NIPFP Working paper series

# Micro-level Price Setting Behaviour in India: Evidence from Group and Sub-Group Level CPI-IW Data

No. 217
27-Dec-2017
Shesadri Banerjee, and Rudrani Bhattacharya

**National Institute of Public Finance and Policy**
**New Delhi**

Working Paper No. 217

# Micro-level Price Setting Behaviour in India: Evidence from Group and Sub-Group Level CPI-IW Data

**Shesadri Banerjee[1] and Rudrani Bhattacharya[2,3]**


## Abstract

In the contemporary literature on macroeconomics, the mainstream frameworks for policy evaluation have recognized the significance of price rigidities emerging from the micro-level pricing behaviour of firms for explaining the short and medium run effects of monetary policy interventions. In this study, we evaluate stickiness in price adjustment for the aggregate Consumer Price Index for Industrial Workers (CPI-IW) and its major components in the context of Indian economy. Our findings broadly suggest greater monthly frequency of price changes and lower duration of price spell for food group, compared to non-food group. After controlling for small price changes due to sector-specific idiosyncratic shocks, stickiness in price-adjustment increases drastically for food components, corroborating to the high inflation persistence observed in the food sector in India in the recent past. We also find evidence of exogenous versus menu-cost driven pricing behaviour in India.


**Keywords:** Price stickiness, Time-dependent, State-dependent, Dip test, Silverman test, Indian economy.

**JEL Classification Codes:** E31, E52, E58

[1]Assistant Professor, Madras Institute of Development Studies, 79 Second Main Road, Gandhinagar, Chennai 600020, Telephone: 0091-44–24412589/24411574/24412295/24419771
Email: shesadri.banerjee@mids.ac.in

[2] Assistant Professor, National Institute of Public Finance and Policy, 18/2 Satsang Vihar Marg, Special Institutional Area, New Delhi 110067, Telephone: 011-26569303/26569780/26569784
Email: rudrani.bhattacharya@nipfp.org.in

[3] The paper is developed in aegis of National Institute of Public Finance and Policy, New Delhi, which is gratefully acknowledged. Mohit Srivastava is acknowledged for his competent research assistance. The usual disclaimer applies.

## 1. Introduction

In the contemporary literature on macroeconomics, the mainstream frameworks for policy evaluation have recognized the significance of price rigidities emerging from the micro-level pricing behaviour of firms for explaining the short and medium run effects of monetary policy interventions (Gali, 2002; Woodford, 2003; Gali, 2008). With the progress of analytical techniques, a strand of theoretical literature on price stickiness has been shaped (Rotemberg, 1982, Calvo, 1983 and Taylor, 1999). Over the years, researchers have identified the role of price rigidity and subsequently, the price setting mechanism of the firms in the dynamic interactions between inflation and output and the conduct of monetary policy in the economy. Given the significant policy implications of the micro-level price setting behaviour, it was much needed to find the empirical evidence for the theoretical conjecture of price rigidity. Since Bils and Klenow (2004), several studies were carried out across different countries in order to evaluate the degree of price stickiness from different perspectives. Following this stream of literature, we present a set of stylized facts on the frequency, size and distribution of price changes for the aggregate Consumer Price Index for Industrial Workers (CPI-IW) and its major components in the context of Indian economy. A battery of statistical measures and tests are instrumented to unearth the degree of price rigidities across the different sectors, synchronization between the frequency and size of price changes, and the behavioural patterns of the price setting mechanism. The results of our analyses would be useful to target appropriate inflation indicator, estimate the real effects of monetary transmission with sectoral pass-through, and design the optimal monetary policy in a multi-sector environment.

## 2. Macroeconomic Implications of Micro Level Pricing Behaviour

Nominal rigidity in the goods market, alternatively known as *price stickiness*, implies the nature of price not to adjust immediately in response to changes in market conditions (Hall & Yates, 1998). The role of price rigidity for generating the short run real effect of monetary policy works in the following way. When all prices in the market changes in response to a nominal shock simultaneously, the relative prices will remain unaffected and hence, the real side of the economy remains unaltered. However, if the market prices are staggered, all the prices will not adjust immediately after a policy shock. This sluggish adjustment entails to the short run movements of the relative prices, causes reallocation of resources and generates the output effects as observed in the data. Such nominal rigidity, which emerges from the price setting behaviour of firms, needs to be assessed in order to understand the microeconomic mechanisms of firm level pricing.

Theoretically, it is well established that degree of price stickiness determines the responsiveness of inflation to changes in the real marginal cost of production and subsequently, pins down the inflation and output gap nexus. It is also shown in the literature that the analysis of welfare loss function of the central banks due to macroeconomic volatilities critically depends on the degree of nominal friction prevailing in the economy. In addition to theoretical relevance, there are several practical implications for the empirical assessments of price stickiness both at the aggregate and disaggregated level Consumer Price Index (CPI). First of all, the persistence of inflation is largely governed by the degree of price stickiness. Second, the empirically observed hump-shaped response of the macroeconomic variables to monetary policy shocks hinges on the degree of price rigidity. Third, estimate of price stickiness directly affects the design of optimal monetary policy for an economy. Fourth, measurements of price stickiness based on aggregate-level data and micro-level data often leads to disagreement regarding the magnitude of nominal friction which is relevant for policy formulation. Finally, disaggregated analysis of price stickiness across the sectors or industries needs to be addressed in order to recognize the policy dilemma of the policymakers when targeting CPI inflation based on the measurement of headline vis-à-vis core inflation.

In view of these crucial implications, we examine the quantitative and qualitative features of nominal rigidity and price setting behaviour of the producers across the sectors using Consumer Price Index data for the industrial workers (CPI-IW) in India.

## 3. Stylized facts on Price Change for Indian CPI-IW Commodity Basket

Empirical evidence on price stickiness, both at the aggregate level as well as firm-level or sector-wise data, is available for the advanced and emerging economies. It is observed that degree of price stickiness, and therefore, the price-setting behaviour are substantially heterogeneous across the countries and the sectors (Dhyne et al., 2009). For example, the frequency of price change in the Euro area is found to be lower than those in the U.S. economy. Again, prices in the U.S. economy change less frequently than those in high inflation developing countries like Brazil, Chile, Mexico, and Slovakia (Klenow and Malin, 2010). Works done by Morande and Tejeday (2008) on Latin America, and Kovanon (2006) on Sierra Leone provide evidence on the sectoral heterogeneity of price stickiness. In the backdrop of cross-country and sectoral heterogeneity, our article explores price rigidity for the Indian economy from CPI-IW monthly data.

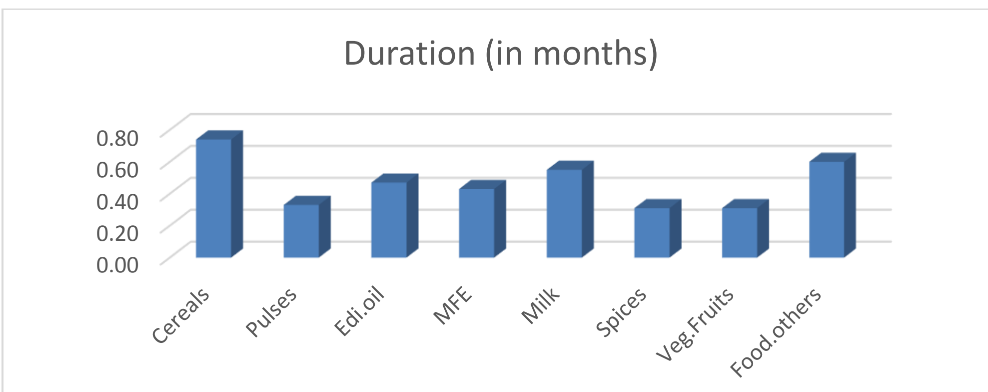
The CPI-IW data are provided by the Labour Bureau. The dataset spans from M01, 2006 to M10, 2016 covering the group and sub-group level observations. We classify the CPI-IW into two groups, namely, food and non-food, which are composed by the respective sub-group items. Our analyses run in two layers. At the outset, we look into the frequency and size of price changes of the group and sub-group level items. Then, we examine the behavioural pattern of price adjustment across the various items of the respective group. Following the relevant literature, we use some of the statistical measures and analytical tools for our purpose. These approaches together reveal the conduct of micro-level pricing for a representative group of commodities with a set of new observations.

### 3.1 Frequency of Price Change

We have examined the degree of price stickiness from the group level CPI-IW data which shows considerable heterogeneity in the price setting behaviour across the sectors within the economy. Using the methods of Indirect Frequency Approach, the frequency of price change is evaluated for each sector.[4] We have come up with the following observations.

First of all, the food sector (88% probability to price change in a month's time) features higher frequency of price change compared to the non-food sector (63%). There exists a modest variation in the intra-sectoral frequency of price change. It appears that half of the items of the food sector (pulses, protein items like meat-fish-egg, vegetable and fruits, and spices) experience price change in a month's time with a probability of 90% or more. For other half of food sector items, like cereals, milk, edible oil, and other foods, the probability comes down within the range of 80% to 90%. In contrast to the food items, non-food sector shows lower probability of price change which hovers around 69% excluding its housing component. The sector of housing service shows significantly lower frequency of price change with the probability of 16%. Probability of price change in the education sector also lies in a lower tier (50%). Medical and clothing items share similar frequency of price change such as 62% and 67% respectively. Fuel and light, transport and communications, and personal care closely resembles in their frequency of price change, which lie between 70% to 74%.

**Figure 1A: Duration of Price Spell for Food Sector**




[4] Following Kovanen (2006) and Morande and Tejeda (2008), we summarized the methodological details of Indirect Frequency Approach. We define an indicator function ($I_{it}$) such that it takes value 1 if the price of an item ($p_{it}$) at date *t* does not change from the previous period, and takes zero otherwise. Using this indicator function over the sample period, we get the value of indicator across the sectors (as given by 1.1), from which we derive the implied duration (as specified in 1.2) of a price spell.

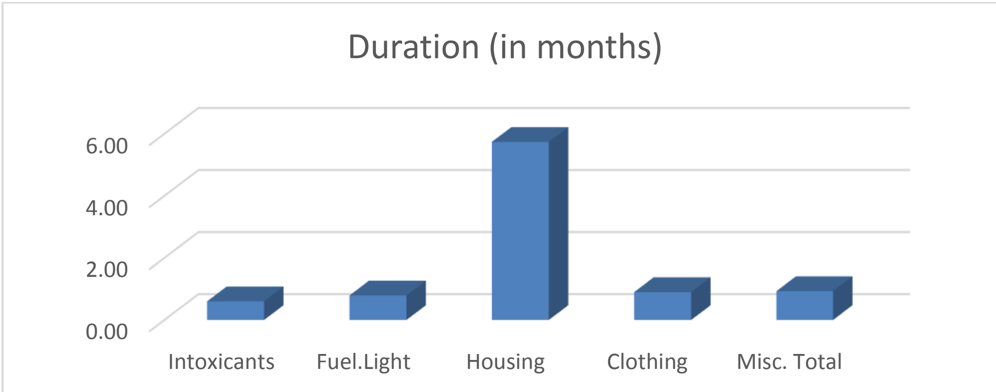
$I_{it} = 1 \; if \; p_{it} \neq p_{it-1}; i = 1, 2, \dots, k \; (number \; of \; sub-groups)$

$= 0 \; if \; p_{it} = p_{it-1}; \; t = 1, 2, \dots n \; (number \; of \; periods)$

$I_i = \frac{1}{n}\sum_{t=1}^{n} I_{it} \quad \forall i = 1, 2, \dots, k$ ............................ (1.1)

$D_i = -\left[\frac{1}{\{\ln(1-I_i)\}}\right] \forall i = 1, 2, \dots, k$ ............................ (1.2)

**Figure 1B: Duration of Price Spell for Non-food Sector**




Following the frequency of price change, the duration of price spell (in months) for the respective sector is computed and plotted in Figure 1A and 1B for the food and non-food industries. Given the observations from the frequency of price change, the plots of implied duration of prices suggest shortest duration of a price for the food products, as opposed to other groups such as education and housing, which are subject to very low frequency of price changes. Overall, the range of price spells across the industries is 5.4 months indicating the scope of sizeable price dispersion on the face of an exogenous shock.

## 3.2 Size of Price Change

In the context of micro-level pricing behavior, a common finding in the literature is that size of price changes, on an average, are large in the emerging markets (e.g., Barros et al. 2009, Konieczny and Skrzypacz, 2005).[5] This motivates us to examine the size of price changes at the group and sub-group level along with the frequency of price changes. We find that the size of price change varies across the product groups moderately (See Figure 2A and 2B).

For food sector, the monthly average size of price change is 0.79% while it is around 0.55% for the non-food sector. However, based on the difference between mean and median within each group, we find more pronounced dispersion (nearly twice greater) in the size of price change for non-food sector than food sector. It is also noticed that irrespective of group, monthly average and median price changes are highly correlated with the frequency of price change. The correlation coefficient between frequency and mean (median) size of price change values 0.55 (0.70) and it is statistically significant. This finding indicates the synchronization in the price changes, i.e., the response of prices to exogenous disturbances or shocks which can potentially alter the desired price of the firms. The positive association between the frequency and size of price changes is in line with the prediction of menu-cost models of

[5] For example, in the U.S. CPI data, Klenow and Kryvtsov (2008) report a mean (median) absolute change in posted prices of 14% (11.5%), while regular price changes are smaller but still large with a mean (median) of 11% (10%). The average consumer price decrease (increase) is 10% (8%) in the Euro area (Dhyne et al. 2006).

price adjustment which suggests that inflation is higher in the markets where price changes are more frequent.[6]

**Figure 2A: Size of price change in Food Items**

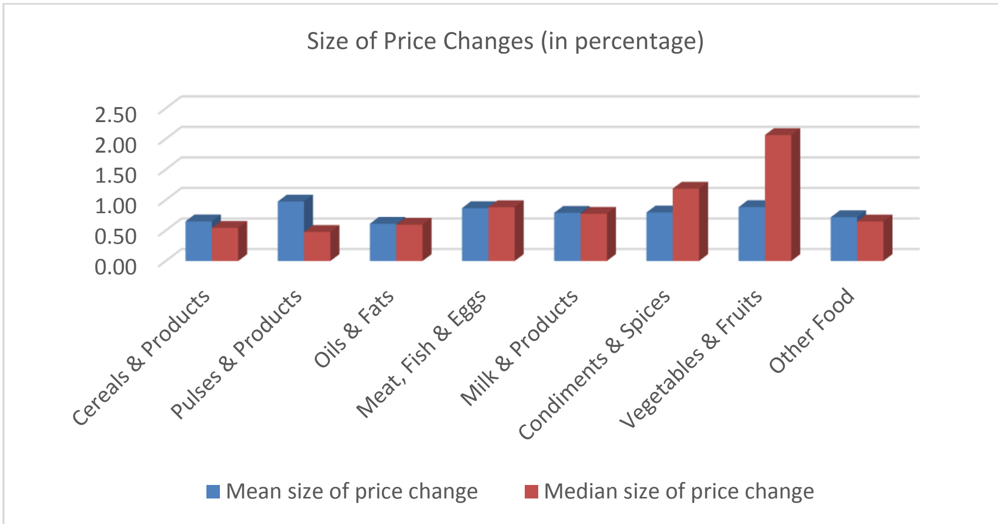
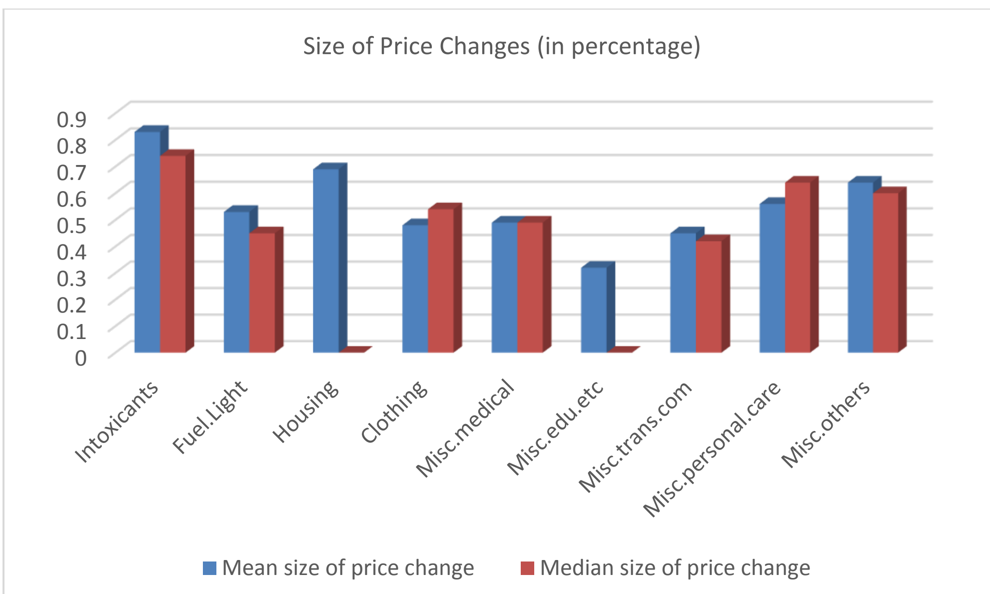



**Figure 2B: Size of price change in Non-Food Items**




Overall, the CPI-IW in India features high frequency of price changes, which can be attributed to the level and variability of inflation, frequency and size of cost and demand shocks, market structure and the degree of competition. While this high frequency of price changes fits well with the evidence of other EMEs, it stands in contrast to the finding of the advanced countries available in the literature. Vermeulen et al. (2007) and Peneva (2009) argue that

---

[6] See Barro (1972) and Taylor (1999).

goods with higher labor intensity are associated with less frequent price changes. But the evidence from CPI-IW data indicates this may not be true for India. In general, labour intensity is expected to be higher in the food sector compared to the non-food sector. Nevertheless, we find higher frequency of price changes for the food sector.

### 3.3 Role of Sector-specific Idiosyncratic Shocks on the Frequency of Price Changes

In the course of our empirical analysis, we have envisaged the role of sector-specific idiosyncratic shocks on the frequency of price changes. Due to impact of high magnitude adverse shocks, producers are often unable to cope up with their cost condition and pass on the burden to the buyers of the market by resetting their prices. Such effect of shocks comes out through the volatility of price change. Internalizing this volatility component in the Indirect Frequency Approach, we re-examine the frequency of price change across the sectors of the CPI-IW.

We observe substantial reduction in the frequency of price change for both food and non-food sector (See Figure 3A and Figure 3B). For food sector, the average (median) frequency of price change declines from 88% (89%) to 19% (18%). For non-food sector, the average (median) frequency of price change goes down from 62% (69%) to 27% (22%). This result emphasizes the role of sector-specific shocks which would affect the price adjustment of the firms in the respective sector. Moreover, it shows that food sector is more vulnerable to the shocks than the non-food sector.

**Figure 3A: Comparing Frequency of Price Changes in Food Sector**

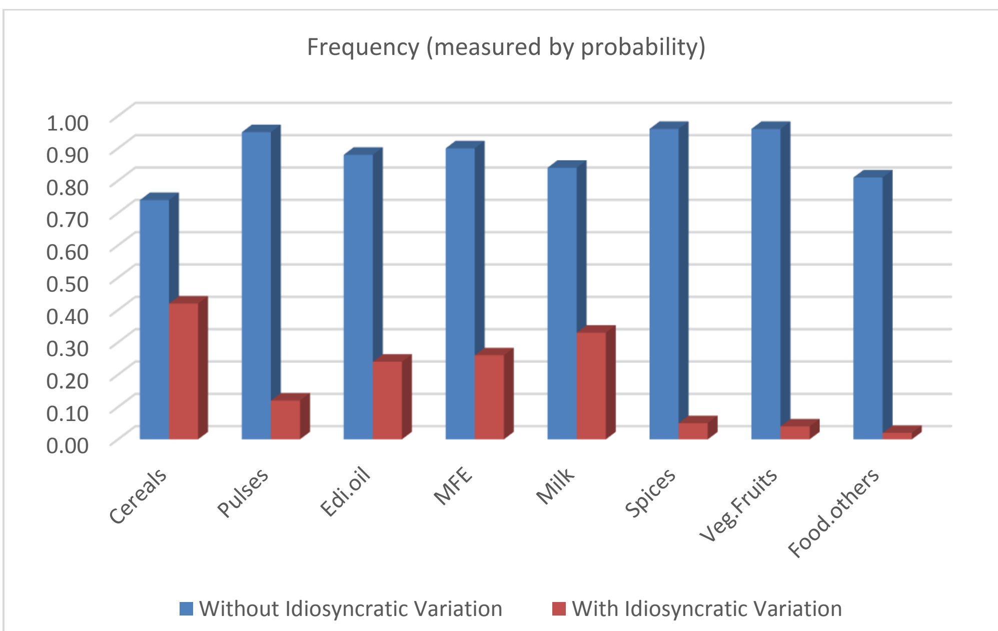
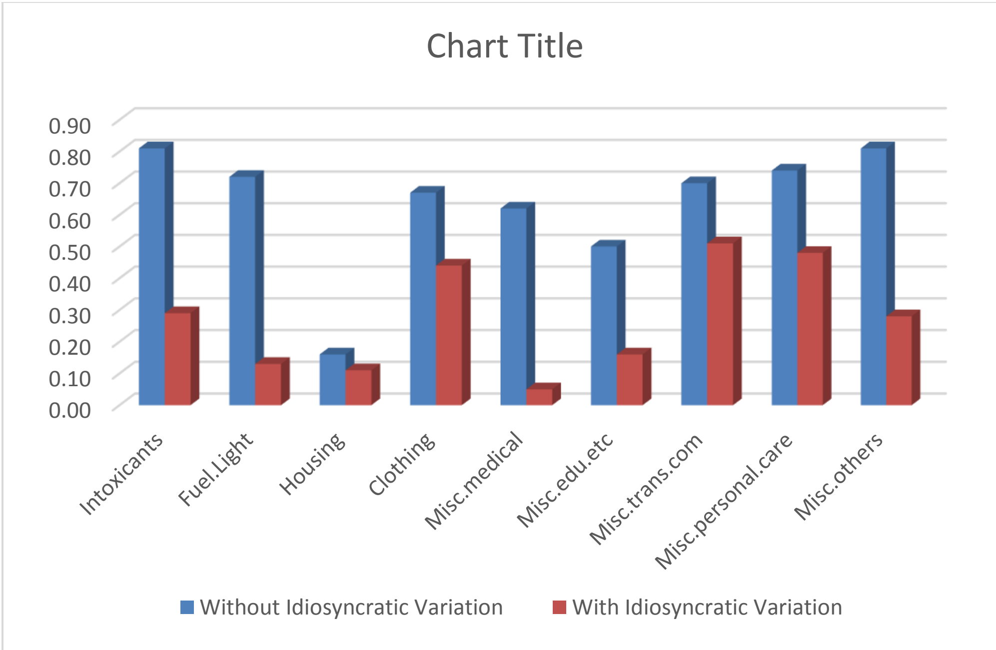


**Figure 3B: Comparing Frequency of Price Changes in Non-food Sector**




### 3.4 Characteristics of price setting behaviour: Time versus State Dependence

Along with the frequency and size of price change, the nature of price setting mechanism has also important implications for the monetary policy transmission in the economy. The price setting behaviour of producers can be either time-dependent (TD) or state-dependent (SD). In a staggered pricing environment, if the timing of price changes by an individual firm is exogenous, price setting mechanism is termed as time dependent. In a TD set up, a firm can adjust price at a fixed interval of time (Taylor, 1980; Taylor, 1999) or randomly (Calvo, 1983). In the literature, two types of exogenous staggering of price changes are available, namely, Taylor-type and Calvo-type price settings. In both cases, it is assumed that the fraction of firms adjusting their prices each period is constant (Klenow and Kryvtsov, 2008). In contrast to TD models, under SD type pricing mechanism, firms endogenously choose the timing of price changes depending on the costs associated to price changes, or menu cost. In this set up, firms choose to change prices if a specific event occurs and they gain by doing so (Klenow and Kryvtsov, 2008; Morande and Tejada, 2008). In other words, the timing and the magnitude of the firms' price changes depend on the state of the economy given the fixed menu costs (Dotsey et al., 1999; Klenow and Kryvtsov, 2008; Morande and Tejada, 2008). The pattern of monetary policy transmission to the real side of the economy differs distinctively under TD and SD type pricing mechanisms. Monetary policy shocks are found to have stronger and persistent effect on real output in TD models compared to SD models (Klenow and Kryvtsov, 2008; Gertler and Leahy, 2008). Given the policy trade-off between inflation and output gap for stabilization, the policy makers would face greater cost of disinflation under TD type price setting mechanism than the SD type pricing behaviour (Guimaraes, Mazini, and Mendonça, 2012). From the perspective of monetary policy transmission in an economy, therefore, it is important to identify empirically the nature of price adjustment mechanism of the aggregate, as well as sectoral prices in the country.

The time-dependence versus state-dependence of price adjustments have direct implications for the number of modes in the distribution of price changes (Cavallo and Rigobon, 2011). Under the time-dependent price adjustment process, distribution of price changes internalizes the distribution of cost changes to some extent. As cost changes tend to have unimodal distribution in a low inflation environment, one would expect to find unimodal distribution of price changes under TD type adjustment mechanism. On the other hand, under state-dependent price adjustment process, small deviations from the optimal price is less costly than the menu cost. As a result, in a low inflation environment, the distribution of price changes tends to have a bimodal distribution around zero percent with a positive and a negative mode (Cavallo and Rigobon, 2011). Hence, the estimation of mode from the distributions of price changes using modality test statistics facilitate to identify the underlying price setting mechanism of the firms. In our analysis, we estimate the number of modes in the distributions of changes in aggregate CPI-IW and its major components using Hartigan Dip test (Hartigan and hartigan, 1985) and Silverman test (Silverman, 1981). Table 1 shows the summary statistics of price changes in CPI-IW and its major components.

**Table 1: Summary statistics of price changes in CPI-IW and major groups**

| Item | No. of changes | Min (%) | Max (%) | Mean (%) | Standard Dev. |
|---|---|---|---|---|---|
| **Cereals & Products** | 83 | -1.65 | 4.04 | 0.65 | 0.85 |
| **Pulses & Products** | 76 | -9.91 | 17.29 | 0.97 | 3.20 |
| **Vegetables & Fruits** | 75 | -234.91 | 231.68 | 0.88 | 30.03 |
| **Milk & Products** | 107 | -0.34 | 3.03 | 0.79 | 0.58 |
| **Meat, Fish & Eggs** | 86 | -3.44 | 4.62 | 0.87 | 1.51 |
| **Oils & Fats** | 74 | -4.52 | 7.72 | 0.61 | 1.78 |
| **Condiments & Spices** | 75 | -235.14 | 240.20 | 0.79 | 30.31 |
| **Other Food** | 94 | -227.30 | 228.15 | 0.72 | 28.48 |
| **Food group** | 89 | -224.07 | 225.34 | 0.76 | 28.12 |
| **Pan, Supari, Tobacco & Intoxicants** | 104 | -0.60 | 4.12 | 0.83 | 0.70 |
| **Fuel & Light** | 76 | -1.53 | 4.96 | 0.53 | 0.97 |
| **Housing** | 21 | 0.00 | 15.62 | 0.69 | 2.11 |
| **Clothing** | 82 | -0.84 | 2.15 | 0.48 | 0.50 |
| **Medical Care** | 75 | -11.16 | 12.81 | 0.49 | 1.67 |
| **Edu. Rec. & Amusement** | 59 | -3.41 | 2.80 | 0.32 | 0.81 |
| **Transport & Communication** | 68 | -2.58 | 2.68 | 0.45 | 0.91 |
| **Personal Care & Effects** | 92 | -0.89 | 1.52 | 0.56 | 0.48 |
| **Misc. Others** | 102 | -0.63 | 2.23 | 0.64 | 0.55 |
| **Miscellaneous group** | 89 | -0.52 | 1.45 | 0.48 | 0.40 |
| **General index** | 95 | -1.66 | 4.47 | 0.66 | 0.81 |

In Hartigan's test, the Dip statistic is calculated to measure the deviation of an empirical distribution from the best fitting unimodal distribution. The Dip statistic is zero when the empirical distribution is unimodal. When the empirical distribution is multimodal, the cumulative distribution has multiple regions of convexity and concavity. In that case, the empirical distribution function stretches until it takes the shape of a unimodal distribution. As larger the stretch needed, larger will be the departure from unimodality and subsequently, larger will be the value of the Dip statistic. Hence, in Hartigan's test, positive Dip values provide evidence to reject the null hypothesis of unimodality.[7]

**Table 2: Results from Modality Tests**

| **Item** | **Dip test** | | | **Silverman test** | | |
|---|---|---|---|---|---|---|
| | Test statistics | p-value | Conclusion | Optimal no. of modes | p-value | Conclusion |
| **Cereals & Products** | 0.076 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 2 | P(m>k=1)=0.56; P(m<=k=2)=0.82 | Bi-modal |
| **Pulses & Products** | 0.034 | 0.3535 | Unimodal | 2 | P(m>k=1)=0.25; P(m<=k=2)=0.63 | Bi-modal |
| **Vegetables & Fruits** | 0.022 | 0.967 | Unimodal | 1 | P(m<=1)=0.51 | Unimodal |
| **Milk & Products** | 0.081 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 1 | P(m<=1)=0.84 | Unimodal |
| **Meat, Fish & Eggs** | 0.029 | 6.54E-01 | Unimodal | 1 | P(m<=1)=0.61 | Unimodal |
| **Oils & Fats** | 0.042 | 0.097 | Unimodal | 1 | P(m<=1)=0.69 | Unimodal |
| **Condiments & Spices** | 0.020 | 0.992 | Unimodal | 3 | P(m>2)=0.71; P(m<=3)=0.55 | Multimodal |
| **Other Food** | 0.089 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 2 | P(m>1)=0.72; P(m<=2)=0.52 | Bi-modal |
| **Food group** | 0.043 | 0.062 | Unimodal | 2 | P(m>1)=0.68; P(m<=2)=0.58 | Bi-modal |
| **Pan, Supari, Tobacco & Intoxicants** | 0.093 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 3 | P(m>2)=0.63; P(m<=3)=0.62 | Multimodal |
| **Fuel & Light** | 0.077 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 2 | P(m>1)=0.71; P(m<=2)=0.57 | Bi-modal |
| **Housing** | 0.024 | 0.916 | Unimodal | 2 | P(m>1)=0.687; P(m<=2)=0.74 | Bi-modal |

[7] For further details, see Cavallo and Rigobon (2011).

| | | | | | | |
|---|---|---|---|---|---|---|
| **Clothing** | 0.143 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 2 | P(m>1)=0.83; P(m<=2)=0.79 | Bi-modal |
| **Medical Care** | 0.114 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 3 | P(m>2)=0.68; P(m<=3)=0.56 | Multimodal |
| **Edu. Rec. & Amusement** | 0.116 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 3 | P(m>2)=0.79; P(m<=3)=0.74 | Multimodal |
| **Transport & Communication** | 0.062 | 5.00E-04 | non-uni-modal, i.e., at least bimodal | 2 | P(m>1)=0.84; P(m<=2)=0.75 | Bi-modal |
| **Personal Care & Effects** | 0.128 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 2 | P(m>1)=0.61; P(m<=2)=0.93 | Bi-modal |
| **Misc. Others** | 0.093 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 3 | P(m>2)=0.54; P(m<=3)=0.81 | Multimodal |
| **Miscellaneous group** | 0.147 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 2 | P(m>1)=0.90; P(m<=2)=0.91 | Bi-modal |
| **General index** | 0.085 | < 2.2e-16 | non-uni-modal, i.e., at least bimodal | 1 | P(m<=1)=0.66 | Unimodal |

Silverman's Bandwidth test is a non-parametric test that uses kernel smoothing technique to determine the most probable number of modes in an empirical distribution.[8] Under this test, the null hypothesis that the true density $f$ possesses at most k modes is tested against the alternative hypothesis that $f$ has more than $k$ modes. For the null hypothesis of $k$ modes, the test statistic is the critical bandwidth, i.e., minimum smoothing required for the smoothed kernel density to have at most $k$ modes. Large values of critical bandwidth are evidence against the null hypothesis, because larger degrees of smoothing are needed to eliminate additional modes in the density estimate. The statistical significance of critical bandwidth is evaluated using bootstrap method. For each bootstrap sample, the minimum bandwidth required to have at most $k$ modes is computed and the probability of it exceeding the critical bandwidth estimated from the data is calculated. This probability provides the significance of the test statistics. The resulting probability is equivalent to the share of bootstraps that have more than $k$ modes when evaluated at the critical bandwidth. The test is performed sequentially starting with critical no. of mode $k$ = 1, … M, until the probability value is sufficiently low, so that we cannot reject the null that the underlying density possesses at most M modes.[9]

[8] For a given sample, it estimates kernel density $f$ as a function of a smoothing parameter or bandwidth $h$ and a Gaussian kernel function K.

[9] For more details, see Silverman (1981); Cavallo and Rigobon (2011); Salgado-Ugarte et al. (1997).

Results of the modality tests are reported in Table 2. The results show that both the tests find that Vegetables and Fruits, Meat, Fish, & Eggs, and Oil & Fats are unimodal, implying that these three groups are subject to time-dependent price adjustment process. On the other hand, Cereals and Products, Other Food Group, Pan, Supari and Intoxicants, Fuel and Light, Clothing, and the aggregate and the components of Miscellaneous Group are detected to have more than one mode by both the tests. Among these cases of multiple modes, Cereals and Products, Other Food Group, Transport and Communications, Personal Care and Effects, and the aggregate Miscellaneous group are found to be bi-modal by the Silverman test.

There are a few instances when the two tests have different views regarding the number of modes in the series. As example, for the aggregate CPI-IW index, under the Dip test, the null of unimodal distribution is rejected; whereas the Silverman test suggest that CPI-IW possesses a unimodal distribution. The similar situation arises for the Milk & Products category. On the contrary, Pulses and Products, the aggregate Food group and Housing are found to be unimodal by the Dip test while the Silverman test suggests these series to have two modes. While the Dip test suggests that the group of Condiments and Spices has one mode, the Silverman's Bandwidth test shows that this group is multimodal.

The variation of the results across two tests can be due to the fact that in reality, price adjustment process of a commodity may not be uniquely time-dependent or state-dependent, rather, a combination of the two (Woodford, 2009; Alvarez, et al., 2010; Cavallo and Rigobon, 2011). As a result, the shape of the distribution function of price changes depends on the relative importance of the two types of pricing mechanisms (Cavallo and Rigobon, 2011). For the series detected as unimodal by both tests, and bi-modal by the Silverman test, we further test for the relative importance of time-dependent versus state-dependent elements in pricing, using Bimodality Coefficient (BC) test. The Bimodality Coefficient is a measure of the proportion of bimodality after correcting for the finite sample bias. The value of BC ranges from 0 to 1, where a value greater than "5/9" or greater than 0.556 suggests bimodality. The results are reported in Table 3.

The series which are detected as unimodal by both the tests namely, Vegetables and Fruits, Meat, Fish, & Eggs, and Oil & Fats, have a BC coefficient lower than the cut off value 0.556, implying that price adjustment mechanism is time-dependent in these series. Hence, we expect to have persistent real effects of monetary shocks in these sectors. Surprisingly, all the series which are detected as bi-modal by the Silverman test, except for Housing, also show the value of BC less than the cut off value 0.556, indicating the predominance of time-dependent element in price setting mechanism in these sectors. These series include Cereals & Products, Pulses and Products, Other Food group, the aggregate Food group, Fuel & Light, Clothing, the aggregate Miscellaneous group, Transport & Communications, and Personal care & Effects. These sectors are also expected to generate more persistent real effects of monetary policy. The BC value for the Housing sector is found to be 0.782, greater than the cut off value, indicating that the price adjustment process is state-dependent unlike the other sectors. Intuitively, a small deviation from the optimal price facing moderate change in demand condition of the housing sector is less costly than incurring the menu cost in this sector.

**Table 3: Results from Bimodality Coefficient Test**

| Item | Modality | Unimodal vs. Bi-modal | Higher relative importance |
|---|---|---|---|
| | Silverman test/ Dip test | BC | |
| **Cereals & Products** | Bi-modal | 0.357 | TD |
| **Pulses & Products** | Bi-modal | 0.270 | TD |
| **Vegetables & Fruits** | Unimodal | 0.018 | TD |
| **Meat, Fish & Eggs** | Unimodal | 0.339 | TD |
| **Oils & Fats** | Unimodal | 0.246 | TD |
| **Other Food** | Bi-modal | 0.015 | TD |
| **Food group** | Bi-modal | 0.015 | TD |
| **Fuel & Light** | Bi-modal | 0.390 | TD |
| **Housing** | Bi-modal | 0.782 | SD |
| **Clothing** | Bi-modal | 0.265 | TD |
| **Transport & Communication** | Bi-modal | 0.280 | TD |
| **Personal Care & Effects** | Bi-modal | 0.394 | TD |
| **Miscellaneous group** | Bi-modal | 0.388 | TD |

Some of the groups are found to have either more than two modes by the Silverman test or non-unimodal by the Dip test. The aggregate CPI-IW index, Milk & Products, Condiments & Spices, Pan, Supari, Tobacco & Intoxicants, Medical care, Edu. Rec. & Amusement, and the Other category in the Miscellaneous group fall into this class. Since testing for the proportion of unimodality versus bi-modality is not applicable for these groups, we instead test whether each of these series consists of one multimodal component or is a combination of multiple distributions with different frequencies, so that it appears as a multimodal distribution. To this end, we fit Gaussian mixture to the data by maximum likelihood through the Expectation-Maximisation (EM) algorithm. If a series is found to be a combination of multiple components, then we fit the data to a single component model. Next, a Likelihood Ratio (LR) test is performed to choose the model among the unrestricted multiple component model and the restricted single component model that best fits the data. The results are reported in Table 4.

**Table 4: Results from Gaussian Finite Mixture Model Test**

| Item | Modality | Gaussian Finite Mixture model | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Silverman test/ Dip test | L_U | df_U | No. of components | L_R | df_R | X^2=-2(L_R-L_U), df=df_U-df_R | p-value |
| **Milk & Products** | Non-unimodal | -111.7253 | 2 | 1 component | | | | |
| **Condiments & Spices** | Multimodal | -418.3608 | 8 | 3 components with unequal variances | -622.6371 | 2 | 408.5575, 6 | 0 |
| **Pan, Supari, Tobacco & Intoxicants** | Multimodal | -122.1034 | 4 | 2 components with equal variance | -136.797 | 2 | 29.38749, 2 | 4.16E-07 |
| **Medical Care** | Multimodal | -127.7863 | 5 | 2 components with unequal variances | -248.9808 | 2 | 242.3891, 3 | 0 |
| **Edu. Rec. & Amusement** | Multimodal | -119.2487 | 6 | 3 components with equal variance | -154.9258 | 2 | 71.35441, 4 | 1.18E-14 |
| **Misc. Others** | Multimodal | -67.95363 | 12 | 6 components with equal variance | -104.4578 | 2 | 73.00854, 10 | 1.16E-11 |
| **General index** | Non-unimodal | -155.8869 | 2 | 1 component | | | | |

The EM algorithm fits a one component model to the aggregate CPI-IW series and the Milk & Products series. Hence, we can infer that the distribution functions of CPI-IW and the Milk & Products group consist of multiple modes, indicating the prevalence of SD element in the price adjustment mechanisms in these series. For the rest of the series, the LR test suggests rejection of the null that the data best fits to a single component model. Therefore, the multiple modes in these series could be due to the fact that each series consists of multiple components of different frequencies. The existence of multiple modes in the distribution function in these series may not necessarily indicate relative importance of SD element in price setting mechanism in these series.

### 3.5 Policy Relevance for Micro-Level Pricing

The degree of price stickiness is one of the determinants of responsiveness of current inflation to output gap in the Phillips curve equation. Higher is the stickiness in price changes, lower is the response of inflation to changes in the real-side activities. It then follows that the extent of price stickiness also determines the optimal weightage assigned to inflation variation in the approximation of a representative consumer's welfare loss that serves as a quantitative basis for choosing the optimal monetary policy rule from a set of alternative policy rules (Rotemberg and Woodford, 1997). Higher is the degree of price stickiness, higher weightage is to be given on inflation variations to minimise the welfare loss. For effective implementation of monetary policy, it is essential to evaluate frequency and duration of price changes at the disaggregated level as well. If these vary substantially across sectors, then the welfare loss might need to be evaluated in a multi-sectoral framework, with sectoral price stickiness determining the optimal weights assigned to sectoral inflation variations.

A well-known dilemma central banks often face is the choice between headline inflation including food and core inflation as the target inflation indicator. Such dilemma is even more profound for emerging economies where food constitutes a substantial share of the consumption basket. The general equilibrium model based welfare analysis suggests that targeting broad CPI is welfare superior (Chang, 2010; Pesenti, 2013; Anand and Prasad, 2010; Soto, 2003). In fact, the majority of the emerging economies practicing Inflation Targeting (IT) monetary policy have chosen broad CPI as the underlying indicator for inflation target. However, the choice of headline inflation is often criticised on the ground that setting a target by the central bank involves medium to long term inflation forecasting which may be affected by large swings in commodity prices. Hence core inflation, i.e., headline inflation net of volatile items such as food needs to be chosen as the target.

India has entered into the IT monetary policy regime in the recent past with overall CPI being the underlying indicator for the inflation target. In this context, our analysis provides a ground for incorporating food in the inflation in the target. Our analysis shows that when small price changes are ignored, food sector records lowest frequency of price changes and long duration of price spell among the major sub-groups of CPI-IW. These findings conform to the high inflation persistence observed in the food sector in India in recent past. Hence, excluding Food group from the target inflation indicator assuming rapid changes in price in this sector may moderate the effectiveness of monetary policy. Overall, the results suggest that analysing the degree and pattern of price adjustment at the sectoral level is important for effective implementation of monetary policy.

## References

Alvarez, F. E., F. Lippi, and L. Paciello, 2010. "Optimal price setting with observation and menu costs," NBER *Working Paper Series*, No 15852, National Bureau of Economic Research.

Barro, Robert, 1972. "A Theory of Monopolistic Price Adjustment", *Review of Economic Studies*, 39(1): 17-26.

Barros, Rebecca, Bonomo, Marco, Carvalho, Carlos and Matos, Silvia, 2009. "Price Setting in a Variable Macroeconomic Environment: Evidence from Brazilian CPI", mimeo.

Calvo, Guillermo A., 1983. Staggered Prices in a Utility-Maximizing Framework, *Journal of Monetary Economics,* 12(3): 383–398.

Cavallo, Alberto and Rigobon, Roberto, 2011. "The Distribution of the Size of Price Changes", NBER *Working Paper No. 16760,* National Bureau of Economic Research.

Dhyne, Emmanuel, Luis J. Alvarez, Hervé Le Bihan, Giovanni Veronese, Daniel Dias, Johannes Hoffmann, Nicole Jonker, Patrick Lunnemann, Fabio Rumler and Jouko Vilmunen, 2006. "Price Changes in the Euro Area and the United States: Some Facts from Individual Consumer Price Data," *Journal of Economic Perspectives*, 20(2): 171-192.

Dotsey, M., King, R., Wolman, A., 1999. "State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output", *The Quarterly Journal of Economics,* 114(2): 655-690.

Gali, J., 2002. New Perspectives on Monetary Policy, Inflation, and the Business Cycle, *NBER Working Papers No 8767,* National Bureau of Economic Research.

_________, 2008. *Monetary Policy, Inflation and the Business Cycle: An Introduction to the New Keynesian Framework*, Princeton University Press, Princeton, New Jersey

Gertler, Mark and John Leahy, 2008. "A Phillips Curve with an Ss Foundation", *Journal of Political Economy,* 116(3): 533-572.

Guimaraes, Bernardo; Mazini, Andre and Mendonca, Diogo, 2014. "State-dependent or Time-Dependent Pricing? Evidence from Firms' Response to Inflation Shocks", mimeo.

Hall, Simon & Anthony Yates, 1998. "Are there downward nominal rigidities in product markets?," *Bank of England working papers No 80,* Bank of England.

Hartigan, J. A. and Hartigan, P. M., 1985. "The Dip Test of Unimodality," *The Annals of Statistics*, 13(1): 70–84.

Klenow, P., and Bils, M., 2004. "Some Evidence on the Importance of Sticky Prices", *Journal of Political Economy,* 112(5): 947-985.

Klenow, Peter J. and Kryvstov Oleksiy, 2008. "State-dependent or Time-dependent pricing: Does it Matter for Recent U.S. Inflation?", *The Quarterly Journal of Economics*, 123(3): 863-904.

Klenow, P. J., and Malin, Benjamin A., 2010. Microeconomic Evidence on Price-Setting, in *Handbook of Monetary Economics* 3A, B. Friedman and M. Woodford (ed.): Elsevier, 2011: 231-284.

Konieczny, Jerzy D. and Andrzej Skrzypacz, 2005. "Inflation and Price Setting: Evidence from a Natural Experiment", *Journal of Monetary Economics*, 52(3): 621-632.

Morande, Felipe and Tejada, Mauricio, 2008. Price Stickiness in Emerging Economies: Empirical Evidence for Four Latin American Countries, *Working Paper No. 286*, Department of Economics, University of Chile, Santiago.

Peneva, Ekaterina V., 2009. "Factor Intensity and Price Rigidity: Evidence and Theory," Finance and Economics Discussion Series 2009-07. Board of Governors of the Federal Reserve System (U.S.).

Rotemberg, Julio J., 1982. "Monopolistic Price Adjustment and Aggregate Output," *Review of Economic Studies*, Oxford University Press, 49(4): 517-531.

Rotemberg, Julio J., and Michael Woodford, 1997. "An Optimization-Based Econometric Framework for the Evaluation of Monetary Policy", in B.S. Bernanke and Rotemberg (eds.), NBER Macroeconomic Annual 1997, Cambridge, MA: MIT Press. 297-346.

Salgado-Ugarte, Isaas Hazarmabeth and Shimizu, Makoto and Taniuchi, Toru, 1997. "Nonparametric assessment of multimodality for univariate data", Stata Technical Bulletin-38.

Silverman, B. W., 1981. "Using Kernel Density Estimates to Investigate Multimodality," *Journal of the Royal Statistical Society*. Series B (Methodological), 43(1): 97–99.

Taylor, John B., 1980. "Aggregate Dynamics and Staggered Contracts," *Journal of Political Economy*, 88(1): 1–23.

___________, 1999. Staggered Price and Wages Setting in Macroeconomics. In: John Taylor, J., Woodford, M. (Eds.). *Handbook of Macroeconomics*, 1B (New York: Elsevier): 1009-1044.

Vermeulen P, Dias D, Dossche M, Gautier E, Hernando I, Sabbatini R, Stahl H, 2007. Price Setting in the Euro Area: Some Stylised Facts from Individual Producer Price Data, *European Central Bank Working Paper, No 727*, European Central Bank.

Woodford, M., 2003. *Interest and Prices: Foundations of a Theory of Monetary Policy*, Princeton University Press, Princeton, New Jersey.

___________, 2009. "Information-constrained State-dependent Pricing," *Journal of Monetary Economics*, 56(*Supplement):* S100 – S124.

## MORE IN THE SERIES

- Hazarika, B., (2017). Decomposition of Gender Income Gap in Rural Informal Micro-enterprises: An Unconditional Quantile Approach in the Handloom Industry, WP No. 216 (Dec).
- Pandey, R., Sapre, A., and Sinha P., (2017). What does the new 2011-12 IIP series tell us about the Indian manufacturing sector? WP No. 215 (Nov).
- Barua, R., Goel, P., and Sane, R., (2017). The Effect of Age-Specific Sex Ratios on Crime: Instrumental Variable Estimates from India, WP No. 214 (Nov).

Shesadri Banerjee, is Assistant Professor, Madras School of Development Studies
Email: shesadri.banerjee@mids.ac.in

Rudrani Bhattacharya, is Assistant Professor, NIPFP
Email: rudrani.bhattacharya@nipfp.org.in

National Institute of Public Finance and Policy,
18/2, Satsang Vihar Marg,
Special Institutional Area (Near JNU),
New Delhi 110067
Tel. No. 26569303, 26569780, 26569784
Fax: 91-11-26852548
www.nipfp.org.in