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Empirical evidences on pricing mechanism in Pakistan: A duration analysis

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Original Paper

Empirical Evidences on Pricing Mechanism in Pakistan: A Duration Analysis

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Abstract This study evaluates the price setting behavior across main cities of Pakistan by employing the micro data from retail price survey. The most contemporary research technique of Duration Analysis is employed where survivor functions are estimated by most illustrious nonparametric Kaplan-Meier and Nelson-Aalen Estimators. Hazard Functions for various product groups are also estimated by employing parametric Weibull Hazard Model. Results confirm that perishable food items have shortest duration of one week for most of the spells, where government regulation caused prices to change more frequently. It is found that on average small cities faced lower hazard and thus comparably lesser price change, whereas, months of March, April and October witnessed relatively high hazard rates. The study classifies nine commodity groups into two categories. First is high frequency group and second is increasing hazard group. These classifications are believed to assist policy makers in assessing inflation dynamics in Pakistan. The study significantly contributes to the existing literature, firstly, by applying more scrupulous nonparametric and parametric techniques of Survival analysis. To the best of our knowledge, this technique is not yet applied in Pakistan for examining the price behavior. Secondly, as the price setting mechanism in Pakistan is not studied before by employing the high frequency micro price data, therefore, panel data estimation contributes significantly to the existing literature.

1 Introduction

This study aims to analyze the price-setting mechanism by employing the most contemporary econometric approaches to micro consumer price data underlying

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the Sensitive Price Index (SPI) in Pakistan. It attempts to determine the degree of price rigidity or flexibility in seventeen main cities of Pakistan as price-setting behavior exhibits significant implications on various microeconomics, macroeconomics, and monetary issues.

Voluminous theoretical literature exists on pricing behavior as it remained a fundamental question among various schools of thought for decades. Despite this, empirical evidence on the subject escalates only in the last couple of decades, probably because of the unavailability of micro statistics on commodity prices previously. Earlier on, studies mainly rely on limited data of any particular commodity or product group. For instance, Weiss et al (1992) studied the pricing behavior of newspapers to analyze the impact of hyperinflation observed in the 1920s in Germany, whereas, Carlton (1986) and Cecchetti (1986) analyzed only industrial prices and magazine cover prices respectively. Similarly, Lach and Tsiddon (1992) investigated the price behavior of food groups from a grocery store in Israel. Fortunately, the admittance of micro-level price data, collected by statistical agencies of every nation, brings new avenues of research in contemporary literature. Several studies in the past few years, especially from developed countries, employed a high-frequency dataset collected for calculating price indices for studying the price-setting behavior. Most of these studies employed a rather simpler frequency approach to investigate price rigidity. However, few studies moved a step forward by applying the most contemporary approach[1] of Duration Analysis for examining the price-setting mechanism.

Internationally, only a few valuable studies applied the nonparametric and (or) parametric approach to Duration Analysis. For instance, Baumgartner et al (2005), applied a nonparametric Kaplan Meier estimator of Duration Analysis for Austria. Lan et al (2013) analyze the hazard functions derived from the nonparametric technique of Duration Analysis for seven large UK supermarkets' food prices and Ikeda et al (2007) utilized the same estimation technique for Japan. Semi-parametric or parametric techniques are employed in the literature, firstly to analyze the impact of important determinants on the price-setting mechanism [for instance, Jonker et al (2004); Lan et al (2013) and secondly to categorize the products into various groups consistent with the theoretical facet of pricing mechanism [for instance,Ikeda et al (2007)]. Similarly, Cavallo (2018) employed the Hazard function as one of the others analyzing tools for Latin American countries and the USA. Most recently, Gorodnichenko et al (2018); Nilsen et al (2018); Antonova (2019); Alvarez et al (2022) employed the Hazard function to explain the price-setting behavior.

Employing the same methodology, the results of the study found that 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 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 and ghee are characterized as having the spells of intermediate durations. On the other end, clothing and footwear, cigarettes, and cooked food reveal the long-standing spells. Results

[1] See Fauzia et al (2018) for the case of Pakistan

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also prove that energy commodities which are regulated or administered by an authority is estimated to face 3.4 of the hazards of the commodities that are not regulated. On average the prices of commodities being experienced at Bannu, Khuzdar and Larkana are 84.7, 77, and 88.9 percent lower hazard respectively. Similarly, in March, April, and October the hazard of price change increased by 8.5, 6.6, and 7.4 percent respectively.

For the case of Pakistan, this is the first attempt that employs the most contemporary research technique of Duration Analysis by using the micro-level panel dataset. In Pakistan, empirically there exist only two important studies carried out by Malik et al (2008) and Choudhary et al (2011) that are based on firm-level primary surveys. Although these studies significantly contributed to the scarce literature on the issue of price-setting mechanism, however, panel dataset is significant in applying both non-parametric as well as rigorous parametric econometric techniques. Hence, this study significantly contributes to the existing literature, firstly, by applying more scrupulous semi-parametric and parametric techniques of Survival analysis. To the best of our knowledge, this technique is not yet applied in Pakistan for examining the price behavior. Secondly, as the price-setting mechanism in Pakistan is not studied before by employing the high-frequency micro price data, therefore, panel data estimation also contributes significantly to the existing literature. The classification of product groups based on the shape of the hazard function would be useful in devising policies, specific to the product group.

Motivated by the significance and inquisitiveness of understanding the price-setting mechanism, this study explores the following queries.

1. How long do the prices of various consumer goods remain unaltered and is this proposition true that the longer the price remains unaltered, the greater the possibility that price will change in the future?
2. Do these probabilities vary across different product groups?
3. Does the aggregation bias and heterogeneity across products alter the standard results of the study? And how the heterogeneity or aggregation bias is controlled?
4. To characterize the product groups into various categories depending on the shape of the hazard functions. This categorization would further help in policy recommendations.

The remaining study is organized as follows. Section II reviews the existing but relevant literature whereas, section III elucidates the methodological and technical aspects of the study. Firstly, the nonparametric estimation method, namely, Kaplan-Meier and Nelson Aalen survivor estimates is explained, which is followed by the Weibull Parametric Estimation Technique. Section IV describes the data and definition of various technical terms employed in the study. In section V, empirical results and analysis are presented in detail. The last section concludes the study.

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2 Literature review

There are few studies exist that endeavor to observe and understand the likelihood of price adjustment over the analysis time by employing a widely used technique in various disciplines recognized as Duration Analysis. Literature-based duration analysis employed non-parametric, semi-parametric, or parametric estimation techniques depending on the assumption made about the function. For instance, Jonker et al (2004) applied the semi-parametric estimation method of survival function - Cox regression - for analyzing the impact of various covariates on the price-setting mechanism in the Netherland. The study found that the rigidity of price depends on the size of the firm and retail outlet. The study also determines that the VAT increase during the study period had been passed onto the consumers completely, whereas, the difference in the pricing mechanism before and after the introduction of the Euro system was also detected.

Similarly, Baumgartner et al (2005) employed a non-parametric approach of duration analysis known as Kaplan Meier estimates of survivor and hazard function. The study found the decreasing aggregated hazard function of price change probably because of the reason of oversampling of products revealing a high frequency of price change. Kaplan-Meier estimator shows strong heterogeneity across various product groups. Most of the literature cited found decreasing hazards function at the aggregated level which means that the probability of price change would be lower the longer the price remained unchanged for any commodity. These results, however, contradict the standard pricing theories and are considered conundrum evidence. Álvarez et al (2005) disentangle the ambiguity by employing the Spanish producer and consumer pricing data. The study proved analytically that the decreasing hazard resulted because of the aggregation of heterogeneous products. The study thus employed the Finite Mixture Model to cluster the items into flexible Calvo, intermediate Calvo, sticky Calvo, and annual Calvo groups to reduce the heterogeneity among products.

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Ikeda et al (2007) explored the price-setting behavior in Japan by employing the monthly micro price data of the consumer price index for the year 2000 to 2004. The study utilizes both nonparametric (Kaplan Meier estimator) and parametric (Weibull Distribution Function) estimation methods of duration analysis. Non-parametric Kaplan Meier estimator produced decreasing hazard function at first because of the existence of strong heterogeneity across items. Hence Parametric Weibull distribution function was estimated to produce in-

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creasing, decreasing, and flat hazard functions for various product groups. According to the estimated hazard function, items were classified into four groups, that is, (i) the flexible group, (ii) the Calvo group, (iii) the Taylor group, and (iv) the increasing hazard group.

Lan et al (2013) analyze the hazard functions of the sales behavior for seven large UK supermarkets' food prices by employing non-parametric and semi-parametric estimation techniques of duration analysis for more than 2 years. The study used a high-frequency weekly scanner food price dataset. The study accounted for multiple sales of each product and considered it pivotal for determining the slope of the hazard function. The study concluded that the longer the food product remained without a sale in the UK; the probability of the product being discounted will increase. Lately, Gorodnichenko et al (2018) employed a high-frequency day-to-day dataset of prices in the online market for the U.S and U.K. By employing the Hazard function, the study aimed to determine the price-setting behavior in online shopping. The study found lengthy spells of prices and imperfection in online markets.

Similar to the above studies, Nilsen et al (2018) also found a downward sloping hazard rate for Norway by employing Kaplan Maier estimates. However, after regulating various factors, the study found flat hazards. They found a time-dependent pricing model for various producers. The findings of the study revealed Modified Calvo Model for various periods. Similar to one of the above studies, Antonova (2019) collected the online prices of various commodities. The study found a high frequency of price change for the commodities that are mostly on sale (short-term price adjustment). The duration of prices for imported commodities is found higher compared to local commodities. The study found that the price-setting behavior in Ukraine followed Time-Dependent Model in contrast to the State-Dependent pricing model.

Most recently, Alvarez et al (2022) discern the heterogeneity in various products by estimating the Hazard function of price change. The study found this important in estimating the impact of monetary shocks. The study also discusses the economic fundamentals of general hazard function and estimates it for explaining the firms optimization. In summarizing, the literature cited above proved the existence of strong heterogeneity across items that resulted in the decreasing slope of the hazard function. While studies that accounted for heterogeneity and aggregation found increasing, flat, or contribution of both hazard rates.

3 Methodology

Survival Analysis is also recognized as the Duration model, Failure Model, or sometimes Time to an Event Analysis. This is the most contemporary technique, which is extensively used in various other disciplines, especially, in medical sciences for examining the patients recovery time after different medical procedures. In Economics, the method of analysis is proved very valuable in investigating issues like unemployment duration, loan retrieval periods, sales

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performance and enrolment drop-out ratio, etc. Likewise, the current study employs the duration model for analyzing the price-setting mechanism of different commodities in the main cities of Pakistan.

The survival model examines the duration of time until an event happens observed or occurs. In the perspective of this study, survival analysis could be described as the likelihood of price adjustment at some point in time t, conditional that the price does not adjust until that time. In other words, survival analysis trails the prices until a failure (that is, price change) occurs or it would be lost from the specific price trajectory (that is, censored observations).

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

Where, $\bar{T}$ is a non-negative random variable, computing the duration of a price spell or time to a failure event (price change).Cumulative density function of the entire durations would then be attained by integrating all the probabilities as:

$$F(t) = P(\bar{T} \leq t) = \int_0^t f(t)\,dt \tag{2}$$

Here, F(t) is a cumulative density function that describes the probability of price spells that survived until t periods and ended by a price alteration. The probability density function f(t)and cumulative density function F(t) would be more evocative if defined in terms of Survivor function S(t) and Hazard function h(t).

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

Equation (3) shows that the survivorship function S(t) is computed as the reverse of the cumulative distribution function of $\bar{T}$. S(t), explains the probability of prices to survive (or remain unchanged) beyond time t. Survivor rate is thus defined as the time or duration, price remains unchanged. Equation (3) shows that at t=0, survivor function S(t) equals one and declines towards zero as t enhances. It is non-increasing and a monotonous function of time t.

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

$$h(t) = \lim_{\Delta t = 0} \frac{P(t + \Delta t > \bar{T} > t | \bar{T} > t)}{\Delta t} = \frac{f(t)}{s(t)} \tag{4}$$

$$h(t) = \lim_{\Delta t = 0} \frac{1}{\Delta t} \frac{P(t + \Delta t > \bar{T} > t) \cap (\bar{T} > t)}{P(\bar{T} > t)} \tag{5}$$

$$h(t) = \lim_{\Delta t = 0} \frac{P(t + \Delta t > \bar{T} > t)}{\Delta t} \frac{1}{P(\bar{T} > t)} \tag{6}$$

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{s(t)} \tag{7}$$

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From the perspective of this study, the hazard function h(t) is defined as the probability of price spells that are ended with a modification in prices, given that it has survived up to t periods since the occurrence of the previous adjustment in prices. Therefore, it explains both: the occurrence of a price amendment and the failure rate of a price spell. The likelihood of a price adjustment is detected to be diminutive in the beginning but enhanced as the time pass thus leading to a change in hazard rate over time.

Cumulative Hazard Function can be easily calculated by integrating the entire hazard rate h(t) overtime. The Cumulative Hazard Function is represented by H(t). It explains the overall hazard or entire possibility of a price adjustment that has been accumulated until time t.

$$H(t) = \int_0^t h(t)dt \tag{8}$$

$$H(t) = \int_0^t \frac{f(t)}{S(t)}dt \tag{9}$$

By simple mathematical adjustments of values, Cumulative Hazard Function H(t) is written as a function of S(t):

$$f(t) = \frac{dF(t)}{dt} = \frac{d}{dt}[1 - S(t)] = -\frac{d}{dt}S(t) \tag{10}$$

$$H(t) = -\int_0^t \frac{1}{S(t)}[\frac{d}{dt}S(t)]dt \tag{11}$$

$$H(t) = -[\ln S(t)] \tag{12}$$

Equations for density function, cumulative density function, and survivor function, respectively can be written as equations 8, 9, and 10 respectively

$$f(t) = h(t)e^{[H(t)]} \tag{13}$$

3.1 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 section explains 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

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nature of the survivor and the hazard function. The non-parametric estimators extensively used in the literature for estimating the survivor and the hazard function are known as Kaplan-Meier Estimator and Nelson Aalen Estimator.

3.1.1 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, $t_0 < t_1 < t_2 < .. < t_s < ... < t_k$ time t is defined as:

$$\hat{S}(t) = \pi s|t_{s \leq t}(\frac{n_s - d_s}{n_s}) \tag{14}$$

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 π 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.

$$\hat{F}(t) = 1 - \hat{S}(t)_s \tag{15}$$

$$\hat{H}(t) = -\ln[\hat{S}(t)_s] \tag{16}$$

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 the survivor function.

3.1.2 The Nelson-Aalen Estimator

Another non-parametric estimator widely used in the literature is by Nelson (1972) and Aalen (1978), known as the Nelson-Aalen Estimator used for the estimation of the survivor and integrated hazard functions. The Nelson Aalen estimator of the cumulative hazard function is:

$$\hat{H}(t_s) = \sum s|t_s(\frac{d_s}{n_s}) \tag{17}$$

The equation above estimates the survivor function which is $e^{[\hat{H}(t_s)}$)] known as the Fleming-Harrington estimator.

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3.1.3 Comparison of Kaplan-Meier Estimator and Nelson-Aalen Estimator

The Kaplan-Meier estimator estimates the survivor function and then hazard and cumulative hazard function are derived; however, the Nelson-Aalen estimator is vice versa. That is, it estimates the cumulative hazard function and then the survivor function is derived. For estimation of survivor and cumulative hazard functions, both the Kaplan-Meier estimator and Nelson-Aalen estimator are asymptotically equivalent and consistent estimators of each other. However, for small samples case, the Nelson-Aalen estimator is better for calculating cumulative hazard function, whereas, the Kaplan-Meier estimator is more advantageous for estimating survivor function. In literature, the Nelson-Aalen estimator is preferred in some cases as it increases with each price change activity even when the Kaplan Meier estimator becomes zero. Thus whenever the Kaplan-Meier estimator becomes zero but future activity is observed in the dataset, the Nelson-Aalen estimator is preferred.

3.2 Parametric Estimation of the Survivor and Hazard Function

Parametric estimation methods extract the information from the data differently compared to that non-parametric methods. The latter method assesses the prices at the time of failure (i-e price change). However, parametric methods employ probabilities for assessing the overall change in the prices in the given interval of time, say, from (t_{0j}, t_j) conditional on the effects of covariates (x_j) during that interval. For instance, consider a price of a commodity that is observed to be censored at the time t_j, then the likelihood contribution could be written as:

$$L_j = S(t_j|t_{0,j}, x_j) = \frac{S(t_j|x_j)}{S(t_j|x_{0j})} \tag{18}$$

Various parametric estimation methods are employed in the literature to assess the hazard and survival function of the subject depending on the nature and objectives of the research. For carrying out the research objectives of this study, the Weibull distribution model opts-in contrast to the exponential distribution model. Weibull distribution model enables us to estimate increasing, decreasing, or flat hazard rates, whereas, the exponential model assumes only constant baseline hazards. Monotonously increasing, decreasing and flat hazard functions classify the group of commodities by estimating only two parameters.

3.2.1 The Weibull Model

Weibull distribution is one of the generalized and widely used models for estimating the survivorship and the hazard function of the subject employed in econometric estimation. The baseline hazard of the Weibull model is:

$$h_0(t) = \rho^{t^{\rho}-1} exp(\alpha_0) \tag{19}$$

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Where is a shape parameter and $exp(_0)$ is the scale parameter estimated from the data. Given several covariates, x_j, the hazard model would be written as:

$$h(t|x_j) = h_0(t)exp(x_j a_x) \tag{20}$$

$$h(t|x_j) = \rho^{t^{\rho}-1} exp(\alpha_0)exp(x_j a_x) \tag{21}$$

$$h(t|x_j) = \rho^{t^{\rho}-1} exp(\alpha_0 + x_j a_x) \tag{22}$$

The cumulative hazard function can be extracted from the equation (16) as follows:

$$H(t|x_j) = \int_0^t \rho^{t^{\rho}-1} exp(\alpha_0 + x_j a_x)dt \tag{23}$$

$$H(t|x_j) = t\rho exp(\alpha_0 + x_j a_x) \tag{24}$$

And Survival Function is:

$$S(t|x_j) = exp[-exp(\alpha_0 + x_j a_x)\rho] \tag{25}$$

$$S(t|x_j) = exp(-\Delta t^{\rho}) \tag{26}$$

The above functions provide a range of monotonically increasing, decreasing, or flat-shaped hazard functions depending on the estimated value of the shape parameter ρ.

The relationship between the shape parameter and the hazard function h(t) is as follows:
For, $\rho = 1$, the h(t) is constant (Weibull model becomes exponential model)
For, $\rho > 1$, the h(t) is monotone increasing.
For, $\rho < 1$, the h(t) is monotone decreasing.

4 Definitions and data description

This study employs weekly data from the retail price survey from the third week of October 2013 to the fourth week of September 2016, conducted by the Pakistan Bureau of Statistics (PBS) for computing the Sensitive Price Index (SPI). At the time of the study, this was the latest data available for estimation. In the survey, fifty-three identical commodities[2] prevailing in seventeen major cities of Pakistan are surveyed from specified stores each week from each city[3]. The stores or outlets surveyed from each city vary depending on the size of the city. The entire commodities of retail price survey of seventeen appraised cities are thus included in the study. The published data is the city average of

[2] List of 53 commodities with their units are available on www.pbs.gov.pk
[3] The coverage of cities and number of markets surveyed are available on www.pbs.gov.pk

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individual price quotes across stores. Hence, the data employed is the average price statistics of each commodity per city per week. Overall, there are 134,249 observations used in the study.

Further, fifty-three commodities are grouped into ten product categories based on the nature of the product. The commodities grouped in each category vary and are listed in A1. The share of product categories in overall commodities is shown in Table 1.

Table 1: Share of Product Groups

Product Groups	Share (%)
1. Staple Food	18.9
2. Perishable Food	9.4
3. Clothing & Footwear	13.2
4. Energy Goods	13.2
5. Other necessities	9.4
6. Cooked Food	7.5
7. Meat & Dairy	13.2
8. Cooking Oil & Ghee	7.5
9. Processed Food	5.7
10. Cigarette	1.9
Total	100

Further, the notion of an observation used in the study means an average price quote recorded on a specific date of a particular commodity prevailing in a specific city. Whereas, a commodity is an elementary or very specific good that is traded in stores of each city. A product category is thus characterized by the set of elementary commodities belonging to the same or defined attributes.
For each elementary commodity (j) of a particular city (k), a price trajectory is observed in the dataset. A price trajectory is a sequence of price quotes for a specific commodity in a specific city. In a price trajectory, the price quotes are recorded for each week of the analysis time with a similar city and commodity for each consecutive week. Examples of price trajectories are plotted in figure 1(a), (b) & (c).

Figure 1 shows some exemplary price trajectories. It is shown that price behavior is very heterogeneous for each commodity in various cities. Some commodities like farm chicken plotted in figure 1(a) revealed frequent price change while others like Cigarettes shows price change at regular interval of time. However, the price of wheat flour in Karachi city is relatively flexible as compared to Quetta city.

A price trajectory of each elementary commodity (j) of the city (k) is a combination of one or multiple price spells. A price spell is defined as a continuous sequence of unchanged prices associated with commodity (j) of the city (k). Hence, the duration of a price spell is the number of weeks between two price changes. Some commodity shows frequent price changes and thus have a shorter duration of each spell while others show sporadic price change thus revealing a longer duration of price spell. Table 2 shows that we have a total of 21,674 price spells in our dataset; however, not all spells are complete spells. Censor-

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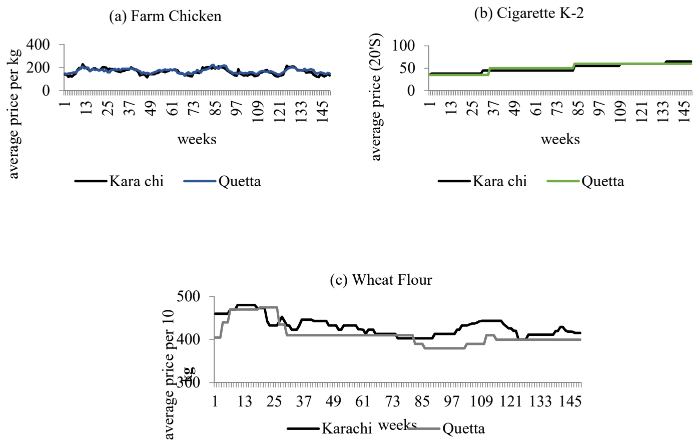

Fig. 1: Author's Illustration

ing of the price spell is a foremost issue of this study. A censored spell is an incomplete spell observed in any particular trajectory. Few spells are observed truncated in the beginning while others are at the end. A price spell whose starting (ending) date of a price change is not observed in the dataset is called a left (right) censored price spell. There are spells of very large durations as well that are truncated on both sides, these are called Doubled Censored Price spells. Table 2 shows that majority of the spells (93.6 percent) are complete spells in this study. While few, 2.9 percent and 3.0 percent, of the price spells, are left and right-censored spells respectively. Only a mere 0.6 percent of the spells are censored on both sides.

Table 2: Number of Censored Spells

Table 2 Number of Censored Spells		
Spells	**Number of Spells**	**Share (%)**
Complete spells	20277	93.6
Left censored spells	627	2.9
Right censored spells	650	3
Doubled censored spells	120	0.6
Total	21674	100

There could be different reasons behind the censoring of a price spell. In this study, spells are censored because the starting (ending) date of a price change did not match the calendar date from which we started (ended) observing the price change behavior. Left censored and double censored price spells, however, are excluded from the estimation process, thus avoiding making crucial assumptions regarding the period before the beginning of the sample. However, it is acknowledged that censoring involves a downward bias in the estimation pro-

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cess as commodities with longer spells of prices are more likely to be excluded because of double censoring.

Table 3 shows the description of product categories in terms of number and length of spells. It is shown that perishable food items have a 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 and 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 respectively.

Table 3: Description of Product Categories

Product categories	No. of spells*	share of spells (%)	share of the product category (%)
Staple Food	4,126	19.7	18.9
Perishable Food	7,298	34.9	9.4
Clothing	143	0.7	13.2
Energy Goods	1,959	9.4	13.2
Other Necessities	106	0.5	9.4
Cooked Food	135	0.6	7.5
Meat &Dairy	4,218	20.2	13.2
Cooking Oil &Ghee	812	3.9	7.5
Processed Food	2,052	9.8	5.7
Cigarette	78	0.4	1.9
Total	20,927	100	100

*Excluding left and double censored spells

Figures 2, 3, and 4 below reveal significant heterogeneity in the number of regular price spells observed by seasonality, cities, and product groups respectively.

Figure 2. Number of Regular Price Spell by Months

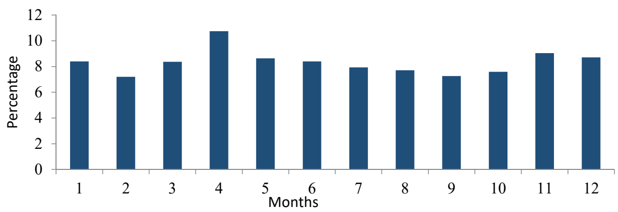

Fig. 2: Author's Illustration

Figure 2 reveals the total number of price spells observed from month1 (January) till month12 (December). It is found that about 11 percent of the total price change occurs in the month of April followed by the month of November. This shows that prices of most of the products change before the end of fiscal

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or financial years. The least price change is observed in the months of February and September.

Figure 3. Number of Regular Price Spells by Cities

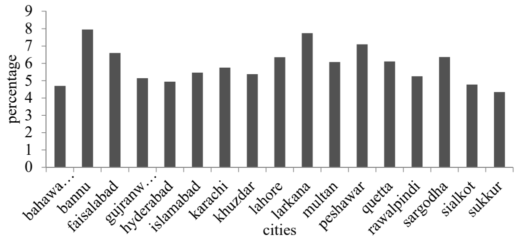

Fig. 3: Author's Illustration

Differences in the number of regular price spells are even more pronounced when analyzed at the city level in figure 3. The highest number of spells is observed in cities like Bannu, Larkana Peshawar, Faisalabad, and Sargodha. It shows that prices of the commodities are relatively short-lived in these cities compared to Bahawalpur, Sukkur, and Sialkot. While other cities like Karachi, Gujranwala, Hyderabad, Islamabad Khuzdar, Multan Quetta, and Rawalpindi show a moderate number of spells. Figure 4 shows considerable heterogeneity in several regular price spells at the level of product groups. Variations in several price spells are most apparent among various product groups. The highest number of regular price spells (thus the short-lived duration) for the perishable food group reports 35 percent share in total spells, followed by 20 percent share each for meat and dairy products and staple food groups. Whereas, energy group and cooking oil and ghee group occupy 8 percent and about 4 percent share in a total number of spells respectively.

Summing up, this section of the study aimed to describe the data set employed in the study at length. In the subsequent section, however, a detailed empirical analysis is carried out for determining the price-setting mechanism in Pakistan.

5 Empirical results and analysis

As discussed above both nonparametric as well as parametric estimation methods are employed in the study. Survivor Functions and Hazard Functions for all commodities at the aggregated level as well as for various product groups are estimated by employing nonparametric Kaplan Meier and Nelson Aalen estimators and parametric Weibull Hazard Model respectively. The duration and the shape of the survivor function can be evaluated more comprehensively by

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Figure 4. Number of Regular Price Spells by Product Groups

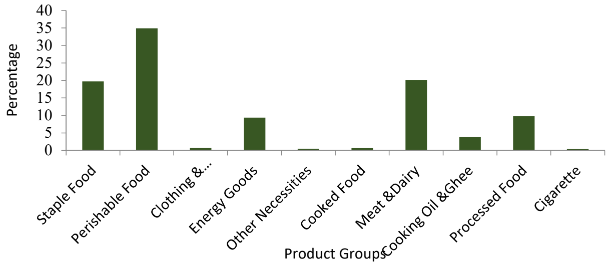

Fig. 4: Author's Illustration

employing nonparametric estimators compared to parametric estimation techniques. Whereas Parametric Estimation Methods are more useful for analyzing the hazard functions than the nonparametric approach. In parametric models, the effects as well as underlying hazard function both are parameterized.

5.1 Survivor Function

Two versions of survivor functions are calculated for each category. Initially, unweighted estimators are calculated, however, considering the potential bias in the dataset noticed by Neves et al (2004); Fougère et al (2007); Ikeda et al (2007)), and various others, a weighted version of all the estimates are also calculated. It was observed that products exhibiting a higher frequency of price change may create bias and thus alter the shape of the functions. Different attempts were made to overcome the bias in different studies. For instance, Neves et al (2004); Fougère et al (2007), and others employed a single spell from each product category which is selected randomly from a complete cluster of spells in the estimation process. However, employing such a method would not provide efficient results as all the available information is not incorporated in the estimation. Hence, following Álvarez et al (2005), the study generated a 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. The analysis below reports the weighted estimates of the Kaplan-Meier and Nelson Aalen survivor functions along with the unweighted estimates to observe the variations.

Figure 5 shows the survivor functions that are estimated as a stepped function through the Kaplan-Meier and the Nelson Aalen estimators and are represented with the solid blue line and red line respectively for all the spells employed in the study at the aggregated level. Figure 5(a) is the un-weighted and Figure 5(b) is the weighted estimates of function.

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Figure 5. Aggregated Survivor Functions

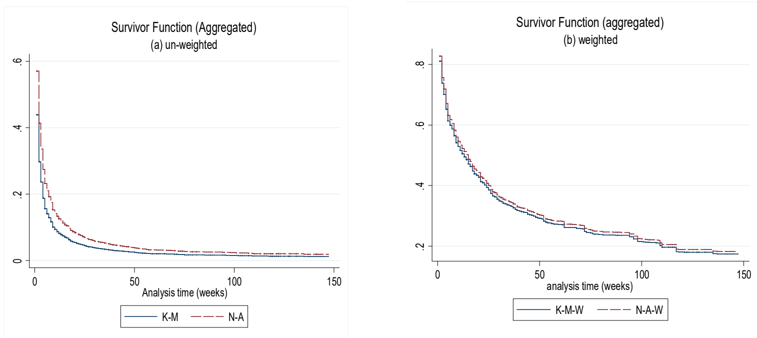

Fig. 5: Author's Illustration

The stepped function of the estimates shown in the figure represents the proportion of spells having t weeks of duration. Figure 5(a) reveals that the majority of the spells exhibit a shorter duration of spells because the step function diminishes quickly in the first few weeks of the observational 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 of the equal weight for each spell. 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 in the fifth week only.

To overcome the existence of this potential bias, a weighted version of the survivor function is recalculated, which is shown in figure 5(b). It is clearly shown in the graph that compared to the un-weighted version; the new weighted survivor function is repelled away from the origin. Weighted estimates of Kaplan-Meier confirm that about 50 percent of spells have a duration of 12 months.

Figure 6 shows the Kaplan-Meier survival estimates for ten different product groups to present a more disaggregated and 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. The reason is obvious. The demand for fruits, vegetables, and other perishable agri-products is extremely stochastic and difficult to predict. In the case of Pakistan, prices of some vegetables like onion, tomato, garlic, etc. are observed to be at their peak during the holy month of Zil-haj. Although a temporary relief is observed by the end of the month, prices start surging again with the arrival of Moharram because of the soaring demand. A similar situation arises with the prices of fruits during the month of Ramadan. High prices, however, crash with the end of seasonal demand. Despite this seasonal cycle, various other phenomena also worked behind extremely volatile prices of perishable goods in Pakistan. For instance, because of the lack of proper storage and marketing mechanisms, the prices of fruits and vegetables alter at different parts of the day.

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This happens mainly because of the fear of being a leftover rotten and spoiled product. This phenomenon is also reflected in the estimates of survival function as 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. A relatively shorter duration is observed in the prices of energy goods because of the volatility in international POL prices. An increase in international oil prices is transmitted to a domestic rise in prices of petroleum and related products, electricity tariffs, and gas charges. Staple food items and cooking oil and ghee are characterized as having the spells of intermediate durations. On the other end, clothing and footwear, cigarettes, and cooked food reveal the long-standing spells. The prices of these product groups are believed to be fixed for a longer period because of the competitive markets and to maintain long-term goodwill among the stakeholders. A wide range of substitution options is also available for consumers on clothing and footwear products as well as for cooked food hotels and restaurants in the country which hinders the frequent change of prices for these products. To overcome the existence of this potential bias, a weighted version of the survivor function is recalculated, which is shown in figure 5(b). It is clearly shown in the graph that compared to the un-weighted version; the new weighted survivor function is repelled away from the origin. Weighted estimates of Kaplan-Meier confirm that about 50 percent of spells have a duration of 12 months.

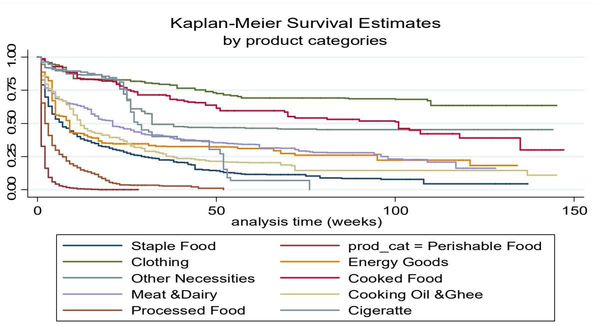

Fig. 6: Author's Illustration

5.2 Hazard Function

indent In this section, Hazard Coefficients and Hazard Ratios are calculated by following the more tractable approach of Lan et al (2013). Here, two covariates namely number of price spells and the order of spell for each product-city price spell are incorporated. These two covariates are important to include in the regression model as the prices of some products change more frequently than other products. Hence, following Lan et.al., (2013) we include the above-mentioned covariates as fixed multiple effects terms. The number of price spells

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is a time-invariant covariate that remains constant for the price of each product of a specific city, while the order of the spells is a time-varying covariate. The third covariate employed in the regression model is a dummy variable regulated that takes the value equal to 1 for the products which are considered as regulated and zero otherwise[4].

The Weibull distribution model is estimated twice in the study. In the first regression, product, city, and seasonal dummies are included, while the second regression is estimated without the inclusion of these dummies. Product and city dummies are important as differences in the production, redeeming, and supplying procedures are varying across products and cities. Similarly, prices in traditional shops are expected to change less frequently than the large superstores. Large superstores usually have their brands and pricing strategy according to the location of the stores, the need of their customers, and the pricing strategies of their rival stores. In countries like Pakistan, supermarkets and hyper-stores are found more in big cities than in smaller ones. As the average city prices for each commodity are employed in this study, this aspect of heterogeneity is incorporated by employing the city dummies. Moreover, prices of some commodities alter only seasonally or after a fixed interval of time, while, others experience price change once or twice a week. Thus, seasonal dummies are considered important covariates for capturing the time-dependent factor.

Table 4 illustrates the estimation results of the Weibull distribution models. In the table, hazard coefficients and ratios both are reported for the overall price change behavior of the entire regular price spells. Hazard ratios are the exponentiated coefficients, which are simply estimated as the exponential of the actual coefficients. For instance, the estimated hazard ratio for the price of regulated commodities is exp (1.227) =3.411, which means, a commodity that is regulated or administered by an authority is estimated to face 3.4 of the hazards of the commodities that are not regulated. In other words, price regulation causes the prices to change about 3.4 times as frequently as prices that are not controlled. Similarly, the coefficient for the number of spells is 0.022, which shows that one more price change observed in commodity or one more spell would increase the hazard by 2% on average because the exponentiated coefficient for the number of the spell is reported as 1.022.

It is worth mentioning here that the study employed the Weibull regression model in contrast to the exponential distribution model as it enables to estimate of increasing, decreasing, or flat hazard rates, whereas, the exponential model assumes only constant baseline hazards. Equation (15) illustrates that baseline hazard is characterized by only two parameters, i-e, and α_0, where the shape of the hazard function in the Weibull distribution model is determined by the estimated parameter and is shown in figure 7 below.

Results of the parametric regression shown in table 4 reject the assumption of a constant hazard rate. Tables A5 and A6, report a Wald test for the null hypothesis of constant hazard for both parametric regressions. The null hypoth-

[4] Regulated products considered in the study are Electric Charges, gas charges, kerosine oil, petrol, diesel, LPG and telephone call local

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Table 4: Estimation Results of Semi-parametric and Parametric Models

Covariates	**Weibull Regression1** **Coefficients**	**Hazard Ratio**	**Weibull Regression2** **Coefficients**	**Hazard Ratio**
Order of spells	0	1	0.002*	1.002*
	0	0	-0.025	0
Number of spells	0.022*	1.022*	0.022*	1.023*
	0	0	0	0
Regulated	1.227*	3.411*	0.281*	1.325*
	-0.133	-0.453	0	-0.033
Constant	-2.256*	0.105*	-2.313*	0.099*
	-0.088	-0.009	-0.075	-0.007
Ln()	-0.046*	-0.046*	-0.105*	-0.105*
	-0.016	-0.016	-0.016	-0.016
	0.955	0.955	0.9	0.9
	-0.015	-0.015	-0.014	-0.014
1/	1.047	1.047	1.111	1.111
	-0.016	-0.016	-0.017	-0.017
City dummies	Yes		No	
Seasonal dummies	Yes		No	
Product dummies	Yes		No	

Figures in parenthesis specify the standard errors
*Indicates 1% level of significance
** indicates 5% level of significance
***indicates 10% level of significance

Weibull Hazard Function (Aggregated)

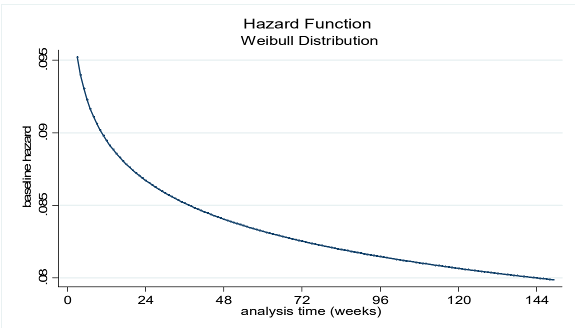

Fig. 7: Author's Illustration

esis for a constant hazard could be written as, $H_0 : \ln(p) = 0$ or equivalently, $H_0 : p = 1$. For the said hypothesis the test statistics are -2.93 and -6.75 for regressions with dummies and without dummies respectively, which are rejected significantly.

The value ¡1 (i-e 0.955) proves the suitability of the Weibull distribution model for this study as figure 6.1 shows monotone decreasing hazard rate. According to Cleves et al (2008), Weibull distribution model is suitable for data exhibiting monotone increasing or decreasing hazard rate. However, the decreasing hazard rate is being considered a conundrum as it is improbable that the longer the price remains fixed, the lesser possibility of the prices being changed in the future. However, taking the heterogeneity among products into account,

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several increasing and flat hazard rates were derived in various studies. For instance, Álvarez et al (2005) found that the aggregation of agents following pricing rules with non-decreasing hazard functions generates an aggregate decreasing hazard function. In the same vein, Fougère et al (2007) accounted for sectoral heterogeneity by employing various covariates and obtained the aligned baseline hazard functions with that of the theoretical models. Similarly, Ikeda et al (2007) accounted for the heterogeneity among price-setters by employing the finite mixture model and estimated several hazard functions classified as flexible, Calvo, Taylor, and increasing hazard group. The price duration could vary across product groups, cities, and time. Different types of commodities exhibit varying behavior of price change. For instance, the age of prices for some commodities is found long-lasting, like, clothing and footwear, while prices of various other commodities are short-lived, like perishable food items.

Table 5[5] shows the estimation results for 9 commodity groups . The null hypothesis of constant hazard, i-e, $H_0 : \; = 1$ or equivalently $H_0 : \ln() = 0$, is rejected significantly for all types of groups. The rejection of the null hypothesis proves the appropriateness of the model. Table 5 reveals that all nine groups exhibit the value of ¿1, thus all the groups must be characterized, either as a high-frequency group or an increasing hazard group.

Table 5: Group-wise Estimation Results; Weibull Distribution

Commodity Groups		
Group1: Staple Food Items	1.102*	-3.418*
	-0.0128	-0.111
Group2: Perishable Food Items	1.571*	-3.358*
	-0.0125	-0.0899
Group3: Clothing & Footwear	1.2011***	-6.072*
	-0.126	-1.315
Group4: Energy Goods	1.267*	-3.319*
	-0.021	-0.138
Group5: Other Necessities	1.325*	-5.605*
	-0.154	-0.97
Group6: Cooked Food Items	1.328*	-7.623*
	-0.124	-1.061
Group7: Meat & Dairy Products	1.807*	-6.321*
	-0.0211	-0.127
Group8: Cooking oil & Ghee	1.035	-2.959*
	-0.029	-0.214
Group9: Processed Food Items	1.300*	-3.516*
	-0.021	-0.155

Figures in parenthesis specify the standard errors
*Indicates 1% level of significance
** indicates 5% level of significance
***indicates 10% level of significance

[5] Product group 10, i-e, cigarette is excluded from the analysis as only single commodity is included in this group, because of which the results are not comparable with the rest of the product groups.

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Figure 8, also portrays the increasing hazard rates for all the groups . Based on figure 8, the above-characterized groups are classified into two categories. The first is the high-frequency group and the second is the increasing hazard group.

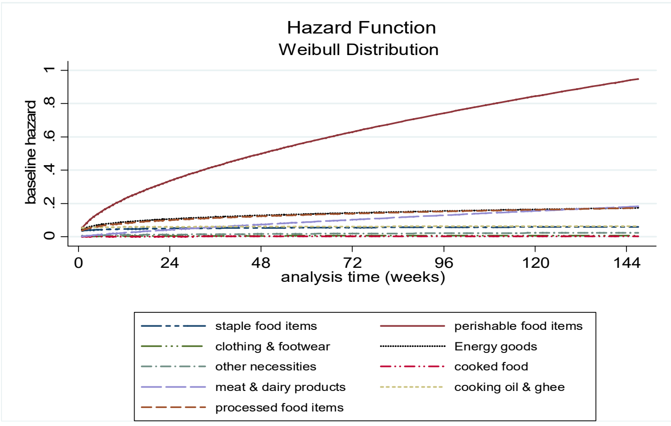

Fig. 8: Author's Illustration

Group 2, i-e, perishable food items, is classified as a high-frequency group. In this group, the frequency of price change is exceptionally high, which is found to be adjusted after about each week. Various perishable food commodities like tomato, onion, banana, garlic and potato are included in this group. As already described, several reasons are associated with the frequent price change of these products in Pakistan, for instance, expected as well as an unexpected rise in demand mostly associated with religious occasions, lack of administrative checks, lack of buyers altercation, various structural problems, inappropriate storage, and marketing mechanisms, etc.

The remaining groups are classified as increasing hazard groups. These staple food groups, clothing and footwear, energy goods, other necessities, cooked food, meat and dairy products, cooking oil and ghee groups, and processed food groups. This classification of groups is found to exhibit moderately increasing hazard rates, which shows that the probability of price change increases, the longer they remained fixed. Despite the methodological variations, these results are comparable with most of the literature, for instance, Álvarez et al (2005); Fougère et al (2007); Ikeda et al (2007); Nchake et al (2015).

As far as the pricing model followed by the commodities included in (i) high-frequency group and (ii) increasing hazard groups are concerned, the literature enlightens two standpoints. (i) According to Nakamura and Steinsson (2008), State-Dependent Pricing Models mostly engender nonconstant hazard functions. Nakamura and Steinsson (2008) pointed toward the relative significance of the type of shock. A permanent shock is more likely the source of persistence divergence from optimal price thus increasing the likelihood of price adjustment and escorting the increasing hazard rates. Whereas, relatively signif-

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icant temporary shocks escort hump-shaped or other nonconstant hazard rates.

(ii) In contrast, Ikeda et al (2007) empirically proved the upward sloping hazard functions to follow the Time-dependent pricing model by applying the methodology developed by Klenow and Kryvtsov (2008). Klenow and Kryvtsov (2008) stated that increasing hazard functions do not essentially connote State-dependent pricing models. They found their results consistent with Mash (2004).

6 Conclusion and Policy Implication

The study describes the price-setting behavior across seventeen large cities of Pakistan by employing the microdata from the retail price survey of fifty-three commodities. The survey was conducted by the Pakistan Bureau of Statistics to construct the Sensitive Price Index (SPI). The weekly dataset employed is from the 3rd week of October 2013 till the 4th week of September 2016. In this way, a total of 134,249 observations are included in the study. Further, these 53 commodities are then categorized into 10 product groups. Most of the analysis done in the study is based on these product groups.

A more contemporary approach is followed in the study, recognized as Survival Analysis. Survivor functions are estimated by employing two illustrious but simple nonparametric estimates of the functions, that is, Kaplan-Meier estimators and Nelson-Aalen Estimators. Whereas, Hazard Functions for all commodities at the aggregated level as well as for various product groups are estimated by employing the parametric Weibull Hazard Model.

The results confirm that the perishable food items have the shortest duration of one week for most of the spells. In this regard it is observed that the prices of perishable commodities rise as a result of soaring demand on special occasions or because of adverse weather conditions and floods. The condition, however, points towards the imperfect marketing mechanism and failure of external policy. In the short run, the most viable policy option is to import perishable commodities like onion, tomato, potato, bananas, and other fruits and vegetables, whose demands are expected to rise, from neighboring countries. Otherwise, the spells of high prices persist in an economy. Results of the study show that processed food groups, energy goods, and dairy and meat products also reveal the shorter duration of spells. In this regard, administrative control over prices could be a good option only if proper checks and balances would be ensured. Whereas, Staple food items and cooking oil and ghee are characterized as having the spells of intermediate durations. While, clothing and footwear, cigarettes, and cooked food reveal the long-standing spells.

The regression results obtained through Weibull Distribution Function show that government regulation caused the prices to change about 3.4 times as frequently as prices that are not controlled. Frequent change in energy prices (which are considered as regulated) directly impact the production and transportation cost. According to Carruth et al (1998), the rising price of energy goods slows down productivity growth and increases inflation, accelerating the rate of unemployment and vice versa. Hence, policymakers need to be cautious

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as the frequent change in energy price alter the prices of other goods and services.

It is found that on average Bannu, Khuzdar and Larkana faced lower hazards and thus comparably lesser price change. In March, April, and October the hazard of price change increased significantly. The results reveal the decreasing hazard rate for the overall price change behavior of the entire regular spells together. The downward sloping hazard functions, however, are believed to arise from the aggregation of heterogeneous commodities. The price duration and spells are believed to vary across product groups, cities, and times. Hence, taking the heterogeneity among products into account, several increasing hazard functions are derived in the study. Based on estimation results, nine commodity groups are classified into two categories. The first is the high-frequency group and the second is the increasing hazard group. Perishable food items are classified as a high-frequency group, whereas, staple food group, clothing and footwear, energy goods, other necessities, cooked food, meat and dairy products, cooking oil and ghee group, and processed food group are classified as increasing hazard group.

These results are believed to assist policymakers in assessing the pricing mechanism and inflation dynamics in Pakistan as price stickiness is fundamental in determining the intensity to which monetary policy could have a real impact on the economy. According to Choudhary et al (2011), monetary policy significantly influences prices with longer duration compared to the smaller ones.

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7 Appendix

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Table 6: Commodities in each Product Group

Group1:	Group2:	Group3:	Group4:	Group5:	Group6:	Group7:	Group8:	Group9:	Group10:
Staple Food Items	**Perishable Food Items**	**Clothing & Footwear**	**Energy Goods**	**Other Necessities**	**Cooked Food Items**	**Meat & Dairy Products**	**Cooking oil & Ghee**	**Processed Food Items**	**Cigarette**
Wheat	Bananas	Long Cloth	Electricity Chages	Energy Saver	Bread Plain	Beef	Mustard Oil	Wheat Flour	Cigarettes
Rice Basmati	Potatoes	Shirting	Gas Charges	Washing Soap	Cooked Beef	Mutton	Cooking Oil (Tin)	Tea (Packet)	-
Rice IRRI-6	Onions	Lawn	Kerosene	Match Box	Cooked Daal	Chicken	Vegetable Ghee (Tin)	sugar	-
Masoor Pulse	Tomatoes	Georgette	Fire Wood	Telephone	Tea	Milk	Vegetable Ghee (Loose)	-	-
Moong Pulse	Garlic	Sandal Gents	Petrol	Bath Soap		Curd	-	-	-
Mash Pulse	-	Chappal Sponge	Diesel	-	-	Milk Powder	-	-	-
Gram Pulse	-	Sandal Ladies	L.P.G.	-	-	Egg	-	-	-
Gur	-	-	-	-	-	-	-	-	-
Salt	-	-	-	-	-	-	-	-	-
Red Chilies	-	-	-	-	-	-	-	-	-

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A2: Weibull Distribution Function by Product Group (a – j)

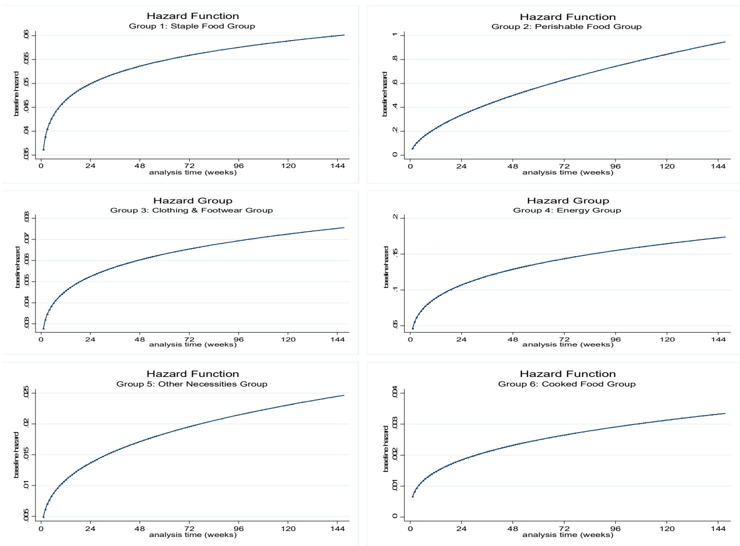

Fig. 9: Author's Illustration

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