Decrypting Inflation Inequality in India*

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Abstract

This paper studies inflation inequality in India for the period 2015-2024 using the consumer price indices and Household Consumption Expenditure Survey (HCES) 2011-2012. I construct consumer price indices for the household quintiles based on Monthly Per Capita Expenditure (MPCE). The analysis of the indices for different quintiles shows a high cross-sectional dispersion of inflation rates across the quintiles. However, the average inflation rates for the entire period of the study are similar for quintiles. Moreover, I find that the volatility of the inflation rate is higher for households in quintiles with lower MPCE. This finding implies that lower MPCE households experience higher volatility in inflation than higher MPCE households. To facilitate the discussion of inflation inequality, I construct inequality intervals using inflation rates for the quintiles. The inequality intervals can be used to inform the discussion on inflation and monetary policy.

Keywords: Inflation Inequality, Consumer Price Index, Monetary Policy

JEL Codes: C43, D11, E31, E50, I30

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1. Introduction

Inflation can be heterogeneous across households based on their income, sector of employment, and location, among others. Even though households in the economy participate in the same markets as consumers, they face inflation differently. The variation in inflation arises from heterogeneity in households' consumption baskets. Since the prices of different goods change at different rates in an economy, the distinct consumption baskets of the households expose them to different inflation rates.

In a major reform in monetary policy in 2016, the Reserve Bank of India (RBI) formally adopted the Flexible Inflation Targeting (FIT)[i]. The primary objective of monetary policy under FIT was explicitly stated as maintaining price stability. The objective of monetary policy was then defined in terms of controlling headline consumer price inflation, as measured by the Consumer Price Index (CPI). However, even when the headline inflation rate measured by the CPI is targeted with the monetary policy, consumer price inflation can vary across households in the economy. It is therefore important to understand if all households are facing similar rates of inflation or if there are households that are disproportionately affected by price fluctuations in the economy.

In this paper, I study the inflation inequality among households in the Indian economy for the period 2015-2024. I examine the cross-sectional dispersion of inflation and the variation of average inflation rates across quintiles based on the Monthly Per Capita Expenditure (MPCE). I also study whether there is heterogeneity in the volatility of inflation experienced by households in different quintiles.

I divide the sample of households in the Household Consumption Expenditure Survey (HCES) 2011-2012 into quintiles based on the MPCE of the households. I then compute the weights for the items in the consumption basket of the households for each quintile. The computation of weights for items in the quintiles is in line with the methodology of the Central Statistics Office (CSO), which is used to calculate weights for items in the CPI index

(CSO 2015). In addition to the weights for items computed using the HCES, I use CPI item indices from the CPI archives to construct the CPI indices for the quintiles. I use the HCES 2011-2012 because the weights for items in the official inflation rates are based on this survey. This study initially replicates the CPI (Combined) index on which the official headline inflation rate is based and then subsequently uses the same methodology to construct the quintile indices and corresponding inflation rates for the quintiles.

Based on the quintile indices, I find that the cross-sectional dispersion of inflation rates is high across the quintiles for the period 2015-2024. However, the average inflation rates for the entire period of the study are similar for quintiles. Interestingly, the volatility in inflation decreases monotonically across quintiles as MPCE increases. This result implies that households in the quintiles with lower MPCE face higher volatility in inflation rates in comparison to higher MPCE households. The analysis also showed that lower MPCE households have a higher share of consumption expenditure on food and fuel in total consumption expenditure in comparison to the higher MPCE households. In general, food and fuel inflation are more volatile compared to other components of CPI, this makes the inflation faced by the lower MPCE households more volatile.

This paper contributes to the existing literature in two ways. Firstly, it formulates a methodology to compute consumer price indices for different income groups. The methodology is formulated along the lines of the methodology laid out by the CSO which is used for the calculation of the CPI. Secondly, this paper contributes by exploring the question of inflation inequality in the context of India. There is an evolving literature on inflation inequality over the years. Broadly, in recent studies, there is emerging evidence of the existence of inflation inequality across households in the economy (Argente and Lee 2021; Jaravel 2019; Kaplan and Schulhofer-Wohl 2017). However, the literature on inflation inequality has largely focused on households in the US and the UK. This study extends the current literature by exploring inflation inequality in the context of India.

I also compare the results of this study with the global trends. The finding of high cross-sectional dispersion of inflation rates is in alignment with the recent literature (Argente and Lee 2021; Jaravel 2019; Kaplan and Schulhofer-Wohl 2017). However, the study also finds that average inflation rates for the entire period of the study are similar for quintiles, which is in contrast with the same literature. In addition, I construct inequality intervals using the inflation rates corresponding to the different quintiles, which can be used to inform the discussion on inflation and monetary policy. I also discuss the suggestion made by the economic survey to explore targeting the inflation rate excluding food inflation (Ministry of Finance 2024). In this context, I highlight the observation of the high share of food and fuel in the total expenditure of lower MPCE households. The exclusion of food inflation in targeting the inflation can disproportionately affect the lower MPCE households.

The rest of the paper is organized as follows. Section 2 provides review of the literature on inflation inequality. Section 3 describes the data used in the study. Section 4 lays out the methodology. Section 5 presents the result of the study. Section 6 discusses the results in the context of current developments in literature and policy. Lastly, section 7 concludes.

2. Literature Review

In the earlier literature, the evidence on the existence of heterogeneity in inflation is mixed across the income distribution. Some studies find that there is no significant variation in inflation across households. Among the earlier works, Garner et al. (1996) calculates an experimental CPI for poor consumers in the US for the period 1984-1994. They find that there was little difference between the calculated experimental CPI for poor consumers and the corresponding CPI for the whole sample. In another study on US consumers, McGranahan and Paulson (2005) construct the inflation measures for 31 demographic groups in the US using the Consumer Expenditure Survey and CPI for the period 1982-2004. The study finds that the group-specific inflation rates are similar to the overall inflation rate and the differences from the overall inflation rate are modest.

In contrast to the findings of no significant heterogeneity in inflation across households, some studies in the earlier literature find a significant variation in inflation across households. Oldfield and Crawford (2002) study the distribution of inflation for households in the UK for the period 1976-2000. They find a high degree of cross-sectional variation in inflation across the households. The study also finds a positive relationship between inflation rates and dispersion in the inflation rates among households, i.e., when the inflation was high, the dispersion also tended to be high. The study underlines that the headline average inflation rate is not close to the actual rate of inflation faced by individual households. On the other hand, Broda and Romalis (2009) use the consumption data on non-durable goods for US households for the period 1994-2005. The study finds that lower-income households face lower inflation than higher-income households.

In another study on US consumers, Hobijn and Lagakos (2005) find that the inflation experiences of US households vary significantly for the period 1987-2001. According to the study, the differences in the experiences are related to the changes in the relative price of education, healthcare, and gasoline. They also find that the cost of living of poor households is most sensitive to fluctuations in gasoline prices.

The evidence of inflation inequality has been ambiguous in the earlier literature. However, in the recent literature, there is an emerging convergence of the views. In a recent study, Jaravel (2019) measures the inflation inequality among US households over the full consumption basket for the period 2004-2015. The study finds that inflation declines linearly across income deciles. In another study, Kaplan and Schulhofer-Wohl (2017) use the Nielsen data which consists of 500 million transactions of US households for the period 2004-2013. The study finds significant heterogeneity in inflation rates at the household level.

Argente and Lee (2021) also study the US households for the period 2004- 2016 using the Nielsen data. The study finds that higher-income households face lower inflation. The study also highlights the ability of high-income households to adjust their shopping behavior to mitigate negative income shocks, as the underlying reason for the differences in inflation rates faced by lower-income and higher-income households. Jaravel (2021) in their review points towards an emerging empirical consensus on the idea that inflation varies across the income distribution as well as across locations.

3. Data

I use the CPI index data released by the CSO to calculate the inflation rates. The current base year for the data is 2012. The prices are collected every month from 1181 villages and 1114 markets in 310 towns, this covers all districts of India (NSO 2022). I focus on the CPI (Combined) and all-India CPI item indices. Items in CPI refer to the commodities in the consumption basket of the consumers. The indices are available at the CPI archives maintained by the Ministry of Statistics and Programme Implementation (MoSPI). There are 299 item indices which comprise the bucket of CPI (Combined). CPI (Combined) index is the index using which the official headline inflation is calculated. The index is available for the period January 2013 to August 2024. The data for the item indices is available for the period January 2014 to August 2024. It must be noted that during this period, the item indices are not available for the period March-May 2020.

In addition to CPI indices data, I use the 68th round of the National Sample Survey (NSS) which is the Household Consumption Expenditure Survey (HCES) 2011-2012 data. HCES geographically covers all parts of India except some areas of Nagaland and Andaman and Nicobar Islands. In HCES, the Type 2 schedule is used for the analysis. The random sample of households for the Type 2 schedule of the HCES consists of 101,651 households. The survey collected information on the quantity and value of household consumption for over 340 items. Since the weighing diagrams and the basket of goods in the CPI are constructed using the HCES 2011-2012 data, HCES is therefore instrumental for CPI (CSO 2015).

The schedules for inquiry in HCES 2011-2012 were of two types: Type 1 and Type 2. In this paper, data collected with the Type 2 schedule of HCES is used to compute the weights for items. The Type 2 schedule consists only of observations with reference period as the Modified Mixed Reference Period (MMRP)[ii]. Since CSO also uses the Type 2 schedule data, using it to compute the weights for items ensures that computed weights for items are comparable to the official weights for items in the CPI (CSO 2015).

4. Methodology

4.1. Computation of Index Weights

The CSO compiles the CPI Indices in two stages. In the first stage, price indices are calculated for elementary aggregates. The aggregates are known as item-level indices. In the second stage, the elementary aggregates are aggregated using consumption expenditure as weights. The aggregation is done using the Laspeyres index formula as follows:

$$P_L = \frac{\sum_{i=1}^{N}(P_i^t \cdot Q_i^0)}{\sum_{i=1}^{N}(P_i^0 \cdot Q_i^0)} \tag{1}$$

where P_i^t represents the price of item i at time t, Q_i^t represents the quantity of item i at time t, and P_L is the Laspeyres index. The index formula can also be written as follows:

$$P_L = \sum_{i=1}^{N} \frac{P_i^t}{P_i^0} \times W_i \tag{2}$$

where W_i is the share of expenditure of item i in the total expenditure. W_i therefore, represents the weight for item i. I use the methodology laid out by CSO to replicate the CPI (Combined) using CPI item indices (CSO 2015). In line with the CSO methodology, I use the HCES data to compute the weights for items in the CPI. The weight for an item is calculated by dividing the total expenditure on the item by all the households by the total expenditure on all the items by all the households.

The consumption items are classified under various groups and sub-groups under CPI, among other levels of classification. The group and sub-group are determined by the first and first six letters of the CPI item code respectively. For example, for the CPI item code "6.1.01.3.1.05.X" the group will be "6" and the sub-group will be "6.1.01". A group is a higher level of classification and a sub-group is a lower level of classification. A group will therefore contain multiple sub-groups. In this example, "6" is the code corresponding to the group "Miscellaneous" and "6.1.01" is the code corresponding to the sub-group "Household goods and services". Please refer to CSO (2015) for a detailed description.

Broadly, the items included in the basket to calculate total expenditure are similar during the calculation of MPCE in HCES and in the calculation of weights for items in the CPI. However, there are two major differences. Firstly, there are differences in the calculation of expenditure on "Housing" in CPI and HCES (Goyal et al. 2021). In CPI, "House Rent" expenditure includes both actual rent expenses as well as imputed rent of owner-occupied houses. However, HCES includes only the actual rent and does not include the imputed rent for the calculation of MPCE. The data for imputed rent expenditure is provided in the HCES data but the imputed rent expenditure is not included in the total expenditure while calculating the MPCE. To address this concern, I include the imputed rent expenditure in the calculation of total expenditure in HCES.

Secondly, the weight for the CPI group "Housing" for the rural sector is zero in the official CPI weights (CSO 2015). It implies that while calculating the CPI weights, CSO does not include the expenditure on housing for the rural sector. To maintain consistency with the CPI weights, I replace the expenditure values under the HCES items corresponding to "Housing" for households in the rural sector as missing. Therefore, the calculation of total expenditure using HCES does not include expenditure for "Housing" for the rural sector.

After accounting for the above differences, I then match the items in HCES with the items in the CPI. However, all the items in HCES could not be matched with the items in CPI. There are unmatched items in the HCES because the items in HCES have to satisfy certain inclusion criteria to get included in the CPI basket (CSO 2015). Furthermore, CSO's methodology for the compilation of the CPI indices combines the weights for the unmatched items in HCES with similar items or other items in the section/group/sub-group in the CPI basket. However, CSO does not provide the details of how the weights for the unmatched items in the HCES are exactly distributed over the other similar items in the CPI basket.

Since the distribution of weights for the unmatched items across the CPI basket is not provided by the CSO, I use the sub-group classification in the CPI to distribute the weights. In the next step, I impute the CPI sub-group of the unmatched items in the HCES. The objective of the imputation is to assign a CPI sub-group to each unmatched HCES item assuming that they were part of the CPI basket. The imputation of the CPI sub-group for an unmatched HCES item is based on the CPI sub-groups of the similar matched items in the HCES. I then use the imputed CPI sub-groups to distribute the weights for unmatched items in the HCES among the items in the CPI within the same CPI sub-group. Further details on the computation of weights for items are provided in Appendix A.

An additional issue in using the item indices was the absence of the item indices for some items during a month. The absence of the item indices can create bias in the computed CPI indices. To address this, I impute the item indices. I use the methodology used by the NSO to impute the item indices during COVID-19 (NSO 2020). The details of the imputation can be found in Appendix B. The CPI item indices after imputation and weights for items computed above are then used to replicate CPI (Combined).

4.2. Computation of Quintile Indices

I divide the HCES households into quintiles based on the MPCE of the households. To divide the sample, I use the household weights provided in the HCES. The summary statistics for MPCE across quintiles are presented in Table 3 in Appendix C. For each quintile, I compute separate weights for items by sub-setting the HCES data for the quintile and then using the methodology laid out above, for each quintile. The Laspeyres index formula for quintiles can be written as follows:

$$P_L^q = \sum_{i=1}^{N} \frac{P_i^t}{P_i^0} \times W_i^q \tag{3}$$

where, P_i^t represents the price of item *i* at time *t*, W_i^q is the share of expenditure of item *i* in total expenditure or the weight for item *i* in quintile *q*, and P_L^q is the Laspeyres index for quintile *q*. The CPI indices for quintiles can then be calculated using the weights for items in the quintiles computed above and the CPI item indices.

It should be noted here that for a particular time period, the price relatives (P_i^t/P_i^0) are constant whereas the weights for items are variable across quintiles. The heterogeneity in weights for items across the quintiles underlies the heterogeneity in Laspeyres indices for the quintiles. The weights for items, on the other hand, are constant across time whereas the price relatives are variable for a particular quintile.

It is important to note that MPCE is used as a proxy for income to divide the households into income quintiles. This is because of the absence of data on household income in HCES. Therefore, the quintiles are also referred to as income quintiles in this paper.

5. Results

I compare the official group weights in CPI (Combined) with the corresponding group weights computed above using the HCES. I add the weights for items in a CPI group, computed with the methodology discussed above, to calculate the weight for the CPI group. I compute the group weights for rural, urban, and combined and compare them with the group weights of CPI (Combined) in Table 1. It can be observed that the computed weights closely match the official weights for the CPI groups.

	CPI weights (Official)			Computed HCES weights		
	Rural	Urban	Combined	Rural	Urban	Combined
Food and beverages	54.18	36.29	45.86	54.17	36.29	45.79
Pan, tobacco and intoxicants	3.26	1.36	2.38	3.26	1.36	2.37
Clothing and footwear	7.36	5.57	6.53	7.35	5.57	6.52
Housing	–	21.67	10.07	–	21.75	10.19
Fuel and light	7.94	5.58	6.84	7.94	5.58	6.84
Miscellaneous	27.26	29.53	28.32	27.28	29.45	28.30

Table 1: Comparison of computed weights and official weights for CPI groups (Source: CSO 2015 and author's calculations)

Figure 1 shows the weights for the CPI groups for the five quintiles. It can be observed from Figure 1 that the weight for the food and beverages group is highest for the first quintile (lowest MPCE) and decreases monotonically across quintiles as MPCE increases. A similar trend is observed for clothing and footwear, and fuel and light. In contrast, the opposite trend is observed for housing and miscellaneous, group weight increases monotonically across quintiles as MPCE increases. The CPI group of *pan*, tobacco and intoxicants, does not show any consistent trend.

It can also be seen from Figure 1 that lower MPCE households have a higher weight for food and fuel in their basket of goods compared to other quintiles. On the other hand, higher MPCE households have a higher weight for housing and miscellaneous in their baskets of goods compared to other quintiles. Since food and fuel in general are more volatile than other components of CPI, this would make CPI for lower MPCE households more volatile than the higher MPCE households.

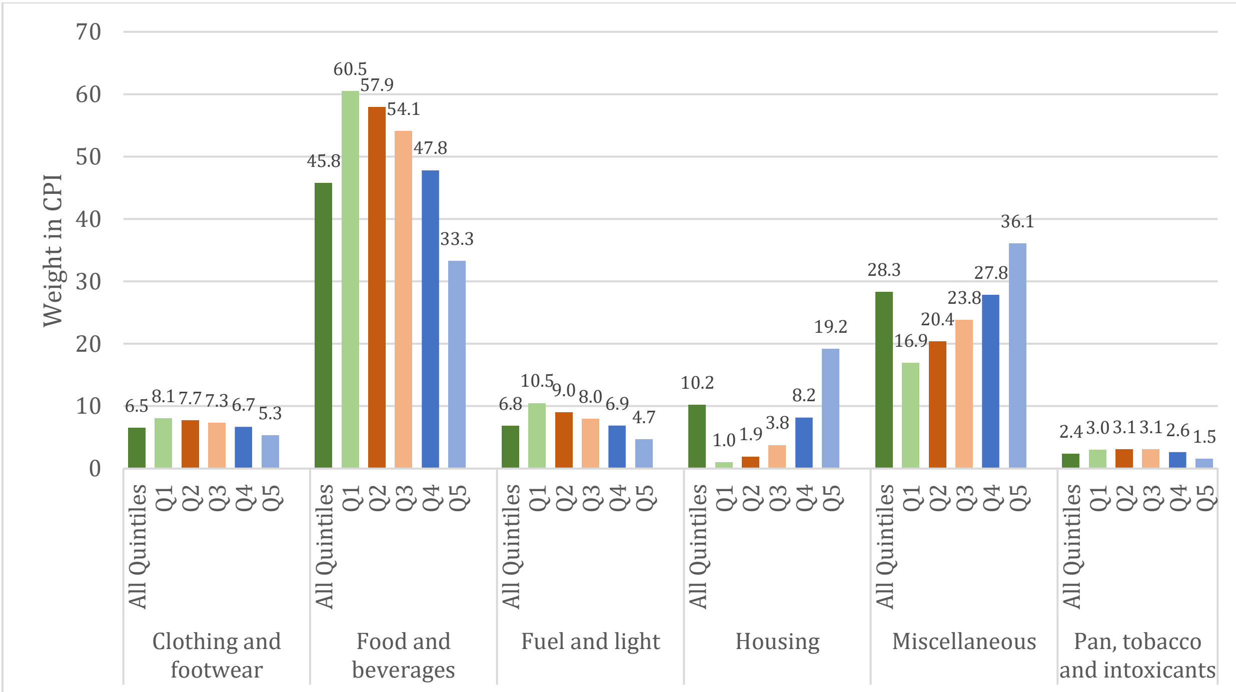

Figure 1: Weights for CPI groups across quintiles (Source: Author's calculations)

The computed index CPI (All quintiles - Computed), which consists of households from all quintiles and replicates the CPI (Combined), follows the CPI (Combined) closely. The error as measured by the difference between CPI (Combined) and CPI (All quintiles - Computed) as a percentage of CPI (Combined) is low and ranges from -0.22% to 0.48%. It can be observed from Figure 2 that the CPI inflation rate (YoY%) calculated using CPI (Combined) and CPI (All quintiles - Computed) are similar. Inflation computed using CPI (Combined) is referred to as CPI Inflation (All quintiles - Official) in Figure 2 to avoid confusion. The deviations of the computed inflation rate from the official inflation rate arise due to the error associated with the distribution of the weights of the unmapped HCES items among the CPI items and the error associated with the imputation of CPI item indices for some months as discussed previously.

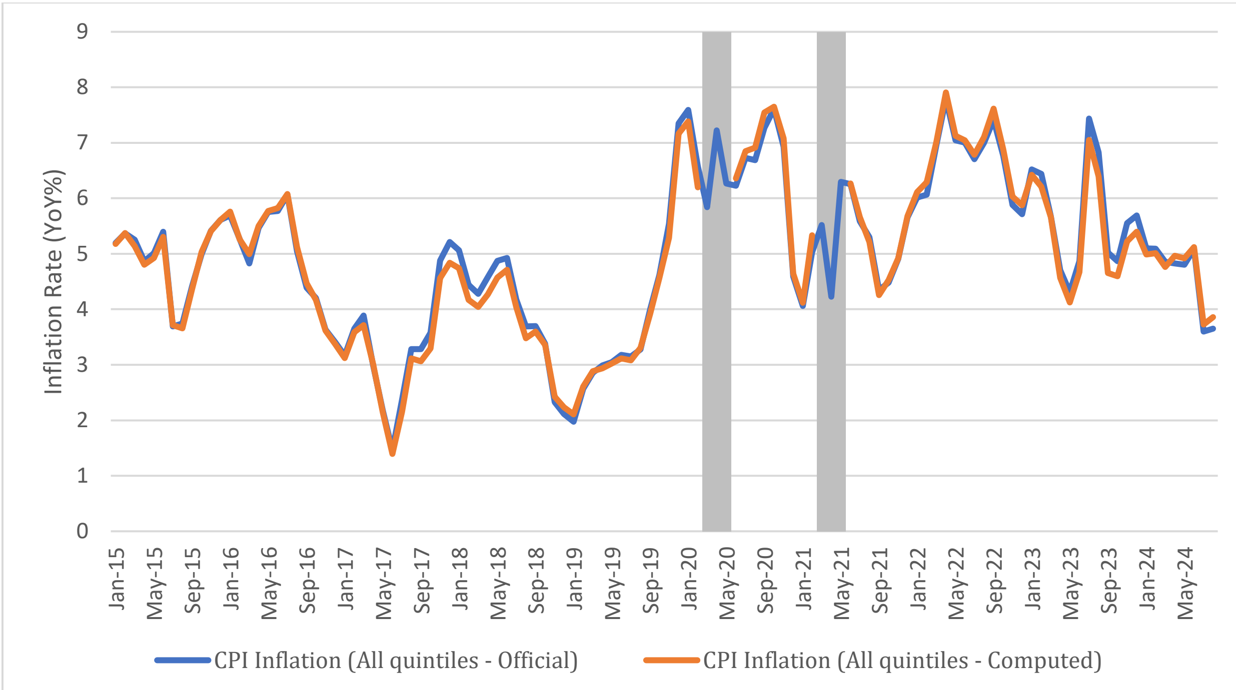

Figure 2: Comparison of official CPI inflation rate (YoY%) with the CPI inflation rate (YoY%) computed using item indices and item weights (Source: Author's calculations)

Note: The shaded region in the figure indicates the periods for which the CPI indices were not computed due to the unavailability of official CPI item indices

Table 2 presents the summary statistics for the official inflation rates, computed inflation rates for the quintiles, and the cross-sectional spread of inflation rates across quintiles. Similar to the headline inflation rate, I calculate the inflation rate as a Year-on-Year (YoY) percentage change in the computed CPI indices for the respective quintiles. The period for which the data is provided is January 2015 to August 2024. There are however gaps in the computed indices since the item indices are not available for the March-May 2020. Due to this, the inflation numbers for March-May 2020 and March-May 2021 could not be computed for the quintiles. Also, to make the summary of the CPI Inflation (All quintiles - Official) comparable to the computed inflation rates, I have removed this time period while calculating the summary statistics for CPI Inflation (All quintiles - Official) in Table 2.

	Mean	SD	Min	Max	N
CPI Inflation (Q1 - Computed)	4.90	2.23	-0.06	9.42	110
CPI Inflation (Q2 - Computed)	4.92	1.96	0.46	8.84	110
CPI Inflation (Q3 - Computed)	4.92	1.75	0.91	8.38	110
CPI Inflation (Q4 - Computed)	4.89	1.48	1.41	7.84	110
CPI Inflation (Q5 - Computed)	4.84	1.03	2.31	7.21	110
CPI Inflation (All quintiles - Computed)	4.88	1.44	1.39	7.91	110
CPI Inflation (All quintiles - Official)	4.92	1.42	1.46	7.79	110
Cross-Sectional Spread (Computed)	1.36	0.76	0.17	3.65	110

Table 2: Summary statistics for computed quintile indices (Source: Author's calculations)

Note: The inflation rates in the above table are calculated as Year-on-Year growth in percentage (YoY%)

I initially analyze the cross-sectional dispersion of CPI inflation rates to understand if inflation rates are different across quintiles for a particular point in time. To study the cross-sectional dispersion of CPI inflation rates across the quintiles, I define cross-sectional spread as the difference between the maximum and minimum inflation rate among quintiles for a particular time. It can be observed from Table 2 that the cross-sectional spread has a mean of 1.36%. This indicates a high cross-sectional dispersion of the inflation rates across the quintiles, where the mean of computed inflation rates for all quintiles is 4.88% for the period of study. The maximum value of the cross-sectional spread is 3.65% and the minimum value of the cross-sectional spread is 0.17%, with a standard deviation of 0.76, indicating variation in the cross-sectional spread over time.

The result of high cross-sectional dispersion does not necessarily imply that the average inflation rate calculated across a long time period is different for quintiles. For this, I compare the average inflation rate for the entire period of the analysis for each quintile. It can be seen from Table 2 that the mean of inflation rates across quintiles are similar with no clear trend. To statistically test the difference in means of inflation rates across quintiles, I run unpaired t-tests (assuming unequal variance) for each pair of computed inflation rates for the quintiles. In all the t-tests, I was not able to reject the null hypothesis of equal means. This indicates that I do not find evidence of a difference in the means of inflation rate for the entire period of study across the quintiles.

Figure 3 plots the CPI inflation rate (All quintiles - Official) and computed CPI indices for the quintiles. It can be observed that in certain instances when the official headline inflation is hitting a peak, the inflation rate for the 1st quintile is even higher. For instance, the highest headline inflation rate in the sample period was 7.79% in April 2022. The inflation rate for the 1st quintile of this period was 9.38%. Similar observations can also be made for the months of October 2020 and January 2020 when the headline inflation rate was 7.61% and 7.59% respectively. The inflation rate for the 1st quintile for the time periods was 8.73% and 9.42% respectively.

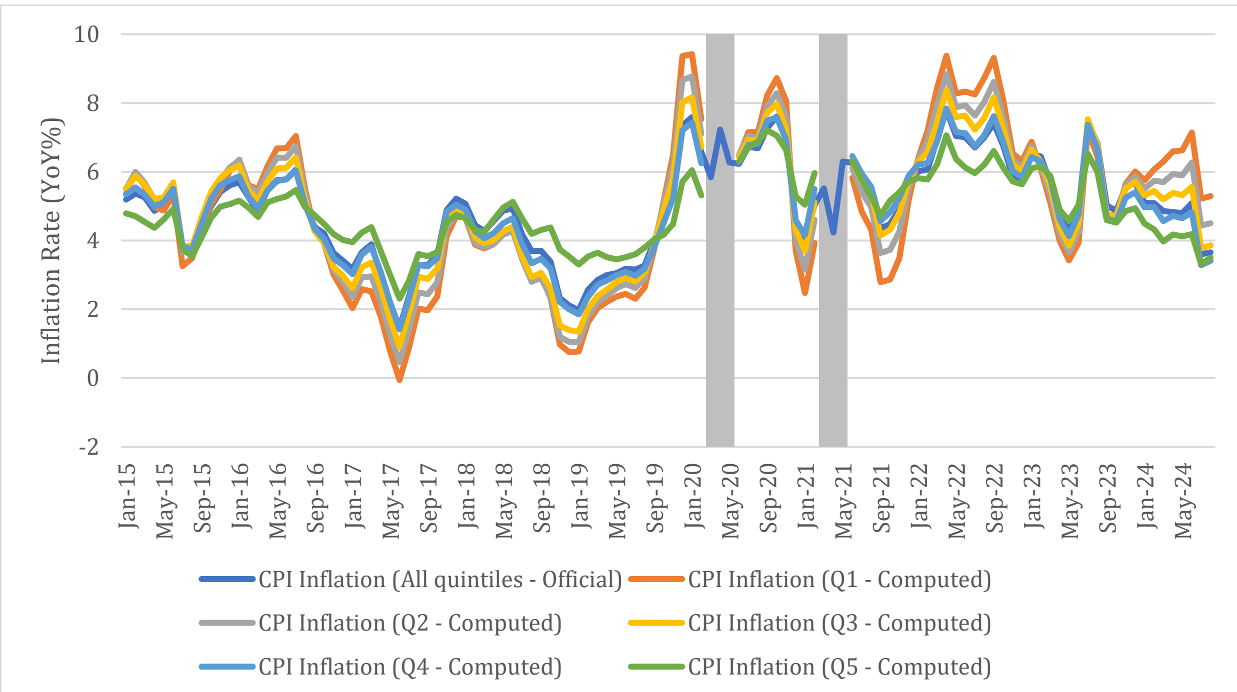

Figure 3: CPI inflation rate (YoY%) of quintiles and CPI (All quintiles- Official) inflation rate (YoY%) (Source: Author's calculations)

Note: The shaded region in the figure indicates the periods for which the CPI indices were not computed due to the unavailability of official CPI item indices

Interestingly, it can also be noted from Table 2 that the volatility as measured by the standard deviation of the CPI index decreases monotonically across quintiles as MPCE increases. This implies that lower MPCE households experience higher volatility in inflation in comparison to higher MPCE households. This result is expected, as we observed in Figure 1 that lower MPCE households have a higher weight for food and fuel in their consumption basket. Since food and fuel are more volatile components of the CPI, the inflation rates of lower MPCE households are expected to be more volatile in comparison to higher MPCE households.

Moreover, we can observe from the minimum and maximum values of the inflation rate in Table 2 that the extreme values of inflation are associated with the 1*st* quintile. Therefore, households in the 1st quintile experienced extremes of the distribution of inflation in comparison to the other quintiles. This can potentially be due to the high volatility in the inflation experienced by the households in the 1st quintile.

The limitations associated with CPI (Combined) and computed CPI indices for the quintiles arise from the biases associated with the Laspeyres index[iii] (Hausman 2003). The biases include (1) The effect of new goods and services, (2) The effect of quality change, (3) The effect of lower price stores: outlet bias, and (4) Substitution bias. The indices built for quintiles will also suffer from similar biases since the quintile indices are also Laspeyres indices.

In addition to the biases of the Laspeyres index, another limitation of CPI in the context of India is the long revision time of item weights. The weights for the CPI items are based on the HCES 2011-2012, which makes them more than a decade old. However, the absence of data for another round of HCES has made the choice of HCES 2011-2012 the best alternative.

6. Discussions

6.1. Comparison with Global Trends

In the recent literature, there is an emerging empirical consensus on the heterogeneity of inflation across income distribution. As previously discussed, Jaravel (2019) studies the US households for the period 2004-2015. The author finds that the annual inflation for retail products was higher for the lower income quintile compared to the top income quintile. Some other recent studies find similar results as well (Argente and Lee 2021; Kaplan and Schulhofer-Wohl 2017)

In alignment with the recent literature, I find that the cross-sectional dispersion is high across quintiles, with cross-sectional spread having a mean of 1.36%. However, in contrast to the recent literature, I find that average inflation rates for the period 2015-2024 are similar for quintiles. Therefore, the evidence for heterogeneity in average inflation rates across income groups in India is not as strong as has been suggested for US households by recent studies (Argente and Lee 2021; Jaravel 2019; Kaplan and Schulhofer-Wohl 2017).

I conjecture that the similarity in the average inflation rates across quintiles can be a result of the inflation targeting in India. Since FIT was adopted in 2016, it implies that except for 2015 the whole period under study is after the adoption of FIT. Under FIT, the monetary policy targets the inflation rate at 4%. If the inflation rate is fluctuating around 4% then the highs and lows of inflation for the income groups can balance each other resulting in similar average inflation rates across quintiles calculated over a substantially long period.

6.2. Implications for Monetary Policy

The FIT framework was formally adopted in India with a CPI inflation target of 4% and ± 2% tolerance band. With the adoption of FIT, CPI became the target index for monetary policy. Against this backdrop, it is important to understand the heterogeneity in CPI inflation rates experienced by different sections of the population. CSO releases indices which help address the heterogeneity in inflation among sections of the population. CPI is released for the rural and urban sectors. Also, CPI is computed for Industrial Workers (IW), Agricultural Labourers (AL), Rural Labourers (RL), and Urban Non-Manual Employees (UNME). However, the current indices do not address the heterogeneity in income groups.

Moreover, discussion around inflation is generally focused on the point estimates of CPI inflation. However, as we have seen in the results, there is cross-sectional dispersion in the CPI inflation across income quintiles. To address the two issues above, I suggest constructing inequality intervals using the quintiles (or percentiles) of CPI. In combination with the point estimate of the overall inflation, it will give us a sense of the dispersion in inflation across the income distribution.

I construct the inequality intervals for a cross-section by using the minimum rate of inflation among the quintiles as the lower bound and the maximum rate of inflation among the quintiles as the upper bound. Figure 4 plots the lower and upper bound of inequality intervals along with the inflation rate for all the quintiles. This study considers only quintiles for simplicity of the analysis. However, the inequality intervals can also be constructed by first calculating household-level indices and then plotting the specific percentiles of the distribution of inflation for each time period. For instance, the range between the 10th percentile and the 90th percentile of inflation rates for each time period can be used to form an inequality interval. There is however a caveat in this approach that the composition of the excluded region should not be skewed. For instance, for the range between the 10th percentile and the 90th percentile of inflation rates, it is important to note the composition of the households in 1st -10th percentile and 91st-100th percentile. If the composition of the excluded portion is skewed towards higher or lower MPCE households then the inequality intervals might not be representative of the whole population.

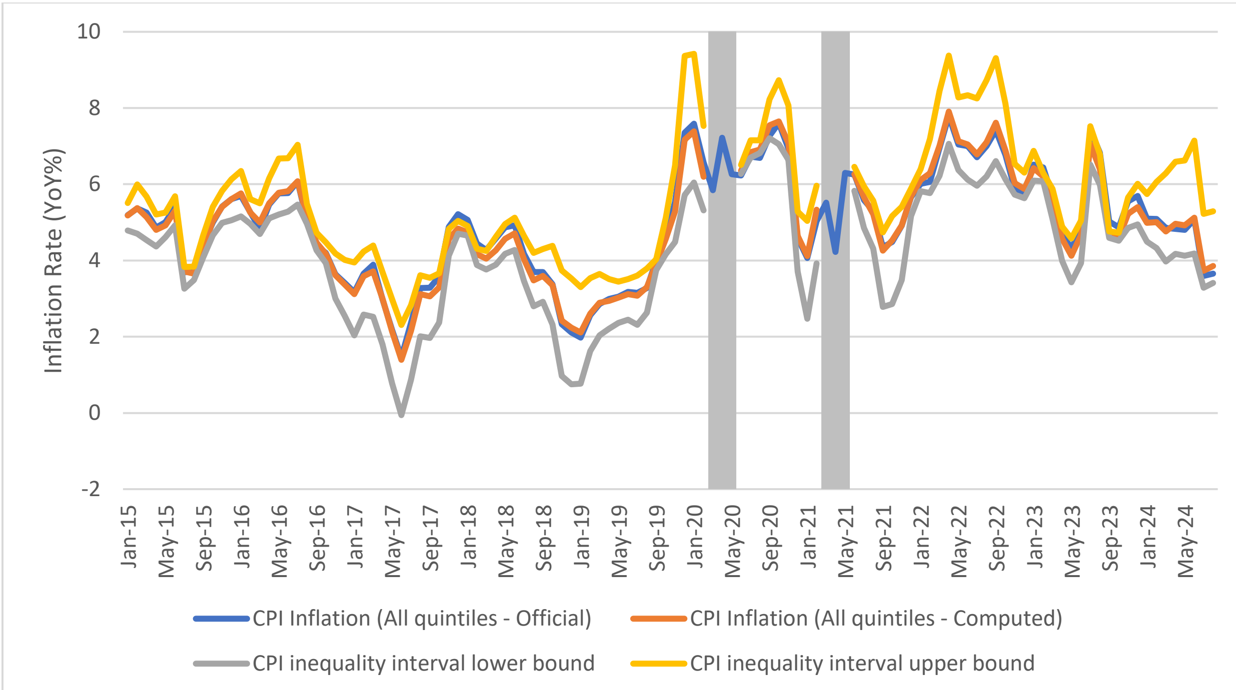

Figure 4: CPI inequality intervals (lower and upper Bound) (Source: Author's calculations)

Note: The shaded region in the figure indicates the periods for which the CPI indices were not computed due to the unavailability of official CPI item indices

6.3. Exclusion of Food Inflation for Inflation Targeting

The Economic Survey for 2023-2024 suggests that the RBI can explore targeting the inflation rate excluding food inflation (Ministry of Finance 2024). The concern here is that the higher food prices are often supply-side driven rather than demand-side. According to the Economic Survey, since monetary policy counters higher inflation by lowering the demand, counteracting the inflation caused by supply-side factors with demand-side changes can be counterproductive.

However, as we have observed in Figure 1, a larger share of expenditure of lower MPCE households is comprised of food and fuel compared to higher MPCE households. If food and fuel inflation are higher compared to other groups in CPI and they are driving the CPI upwards, the lower MPCE households will be disproportionately affected. Moreover, if the central bank is not reigning in the inflation with demand-side measures this can result in an increase in prices of goods which are part of clothing and footwear, housing, and miscellaneous groups in CPI. This can further lead to even higher inflation for lower MPCE households, which are already facing high food and fuel inflation. Further, this can show up in the increase in the demand for wages of the lower MPCE households and can result in a wage-price spiral.

7. Conclusion

In this paper, I study the inflation inequality in India for the period 2015-2024 using the CPI indices and HCES 2011-2012 data. I construct the CPI indices for quintiles based on the MPCE of households in the HCES. I then examine the heterogeneity of inflation rates across income quintiles. I also study the heterogeneity of volatility of inflation rates across income quintiles.

I find a high cross-sectional dispersion of the inflation rates across the quintiles. However, I find that the average inflation rates for the entire period 2015-2024 are similar for the quintiles. An interesting finding of this study is that the volatility of the computed CPI indices decreases monotonically across quintiles as MPCE increases. This implies that the lower MPCE households experience higher volatility in inflation compared to higher MPCE households. This is also backed up by the fact that the consumption basket of lower MPCE households has a higher contribution of food and fuel, compared to higher MPCE households. Since food and fuel are in general more volatile compared to other components of CPI, this makes the inflation experienced by the lower MPCE households more volatile. Potentially as a result of high volatility, households in the lowest quintile also experience inflation at the extremes of the distribution in comparison to other quintiles.

The limitations of this study emanate from the limitations of the Laspeyres index. Laspeyres index is used to calculate the current CPI Indices. The index is easy to interpret and has a fixed reference basket. However, it can have potential biases. Since the price indices for quintiles are also Laspeyres indices, they also suffer from similar biases.

I also compare the results with the literature on inflation inequality globally. In recent studies, there is an emerging consensus that inflation varies with income distribution. In agreement with the current literature, I observe heterogeneity in inflation in cross-section. However, I do not observe heterogeneity in terms of the average inflation rates of the quintiles suggested by recent studies.

With the adoption of the FIT framework in 2016, CPI has become the target index in monetary policy. However, the discussion around CPI inflation is centred around the point estimates of CPI inflation. In this study, I construct inequality intervals using the CPI inflation rates for the quintiles. The inequality intervals can be used to inform the discussion on inflation and monetary policy.

I further touch upon the suggestion in the recent economic survey to exclude food inflation while targeting the inflation rate. In this study, we observed that the CPI for lower MPCE quintiles is highly comprised of food and fuel. The exclusion of food inflation from targeting can result in higher food inflation affecting the lower MPCE households disproportionately.

In conclusion, this paper studies the incidence of inflation inequality for the period 2015-2024. This study finds a high cross-sectional dispersion of inflation rates. However, the average inflation rates for the entire period of the study are similar for the quintiles. Interestingly, this study gives evidence of higher volatility in inflation experienced by lower MPCE households. The paper suggests constructing inequality intervals using the CPI indices for quintiles (or percentiles) to bring heterogeneity in inflation rates in the policy discussion.

Appendix A: Computation of Item Weights in CPI using HCES

I compute the item weights in the CPI index in three steps. Firstly, I match the items in CPI with the items in HCES. It is important to note that CSO imposes criteria to select HCES items for the CPI basket (CSO 2015). Therefore, not all items in the HCES survey are part of the CPI basket. As a result, in HCES, I was able to match 298 items out of the 347 items to CPI item indices. I was not able to match 49 items in HCES with any item in the CPI. On the other hand, when I map the names of the items in 299 all India item indices to HCES item codes. I was able to match all item names in CPI to HCES except “Monthly Maintainance charges”.

Secondly, I impute the CPI sub-groups of 49 unmatched items in HCES. In the official methodology to construct the CPI index, the shares of expenditure of items which are not included in the CPI basket are either merged with similar items or distributed over other items over the section/group/sub-group in the CPI (CSO 2015). However, the methodology does not mention the exact merging or distribution of the weights. To resolve this, I impute the CPI sub-group for the unmatched HCES items. I initially sort the item codes in the HCES in the order that they appear in the survey schedule. As a rule, I impute the CPI sub-group of the item with the CPI sub-group of the previous item which is non-missing. In case the HCES item for which the sub-group is be imputed is first in the items under a sub-total of HCES, I impute the next non-missing element. I make exceptions to the rule based on judgement when the item seems more suited to a different CPI sub-group.

Thirdly, I distribute the cumulative weight of unmatched items in HCES items. I distribute the weights of the unmatched HCES items equally across the CPI items in the same CPI sub-group. The logic behind the distribution of item weights in this manner is to construct CPI along the lines of the methodology of CSO. Since we do not exactly know how the exact distribution is carried out, this is one of the methods to distribute the item weights with minimum assumptions.

Appendix B: Imputation of Item Indices

The monthly data for 299 item indices had 1.29% of observations as missing (481 out of 37,375 observations). The item indices used in the analysis cover the period January 2014 to August 2024, excluding the months of March-May 2020. To impute these item indices, I use the methodology used by the NSO to impute the item indices during COVID-19 (NSO 2020). The imputed item indices are calculated as follows:

$$(Imputed\ Index)_{i,t} = Index_{i,t-1}\ \times Avg(\frac{Index_{i,t}}{Index_{i,t-1}}) \tag{4}$$

where, $(Imputed\ Index)_{i,t}$ represents the imputed index for item i at time t, $Index_{i,t-1}$ represents the price index of item i at time $(t-1)$, and $Avg(\frac{Index_{i,t}}{Index_{i,t-1}})$ is the average of the ratio of the price index for item i at time t and the price index for item i at time $(t-1)$. Using this imputation, 477 item indices were imputed. The remaining item indices could not be imputed using the above formula because they were at the start of the sample period i.e. January- April 2014. To impute the item indices for these time periods, I use the following formula:

$$(Imputed\ Index)_{i,t} = Index_{i,t+1}\ /\ Avg(\frac{Index_{i,t}}{Index_{i,t-1}}) \tag{5}$$

Appendix C: Summary Statistics for MPCE across Quintiles

Quintiles	Mean	SD	Min	Max	Number of households (unweighted)	Number of households (weighted)
1	777.04	145.21	136.81	982.59	14,429	50,074,052
2	1,146.68	97.65	982.59	1,323.46	17,162	50,083,564
3	1,540.31	139.13	1,323.51	1,814.11	20,643	50,061,024
4	2,229.10	283.68	1,814.12	2,814.98	23,538	50,089,296
5	5,064.52	4,232.23	2,815.04	166,158.77	25,879	50,054,652
All Quintiles	1,908.35	2,147.57	136.81	166,158.77	101,651	250,362,588

Table 3: Summary statistics for MPCE (Using household weights in HCES)

Note: All the figures in the columns Mean, SD, Min, and Max are in Rupees. All columns except Number of households (unweighted) are computed using household weights in the HCES

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[i] In 2015, Government of India and the Reserve Bank of India signed the Monetary Policy Framework Agreement (MPFA). After the MPFA, Flexible inflation targeting (FIT) was formally adopted with the amendment of the RBI Act in May 2016. Under FIT, the central bank targets a consumer price inflation of 4% with a 2% tolerance band around it (Das 2020).

[ii] The reference period for the Type 2 schedule is the Modified Mixed Reference Period (MMRP). HCES 2011-2012 uses three reference periods to calculate MPCE at the household level. The three methods are Uniform Reference Period (URP), Mixed Reference Period (MRP), and Modified Mixed Reference Period (MMRP) (NSSO 2013). The MMRP estimates are expected to be less biased compared to MRP and URP due to lower recall error. This was because of a shorter recall period for several food items compared to MRP and URP.

[iii] The Laspeyres index serves as the upper bound for the Cost of Living Index (COLI) and the Paasche index serves as the lower bound for the COLI (Hill 2004). COLI can be defined as $COLI_{t,t+k} = \frac{e(p_{t+k},u)}{e(p_t,u)}$, where $e(p,u)$ is an expenditure function which measures the minimum expenditure required to attain the utility level u with prices given as p. The important feature of the Laspeyres and Paasche index which makes them the bound for COLI is that they do not allow the substitution of goods by households or Individuals. Therefore, both indices suffer from substitution bias.