue of price stickiness is important in terms of policy implications. Despite this, developing countries like Pakistan are lagged far behind.Hence, this study is the foremost attempt to analyze the price-setting mechanismby employing micro-level price statistics.

Keywords: Price Level, Aggregate Prices, Commodities, Duration Analysis
JEL Classification: E31, E30, Q020, C410

1. Introduction:

The behavior and dynamics of prices are key features in setting an appropriate monetary policy for the inflation target. A fact in macroeconomics explains that prices do not essentially change instantlyas a result of economic shocks, but evidenceof an interval of the unadjusted spell is observed. For the presence of such inflexibility in the price adjustment procedure, several explanations are present in the existing literature, dependent on the nature of the product/ services and prevailing economic situations[1]. The study thus aims to explorethe price variation mechanism inthe case of Pakistan.

Theoretical and empirical efforts had been initiated decades ago in developed countriesfor explaining the effect of monetary policy on the existence of price strictness[2]. Thehuge literature advanced countries verify that the issue of price stickiness is important.

Despite advancement in the literature on nominal rigidities/ flexibilities in developed nations, developing states, like Pakistan, are lagging. For the case of Pakistan, asignificant study was carried out by Choudhary et al. (2011). The study was grounded on 1189 structured interviews about the price-setting of the recognizedmanufacturing firms and the service industries. This study is, however, the first attempt thatassesses the price-setting mechanismby employing the micro-level price statisticsof Pakistan. In this research, the price setting mechanism is described across the major cities by using the micro-data from a retail price survey, collected by the Pakistan Bureau of Statistics (PBS), to calculate the Sensitive Price Index (SPI).

The study detects and understands the probability of price alteration by using the extensively used method in numerous disciplines known as Duration Analysis. The study uses a non-parametric assessmenttechniqueidentified as Kaplan-Meier (KM) estimators. Survivor functions,hazard functions, and cumulative hazard functions are calculated by using K-M estimators. The hazard functions graphed the probability of price changes against the time elapsed since the earlierprice change. The nature and the shape of hazard functions and survivor functions on accumulated as well as at the level of products' group describevarious significantcharacteristics of the pricing mechanism.

The survivor estimationsshow that the perishable food items and the processed food commodities have the shortest length of spells. Perishable food commodities show thataround 70 percentof the spells have a duration of one week, while, 86 percent of energy commodities have a duration of 9 weeks. Staple food commodities and cooking oil & ghee group are considered as having an intermediate length of spells. In contrast, clothing & footwear, cigarettes, and cooked food commoditiesshow longer spells of price. Another significant outcome found in the research is that the hazard rate is decreasing. This result, although, contradicts the standard theories on price setting, but consistent with most of the literature that employed micro-level CPI statistics. It is suggested that decreasing hazard rate results mainly because of the aggregation of various heterogeneous products and price setters. Results show that on the aggregated level, the hazard rate is highest at the shorter duration of spells.

The remaining study is organized as follows. In the following section,the microdata used in the computationisdescribed. In section 3, the methodological and technical facet of the study is explained. More specifically, survival and the hazard functions are explained, followed by the technical description of Kaplan-Meier survivor estimates. In section 4, the empirical results and analysis are presented. The last section concludes the study.

2. Data Description:

The computation of this research study is based on the Retail Price Survey conducted regularly (weekly) by the Pakistan Bureau of Statistics (PBS), Government of Pakistan (GoP), forcalculationof the Sensitive Price Index (SPI). SPI is calculated weekly and is based on the basket of 53 items. Prices of these commodities are collected every week from seventeen(17) major cities of Pakistan. In this survey,

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[1] See Blinder et al. (1994) for a comprehensive list of theories.

[2] To name a few studies; Cecchetti (1986), Carlton (1986), Kashyap (1995), Blinder et al. (1998), Taylor (1999), and more recently Bils and Klenow (2004), Klenow and Kryvtsov (2008), Alvarez and Hernando (2005), Aucremanne and Dhyne (2004), Baudry et.al. (2004) Fougere et.al. (2007), Baumgartner et.al. (2005), Dias et.al. (2004, 2005), Hoffmann and Kurz-Kim (2005), Jonker et.al. (2004), Lunnemann and Matha (2005), Veronese et.al. (2004), Fabiani et al. (2006), Nakamura and Steeinsson (2012).

similarcommodities are surveyed at several outlets/shops in every city. The total outlets/shops surveyed in these citiesaredifferent, while, as high as thirteen (13)shops in Karachi and as low as one (1)shop in small cities like Gujranwala, Bahawalpur, Sargodha, Larkana, Sialkot, Khuzdar, and Bannu[3].

The recentresearch study employs all fifty-three (53)commodities[4]for analyzing the price-setting mechanism in the main cities of Pakistan. The employedstatistics, however, are city averages of different prices across different shops. For instance, the price of wheat (10 kg)was surveyed at 6 different shopsinRawalpindi. The bureau averaged these six prices and provided the city average price of wheat. Hence, the price data at the level of outletsare not accessible. The price statisticsused in the calculationare from the third week of October 2013 to the fourth week of September 2016. Hence,overall, 134,249 observations are involved in this study.

Additionally, these fifty-three (53)items are grouped into ten (10)categories. The empirical analysis of the study is grounded on these commodity groups. The number of items contained in each group differs and isrecorded in Annexure 2.The proportion of each group is demonstrated in Table 1.

Table 1: Proportions of Commodity Groups

Groups	Share (%)
1. Staple-food group	18.9
2. Clothing/ footwear group	13.2
3. Energy group	13.2
4. Meat/ dairy group	13.2
5. Perishable-food group	9.4
6. Other necessities group	9.4
7. Cooked-food group	7.5
8. Cooking oil group	7.5
9. Processed-food group	5.7
10. Cigarette group	1.9
Total	100

Source: Authors Calculation

Table 1illustrates that the proportion of staple food commodities is aroundnineteen percent, which is the maximumof all other groups. The energy group,clothing & footwear group, and meat & dairy group, each have 13.2 percent shares. Itemscontained in the perishable group and other necessities group took 9.4 percent share each. Cookedfood and cooking oil groups have a proportion of 7.5 percent. Whereas, the processed food group hasonlya 5.7 percent share. Then, the cigarettehas just a 1.9 percent share.

3. Methodology:

Duration Analysis is also known as the Survival model, Hazard Function, Failure Model, or Time to an Event model. The technique of duration analysis is extensively used in the field of medical sciences to

[3]Appendix 1 describes the coverage of cities and number of markets surveyed.

[4]The table describes the list of all the commodities included in the study is given in appendix 2.

examine the success, failure, or patient's recovery period from various medical processes. However, in Applied Economics this technique is very useful in analyzing various issues like duration of unemployment spells, loan recovery periods, enrolment drop-out rates, and sales behavior of various superstores, etc. In this study, we employ this technique to analyze the micro price-setting behavior of various commodities in major cities of Pakistan.

Survivor and the Hazard Functions:

The Survival analysis investigates the duration of time till the event under study happens to occur. For instance, in the context of the current study, it would be defined as the probability of price change at some time t, conditional that the price does not change until that point in time. In other words, we analyze the regular price spell of any particular commodity which is terminated by a price change. More specifically, prices are trailed until an event occurs (price change or a failure) or we lose them from the observed price trajectory (censored observations).

Statistically, the probability density function of a time to a price change (or failure) is written as:

$$f(t) = \lim_{\Delta \to 0} P(t + \Delta t > T > t)/\Delta t \quad (1)$$

Where, T is a non-negative random variable, calculating the duration of a regular price spell or time to an event (price change or failure).

The cumulative density function of all durations of price spells would then be obtained by integrating these probabilities:

$$F(t) = P(T \leq t) = \int_0^t f(t)dt \quad (2)$$

Here, $F(t)$ is a cumulative density function that explains the probability of price spells that survived up to t periods and are finished by a price change.

The above probability density function $f(t)$and cumulative density function $F(t)$are more evocative to be defined in terms of Hazard Function $h(t)$ and Survivor function$S(t)$.

$$S(t) = \mathrm{P}\ (T > t) = 1 - F(t) \quad (3)$$

The above function $S(t)$ is a survivorship function which is calculated as the reverse of the cumulative distribution function of$T$. $S(t)$ defines the probability that the prices would survive (or remain unchanged) beyond time$t$. Survivor rate would then be defined as the duration or span of time,the price remains unaltered. The above survivor function shows that $S(t)$ equals one at t=0 and declines towards zero as t increases. It is a monotone and non-increasing function of time t.

The hazard function $h(t)$ (or conditional failure rate) is defined as the probability (limiting) that the price change (or failure event) occurs in a given period, conditional upon the prices having survived to the beginning of that period, divided by the width of the period:

$$h(t) = \lim_{\Delta t = 0} \frac{P\ (t + \Delta t > T > t | T > t)}{\Delta t} = \frac{f(t)}{S(t)}$$

$$h(t) = \lim_{\Delta t = 0} \frac{1}{\Delta t} \frac{P\ (t + \Delta t > T > t) \cap (T > t)}{P(T > t)}$$

$$h(t) = \lim_{\Delta t = 0} \frac{P\ (t + \Delta t > T > t)}{\Delta t} \frac{1}{P(T > t)}$$

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} (4)$$

In the context of the current study, the hazard function$h(t)$ shows the probability of a regular price spell which is completed by a change in price, given that it has survived up to t periods since experiencing the previous change in prices. Hence it defines both the failure rate of a price spell and the occurrence of a price change. The probability of a price change is observed to be small at the start but augments over time thus leading to a change in hazard rate over time.
Cumulative Hazard Function is then obtained by integrating all the hazard rates $h(t)$ over time. The Cumulative Hazard Function denoted by $H(t)$ defines the total hazard or total possibility of a price change that has been accrued till time t.

$$H(t) = \int_0^t h(t) dt \quad (5)$$

$$H(t) = \int_0^t \frac{f(t)}{S(t)} dt \quad (6)$$

By simple transformation of values, we can obtain Cumulative Hazard Function $H(t)$ interms of Survivor Function as follows;

$$f(t) = \frac{dF(t)}{dt} = \frac{d}{dt}[1 - S(t)] = -\frac{d}{dt} S(t)$$

Hence;

$$H(t) = -\int_0^t \frac{1}{S(t)} \left[\frac{d}{dt} S(t)\right] dt$$

$$H(t) = -ln[S(t)] \quad (7)$$

Equations for Survivor function, cumulative density function, and density function respectively can be written as;

$$S(t) = e^{-[H(t)]} \quad (8)$$

$$F(t) = 1 - e^{-[H(t)]} \quad (9)$$

$$f(t) = h(t) e^{-[H(t)]} \quad (10)$$

Non-Parametric Estimation of the Survivor and Hazard Function:
Survival Analysis or the Duration Analysis can be done by employing one or all three estimation methods, namely non-parametric, semi-parametric and parametric estimation techniques depending on the assumption made about the Survivorship Function or the impact of covariates on survival incidence.

This study considers the non-parametric estimation technique to calculate the Survivor and Hazard Functions. Non-parametric estimation technique made no prior assumptions about the functional forms of survivor, hazard, and cumulative hazard functions. Hence, this method of estimation is widely recognized in the literature because of the simple estimation technique, where the effects of covariates are not incorporated. This method is very useful in analyzing the shape and nature of the survivor and the hazard function.

The non-parametric estimator extensively used in the literature for estimating the survivor and the hazard function is known as Kaplan-Meier Estimator.

The Kaplan-Meier Estimator:

The non-parametric estimator of the Survivor and the Hazard function developed by Kaplan and Meier (1958), also known as the Product Limit Estimate of Survivor Function S(t), with observed failure times, $t_0 < t_1 < t_2 < \cdots < t_s < \cdots < t_k$,at time t is defined as;

$$\hat{S}(t) = \prod_{s|t_s \leq t} \left(\frac{n_s - d_s}{n_s}\right) \quad (11)$$

Where; d_s is the number of failures (price change) at the time t_s. n_s is the risk set or number of prices at risk of making a transition (completing their spell) at the time t_s. The product ($\prod$) is for all failures (price change) less than or equal to t.

From the above equation, Failure Function (cumulative density function) and Cumulative Hazard Function can also be estimated by the following equations respectively.

$$\hat{F}(t_s) = 1 - \hat{S}(t_s) \quad (12)$$

$$\hat{H}(t_s) = -ln[\hat{S}(t_s)] \quad (13)$$

The Kaplan-Meier estimator estimates the survivor function and then the hazard and cumulative hazard function can be derived by employing equations (12) and (13). For estimation of survivor and cumulative hazard functions, the Kaplan-Meier estimator is more advantageous for estimating survivor function.

4. Empirical Results and Analysis:

In this section, we estimate the survivor and the hazard functions for all products at the aggregated level as well as for various product groups by employing the nonparametric estimation method discussed above. The significance of non-parametric estimation over parametric and semi-parametric estimation is that the duration and the shape of the survivor and the hazard function can be evaluated more comprehensively.

Two versions of survivor functions, cumulative hazard functions, and unconditional hazard rates are calculated for each category. Initially, un-weighted estimates of price spells are calculated. However, considering the potential bias in the dataset, noticed by Dias et. al. (2005), Fougere et. al. (2005), Ikeda &Nishioka (2007), and various others, we estimated the weighted version as well. It was observed that products exhibiting a higher frequency of price change may create bias and thus alters the shape of the hazard functions. Different attempts were made to overcome the bias in different studies. For instance, Dias et. al. (2005), Fougere et. al. (2005), and others employed a single spell from each product category selected randomly from a complete cluster of spells in the estimation process. However, employing such a method did not provide efficient results as all the available information is not incorporated in the estimation. Secondly, we apply the CPI weight to each product in estimation. However, these weights did not alter the results significantly. Finally, following Alvarez & Hernando (2004) we generate the weighting scheme by dividing the CPI weights by the total number of spells at the product-city level. This adjustment normalizes the frequency of shorter spell durations noticeably. In the analysis below we report the weighted estimates of the Kaplan-Meier survivor function along with the un-weighted estimates to observe the variations.

Survivor Function:

Figure 1 shows the survivor functions estimated as a stepped function through the Kaplan-Meier estimator represented with the solid blue line for all the spells employed in the study at the aggregated level. Panel (a) of figure 1 is the un-weighted and panel (b) is the weighted estimates of function. The stepped function shown in the figure represents the proportion of spells having "t" weeks of durations. Panel (a) reveals that the majority of the spells exhibita shorter duration of spells because the steps diminish quickly in the first few weeks of the observation period. Only a few products show evidence of longer duration which are represented by the longer steps parallel to the x-axis. The observed shape of the survivor function is because we assigned equal weight to each spell in panel (a). Thus the shape of the graph is dominated by the spells of shorter durations. Unweighted Kaplan Meier estimates show that about 85 percent of the spells fail inthe fifth week only. Similarly,Appendix 3 shows that the perishable food items havea share of 34.9 percent in total spells but have the mean (median) duration of a spell of 1.73 (1) weeks only. Similarly, meat &dairy products and staple food items have a share of 20.2 and 19.7 percent of total spells, however, exhibit only 6.06 (2) and 4.5 (1) weeks of a mean (median) duration of price spells. This proves that the shape of the survivor function is strongly influenced by the shorter spelled duration thus creating a bias.
Hence to overcome this potential bias, a weighted version of the survivor function is recalculated, which is shown in panel (b) of figure 1. It is visibly clear in the graph that the new weighted survivor function is repelled away from the origin compared to panel (a). Weighted estimates of Kaplan-Meier confirm that about 50 percent of spells have a duration of 12 months. The significant variation between the weighted and unweighted version of the survivor function can be realized by the fact that about 80 percent of the un-weighted spells have a duration of about 5 weeks only. This over-weighted shorter duration of spells is normalized in the weighted version as 80 percent of the spells are characterized by about 110 weeks of duration or less.

Figure 1

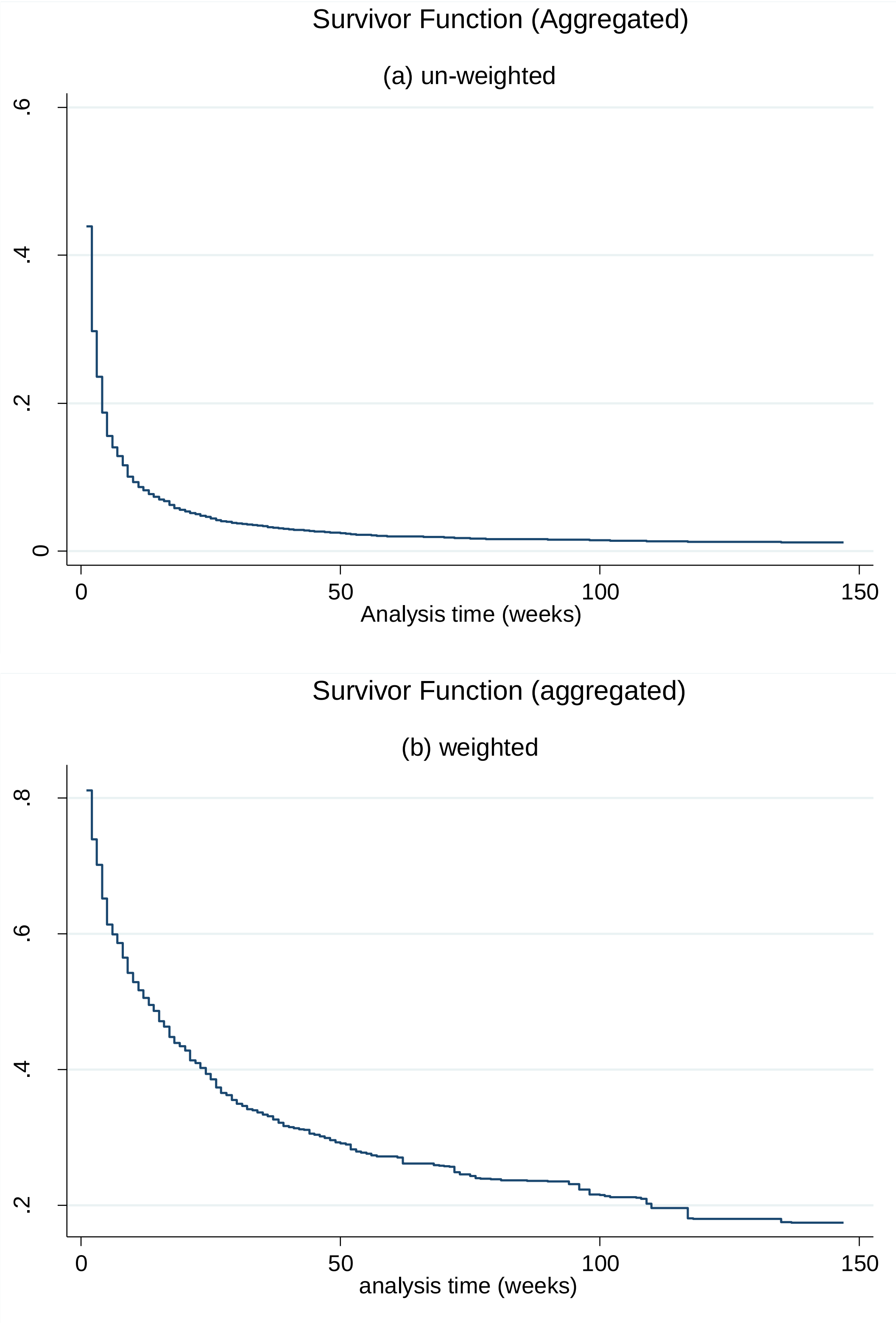
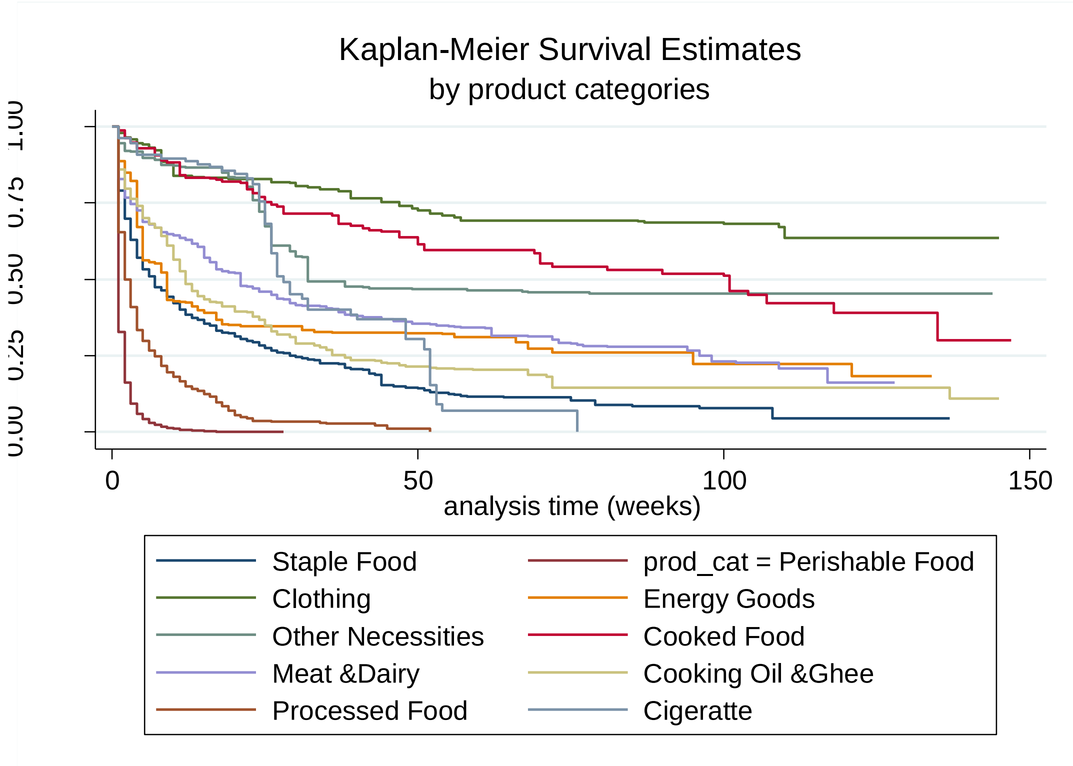


Figure 2 below shows the Kaplan-Meier survival estimates for ten different product groups thus understanding a clearer picture. Processed food and perishable food items have the shortest duration of spells. The survivor function for perishable food items diminishes very fast as about 70 percent of the spells have a duration of just one week. For this commodity group, none of the spells survives for more than 28 weeks. For the processed food group all the spells terminate by 52 weeks. 86 percent of energy goods have a duration of 9 weeks only. Staple food items and cooking oil & ghee are characterized as having spells of intermediate durations. On the other end, clothing & footwear, cigarettes, and cooked food reveal the long-standing spells.

Figure 2



Hazard Functions:

Unlike the survivor function, the hazard function reveals the probability or the likelihood of price adjustment over the analysis period (weeks). By graphing the hazard function, we can predict if the product is following the time-dependent pricing models or not by analyzing the sensitivity of price change against the time duration of the price spell. The time-dependent model entails that the likelihood of price change for a particular commodity does not change with time.

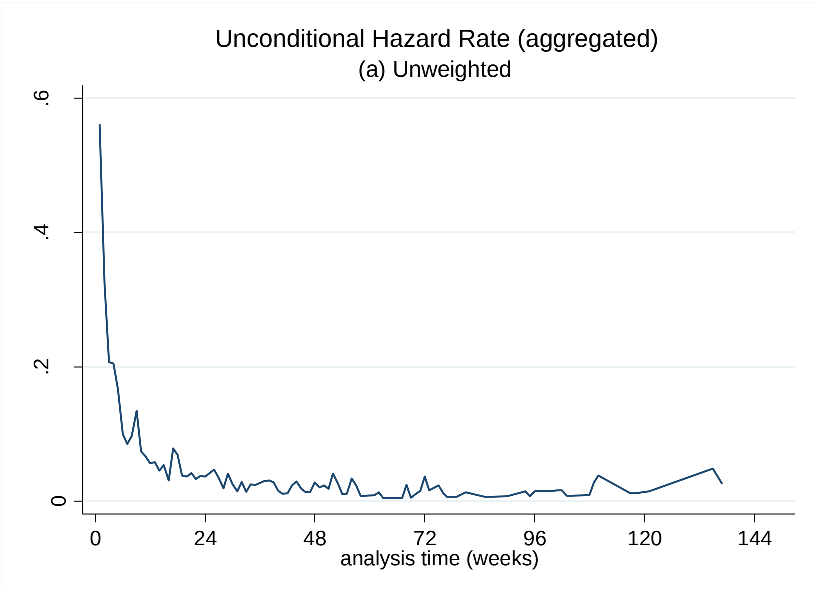
In this section,the unconditional hazard rates of price spells are calculated for the aggregated dataset as well as for various product groups. Panel (a) of figure 3 is the un-weighted and panel (b) is the weighted version of the function. Panel (c) is graphed to account for the multiple spells of price duration of each product. It would be worth mentioning here, that the application of survival analysis in examining most of the issues isrelated to biomedical sciences, in which event happens to occur only once, which is relatively simple. The same is true for various economic issues, for instance, unemployment spells and loan recovery periods, in which we seldom observe the occurrence of multiple events. However, in analyzing the duration of regular price spells for any particular commodity, we have to deal with frequent price changes over a period of time. Hence, incorporating such an important feature of multiple price spells is believed to improve our estimation results of hazard functions. Taking an appropriate account of multiple price spells per commodity also reduces the impact of heterogeneity on hazard function as several spells per commodity come under consideration. Hence, following to Lan et. al. (2012), multiple spells are distinguished as the delayed entry of spells in the estimation process[5]. Entire 20,927 spells are grouped into 781 units (commodity*city) for serving the purpose.

[5] For detail description of multiple price spells, see Lan et. al. (2012)

The first glimpse of all the panels reveals the shape of the hazard rate to be decreasing. Unfortunately, these results contradict the standard theories on price setting mechanism as one of the most common aspects of all the pricing models, for instance, Taylor model, Calvo model, truncated Calvo model, state-dependent model, etc. is that the hazard rate is a non-decreasing function but could have a series of spikes or barbs. Decreasing hazard rate, therefore, misinterpreted that the probability for a product to change its price will be lower, the longer the prices remain unchanged. However, our result of the decreasing hazard rate is consistent with most of the international literature on the duration analysis of micro CPI datasets[6]. Alvarez et. al. (2005), and Fougere et. al. (2005) among others proved that decreasing hazard rate results mainly because of the aggregation of various heterogeneous products and price setters. It is comprehended in the studies that the micro datasets are gathered from various commodity groups, price setters, store types, brands, etc. Prices of some of the products like perishable food items change frequently while others like services remain the same for relatively long periods. Similarly, prices in big superstores change more frequently compared to that of traditional shops. Alvarez et. al. (2005) found that the aggregated hazard rate nearly always decreases if heterogeneity effects are not accounted for[7]. Empirically it has been proven that even if the hazard rate is non-decreasing at the individual product level at the onset would result in decreasing hazard rate on the aggregated basis[8].

The hazard function illustrated in figure 3 neglects any heterogeneity and aggregation bias that may affect the shape of the hazard function. It shows that on the aggregated level the hazard rate is highest at the shorter duration of spells. Panel (b) reveals a relatively high hazard rate for the spell duration at around 120th week. Panel (c) also reveals almost the similar shape of the hazard function in which even sharper and more frequent spikes are noticed. However, the frequent spikes and barbs in the diagram show the existence of high volatility in the duration of price spells. As already discussed, the main reason for downward sloping hazard is the aggregation of shorter and longer duration of price spells. For instance, the proportion of short-duration price spells is relatively large in this study as around 40 percent of the total products constitute 75 percent of the shorter duration of price spells.

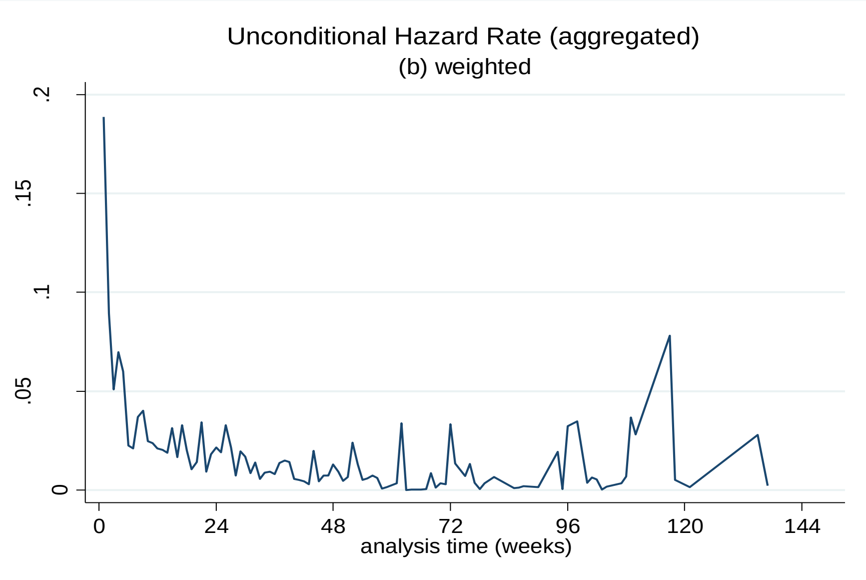
Figure 3:

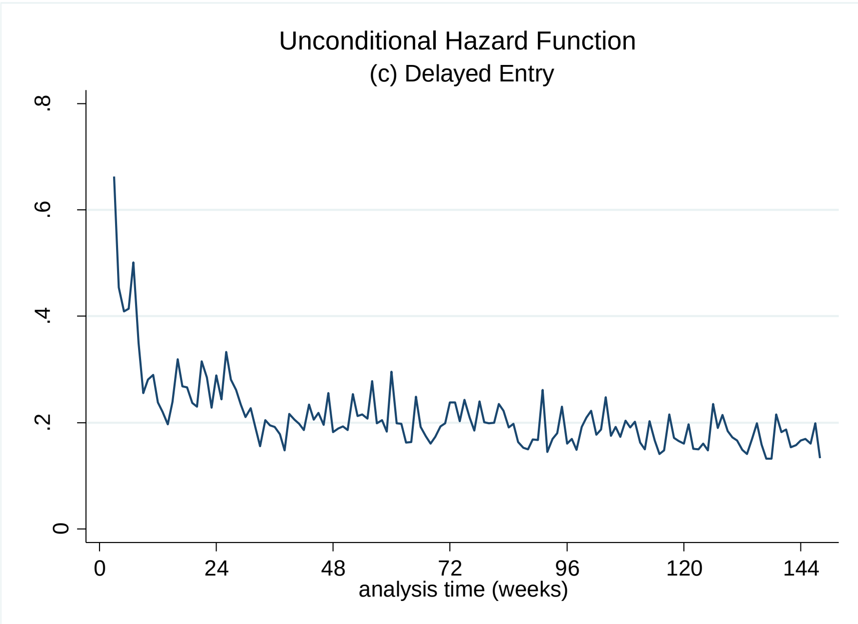


[6] For instance Alvarez et. al. (2005), Fougere et. al. (2005), Dhyne et. al. (2005) etc.

[7] To account for the heterogeneity effect is out of the scope of this study but could be addressed in the future research.

[8] See Alvarez et. al. (2005)

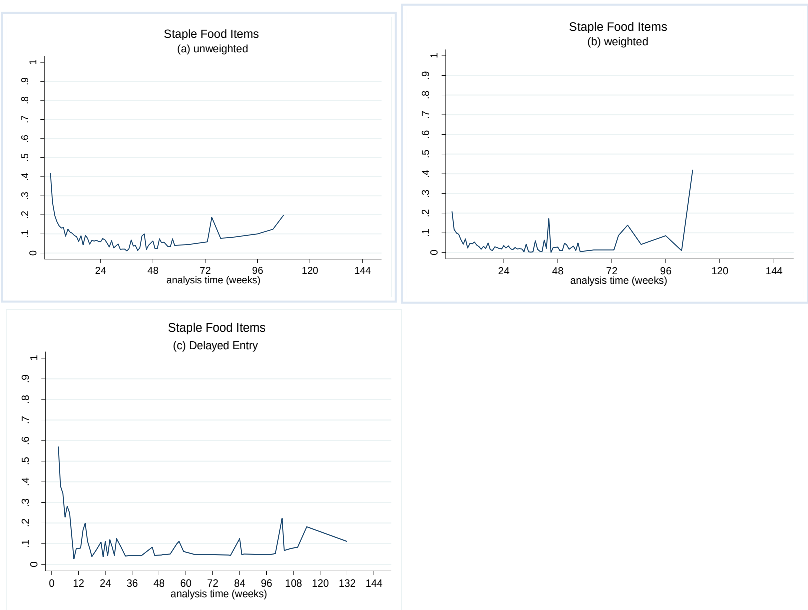


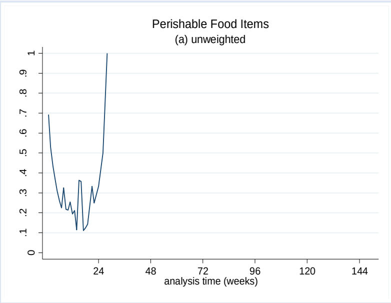


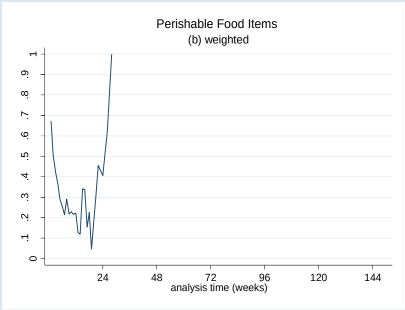
Hazard functions for ten different groups are thus calculated to lessen the heterogeneity effect. For each group, although, both weighted and unweighted versions are graphed in Figure 4, however, the difference between these versions is not very pronounced. The estimated hazard rates at the group level reveal some more interesting results.

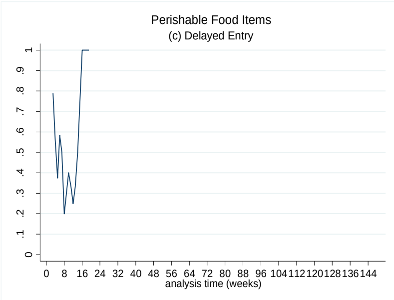
At a relatively disaggregated level, some groups still portray decreasing hazard rate, while others show flat and flat then increasing hazard rate. The reason could still be the heterogeneity as groups are aggregated at products, city, and store type levels. For instance, the hazard function for the Staple food items group is nearly flat with frequent spikes then is increasing after almost two years period. However, two prominent spikes at about 12 months and 18 months could be noticed in panel (b). Panel (c), however, shows relatively regular spikes initially after every week of the last price change till eight to nine months. After that, a flat hazard followed by a spike after every 3 to 6 months is noticed. For perishable food items, the probability of price change (hazard) is very high at a shorter duration and about 6 months. All three panels show a similar sharp decline in hazard rate after the first week. The prices are found to be adjusted on a relatively regular basis between the first six weeks. For this group, lengthy durations are not detected at all. Clothing and footwear products, however, depict a nearly flat hazard rate with a very low probability of price change. Energy products, on the other hand, reveal a very high probability of price change during shorter durations. Frequent spikes are noticed during the first 6 months and from then hazard rate is continuously increasing. However, panel (c) of energy goods reveals a decreasing hazard rate after the price change observed in the sixth month which again rises after about a year. A flat hazard rate is then observed for quite a long time since the last change in price and then decreases again. The hazard function for other necessities is almost flat with a very low probability of price change. Cooked food, however, reveals a nearly increasing hazard rate with noticeable spikes at 6, 12, 18, and 24 months in panels (a) and (b). Meat & dairy products' group and cooking oil & ghee product's grout depicts high hazard in the shorter duration. Hazard function increases after 18 months for cooking oil and ghee products. Hazard function for processed food items shows a similar nature of price change to that of perishable food groups. Hazard is found to be high at a smaller duration period. It is found that after almost about 6 months hazard function is continuously increasing. The point of interest for this group is that none of the duration spells stays lengthier than a year. For cigarettes, the hazard function in the first two panels is flat then increasing and fairly good spikes are found after every 6 months. However, in panel (c) sharp decrease then flat followed by an increasing hazard rate is found.

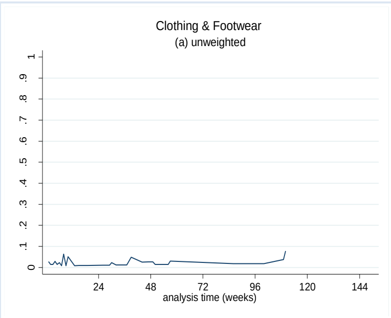
Figure 4

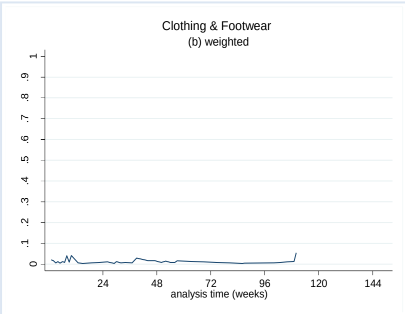


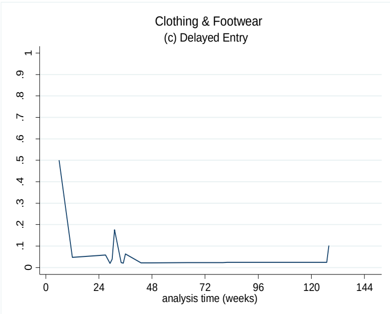

Perishable Food Items
(a) unweighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

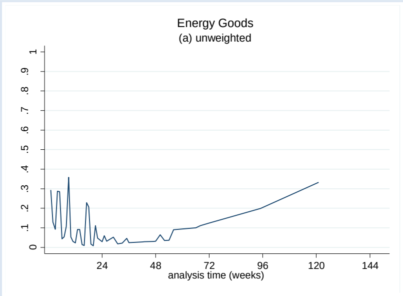

Perishable Food Items
(b) weighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

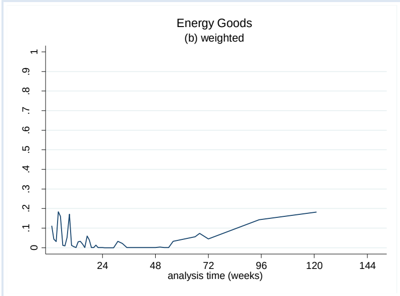

Perishable Food Items
(c) Delayed Entry
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
0 8 16 24 32 40 48 56 64 72 80 88 96 104 112 120 128 136 144
analysis time (weeks)

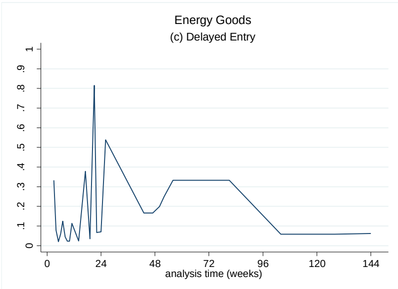

Clothing & Footwear
(a) unweighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

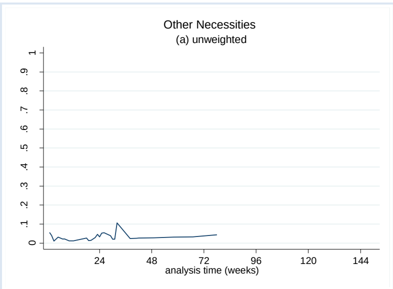

Clothing & Footwear
(b) weighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

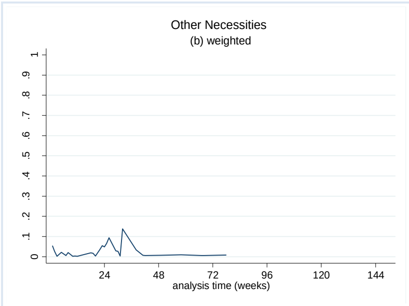

Clothing & Footwear
(c) Delayed Entry
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
0 24 48 72 96 120 144
analysis time (weeks)

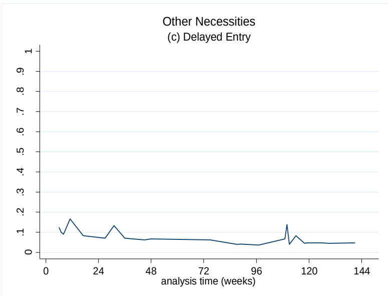

Energy Goods
(a) unweighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

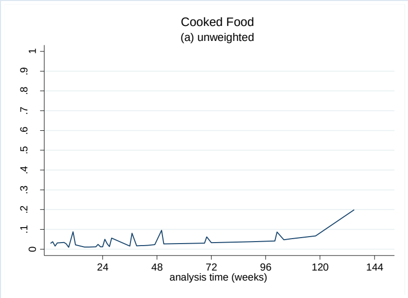

Energy Goods
(b) weighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

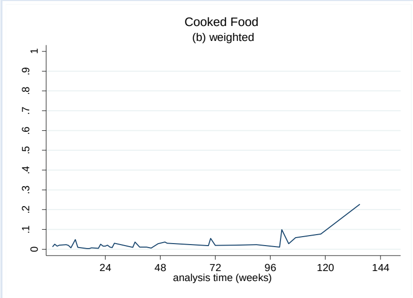

Energy Goods
(c) Delayed Entry
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
0 24 48 72 96 120 144
analysis time (weeks)

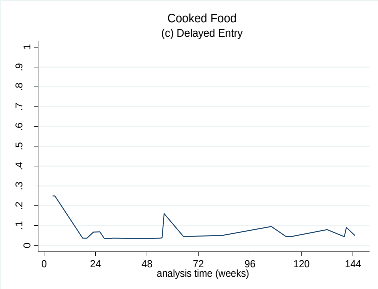

Other Necessities
(a) unweighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

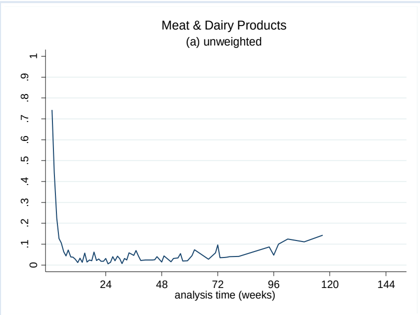

Other Necessities
(b) weighted
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
24 48 72 96 120 144
analysis time (weeks)

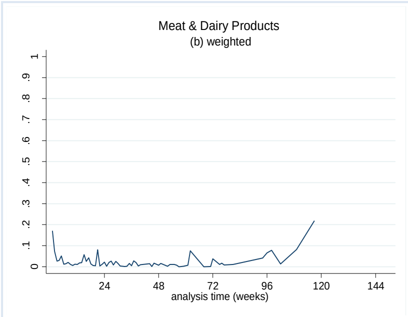

Other Necessities
(c) Delayed Entry
0 .1 .2 .3 .4 .5 .6 .7 .8 .9 1
0 24 48 72 96 120 144
analysis time (weeks)

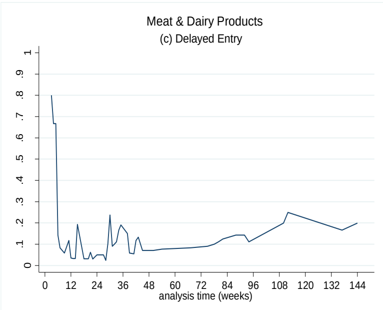

Cooked Food
(a) unweighted
analysis time (weeks)

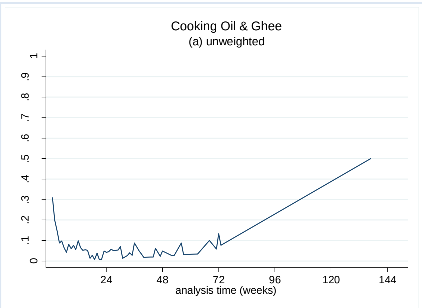

Cooked Food
(b) weighted
analysis time (weeks)

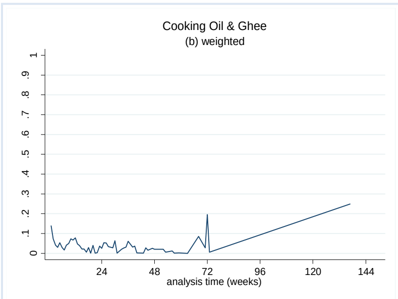

Cooked Food
(c) Delayed Entry
analysis time (weeks)

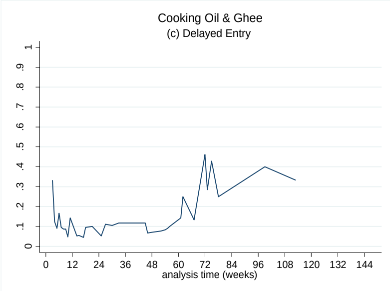

Meat & Dairy Products
(a) unweighted
analysis time (weeks)

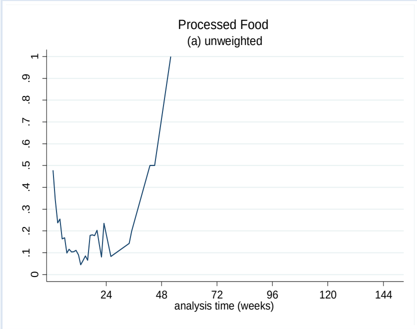

Meat & Dairy Products
(b) weighted
analysis time (weeks)

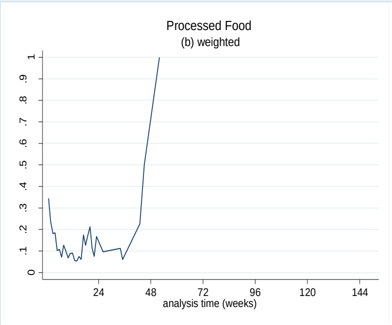

Meat & Dairy Products
(c) Delayed Entry
analysis time (weeks)

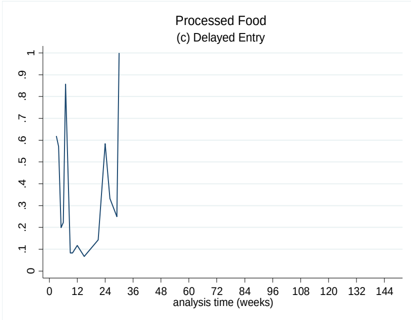

Cooking Oil & Ghee
(a) unweighted
analysis time (weeks)

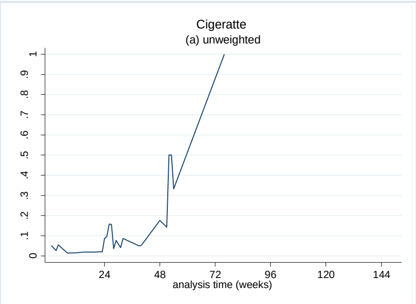

Cooking Oil & Ghee
(b) weighted
analysis time (weeks)

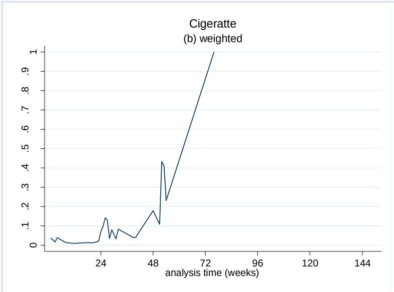


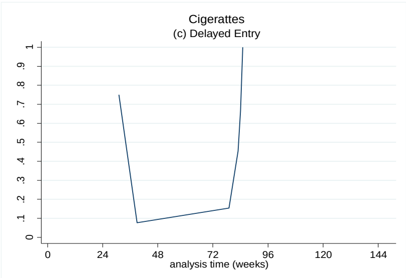












4. Conclusion:

An attempt is made in this chapter to analyze the consumer price behavior by employing the microdata collected for the calculation of SPI by the Pakistan Bureau of Statistics, Government of Pakistan. For the computation and analysis, 20,927 spells of varying durations are employed, which are grouped into 781 units (commodity-city). In this study,a more contemporary approach is followed, recognized as duration analysis. Survivor function, cumulative hazard function, and the hazard rates are estimated by employing an illustrious but simple nonparametric estimate of the functions, that is, Kaplan-Meier estimators.

The results confirm that the perishable food items have the shortest duration of one week for most of the spells. Processed food groups, energy goods, and dairy & meat products also reveal the shorter duration of spells. Whereas, Staple food items and cooking oil & ghee are characterized as having spells of intermediate durations. On the other end, clothing & footwear, cigarettes, and cooked food reveal the long-standing spells. Another important result found in the study is that the hazard rate is found to be decreasing whichcontradicts the standard theories on price setting mechanism, however consistent with most of the international literature on the duration analysis of micro CPI datasets. It is suggested that decreasing hazard rate results mainly because of the aggregation of various heterogeneous products and price setters. It is concluded in the chapter that the results obtained so far do not indicant support for any particular pricing theory, for instance, time-dependent or state-dependent pricing theory. The results thus indicate the existence of the elements of both state-dependent as well as time-dependent elements which could be explored at length in the future by employing the semi-parametric and parametric estimation methods.

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Appendix 1

S.No.	**Cities**	**Markets**
1	Islamabad	4
2	Rawalpindi	6
3	Gujranwala	1
4	Sialkot	1
5	Lahore	7
6	Faisalabad	2
7	Sargodha	1
8	Multan	3
9	Bahawalpur	1
10	Karachi	13
11	Hyderabad	4
12	Sukkur	2
13	Larkana	1
14	Peshawar	3
15	Bannu	1
16	Quetta	2
17	Khuzdar	1
Total		**53**

Source: PBS, GoP

Appendix 2: List of Commodities

s.no.	**commodities**	**s.no.**	**commodities**	**s.no.**	**commodities**
1	Wheat	19	Vegetable ghee (loose)	37	Shirting
2	Wheat flour	20	Mustard oil	38	Sandal gents (bata)
3	Basmati rice (broken)	21	Cooking oil (dalda)	39	Sandal ladies (bata)
4	Rice irri-6	22	Potatoes	40	Chappal sponge (bata)
5	Masoor pulse	23	Onions	41	Kerosene oil
6	Moong pulse	24	Tomatoes	42	Firewood
7	Mash pulse	25	Bananas	43	Energy saver
8	Gram pulse	26	Salt	44	Matchbox
9	Beef with bone	27	Red chilies	45	Washing soap
10	Mutton	28	Garlic	46	Bath soap (life buoy)
11	Eggs	29	Tea packet	47	Chicken farm
12	Bread plain	30	Tea (prepared)	48	Gas charges
13	Sugar	31	Cooked beef (plate)	49	L.P.G.
14	Gur	32	Cooked dal (plate)	50	Electric charges
15	Milk fresh	33	Cigarettes K-2	51	Petrol
16	Milk powdered (nido)	34	Long cloth	52	Diesel
17	Curd	35	Lawn	53	Telephone Charges
18	Vegetable ghee (tin)	36	Georgette		

Source: PBS, GoP

Appendix 3:Description of Product Categories

Product categories	No. of spells*	share of spells	share of a product category	Mean	Extended mean	25 percentile	Median	75 percentile
Staple Food	4,126	19.7	18.9	6.06(***)	6.2	1	2	7
Perishable Food	7,298	34.9	9.4	1.73	1.7(**)	1	1	2
Clothing	143	0.7	13.2	86.53(***)	174.1	19	110	-
Energy Goods	1,959	9.4	13.2	8.39(***)	8.7	1	4	8
Other Necessities	106	0.5	9.4	70.8(***)	129.7	22	32	-
Cooked Food	135	0.6	7.5	64.07(***)	82.4	12	42	-
Meat &Dairy	4,218	20.2	13.2	4.5(***)	4.6	1	1	2
Cooking Oil &Ghee	812	3.9	7.5	14.18(***)	14.9	1	3	13
Processed Food	2,052	9.8	5.7	3.8	3.8(**)	1	2	4
Cigarette	78	0.4	1.9	31.37	31.47(**)	23	27	52
Total	20,927	100%	100%	6.08(***)	6.5	1	1	3

*excluding left and double censored spells
** No extension needed
*** largest observed analysis time is censored, mean is underestimated

Source: Author's calculation