Disaggregate Food Inflation in India

Analysis of Regional Factors

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Inflation may vary across space and commodities due to differences in region-specific or idiosyncratic factors such as climate, local culture, and the existing institutional set-up. These factors cause disaggregate, or regional, inflation, which in turn coalesces into aggregate inflation. Food inflation is a typical example. Spatial factors and rainfall are the most important determinants of disaggregate food inflation. Local inflation differs from aggregate inflation; the rate of inflation varies by city and commodity; and the determinants of rural and urban inflation are different. In addition to demand management policies, aggressive supply-side policies are the need of the hour.

(Appendix Tables 1–7 and Figures x1–x61 accompanying this article are available on the *EPW* website.)

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Most central banks probably bank on the strong theoretical argument that local inflation is no different from national inflation (Clark 1984), but inflation varies across space and commodities due to differences in region-specific factors like climate, local culture, and the existing institutional set-up (Beck et al 2009). These idiosyncratic factors, in turn, depend on regional fiscal policy measures, market regulations, production structures, and trade patterns. These factors may influence either the demand for or supply of a commodity or of all commodities in a region and, thereby, the rate of inflation. A policy implemented at the aggregate level may impact regions differently, and cause price distortions (Deaton and Dupriez 2011), as the impact of different economic shocks differs by region (Pino et al 2016).

It is important to understand regional inflation. Central banks use the inflation forecast as the nominal anchor for monetary policy; disaggregate inflation is critical in forecasting headline inflation, at least in large countries like India (Deaton and Dupriez 2011). Analysing inflation by region and commodity may help to understand why inflation differs by region in a country; it may help also to discover the persistently inflationary disaggregate components of core inflation (Zaffaroni 2004). Regional convergence of inflation may not be possible, but knowing the extent of divergence is crucial in forecasting aggregate inflation.

An understanding of disaggregate and regional inflation may prove to be a better complement to core inflation in identifying the key drivers of aggregate inflation and improving inflation forecasts. Realistic estimates of real incomes of different regions can be obtained only with a proper understanding of regional inflation; in its absence, the wage indexation process at the regional level will estimate the inflation in a region incorrectly, give rise to faulty wage price spirals, and add severely to the already grotesque problem of rising inflation and inequality.

An understanding of disaggregate inflation (by region or commodity) is crucially important for the macroeconomy and policymakers, but only a few studies deal with disaggregate inflation (Beck et al 2009; Clark 1984). The literature can be classified into studies that attempt to identify the factors behind regional variation in inflation and those that look for possible co-movements and eventual convergence among the prices. Since convergence in prices leads to divergence in inflation, following the law of one price, price convergence among a country's regions points at inflation divergence within those regions.

The literature on disaggregate inflation is based majorly on sectoral disaggregation, that is, by splitting the headline inflation into its components (inflation caused due to food items, or food inflation) and core items of the price index used as a measure of inflation (core inflation). These studies use as empirical tools different variants of panel regression techniques on spatial regressions and principal component analysis. Beck et al (2009) study the heterogeneity or regional inflation dynamics within and across the euro area and compare them with that in the United States (US) using principal component analysis and regression analysis and disaggregated data on the consumer price index (CPI). The authors find that inflation majorly depended on area-specific factors, and that disaggregated regional inflation was an important factor in explaining aggregate inflation in the US and the euro area.

Using space state models, Marques et al (2009) study the inflation dynamics for a representative set of tradable commodities in Chile. With the help of a simple model that explains divergence in inflation within a monetary union, the authors conclude that spatial aspects and transportation cost are significant determinants of regional inflation. Özgör (2013) found substantial divergence in inflation rates across the regions of Turkey. Osorio and Unsal (2011) find that idiosyncratic supply shocks drive much of Asia's inflation.

Darbha and Patel (2012) analyse the time series and cross-sectional dynamics of inflation in India using panel regression analysis and find that most of the current inflation was the result of cross-sectional factors. Mohanty (2011) analyses the inflation dynamics with respect to different commodity groups at the macro level, compares the inflation of these commodities with global inflation, and concludes that inflation expectations should be anchored so that consumers do not mark up their long-run inflation expectation based on short-run higher-than-average inflation.

Majumder et al (2014) study the spatial variation in prices in India using National Sample Survey Office (NSSO) unit-level data. The study found significant variations in prices across states. Majumder et al (2014) analyse the temporal variation in prices using NSSO data; there was evidence for temporal differences in prices across states. Patnaik (2016) studies the statewise variation in inflation of India by testing for convergence in prices across states and using panel unit root tests; he concludes that inflation divergence among states was due to price convergence.

Goyal and Baikar (2014) attempt to assess the impact of rural wages for unskilled male labourers on inflation in India using a dynamic panel data model. The study found that the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) increased real wages and drove food inflation. Malhotra and Maloo (2017) study aggregate food inflation using machine learning techniques. Elaborate studies on food inflation in India and its causes have been carried out (Nair and Eapen 2012; Guha and Tripathi 2014; Bhattacharya and Sen Gupta 2015) and second-round effects of food inflation, using different variants of core inflation, have been estimated (Raj and Mishra 2011; Bhattacharya and Sen Gupta 2015; Anand et al 2014).

From this review of the literature, it can be concluded that there is a dearth of studies on disaggregate inflation at the regional level for a large country like India. Also, most studies ignore the impact of the third dimension, space, on inflation. Using standard econometric techniques to model inflation without considering the impact of spatial influence raises problems associated with the curse of dimensionality. Spatial effects help trace idiosyncratic factors of prices and, therefore, inflation. A disaggregate study of all the components of inflation is beyond the scope of this article. It attempts a rigorous empirical and descriptive study of the inflation of food items at the regional level using unit-level data derived from the 61st and 68th quinquennial rounds of the Consumer Expenditure Studies (CES), collected by the NSSO of the Ministry of Statistics and Programme Implementation (MoSPI). These data are collected once in five years, and the most recent quinquennial round on CES was conducted in 2011–12; as a result, the latest unit-level data on CES are available only till 2011–12. Food inflation has been chosen because of the increasing empirical evidence of its second-round effects on headline inflation. Also, food inflation is more persistent than non-food inflation, and food shocks are strongly propagated into non-food shocks (Walsh 2010).

This article tries to trace regional variations in inflation and the compound annual growth rate (CAGR) of select food items using the CPI–industrial workers (CPI–IW) centre-wise data and the NSSO–CES data (61st and 68th rounds). It attempts to empirically find out the determinants of the inflation rates of these items at the regional level (proxied by the CAGR of NSS–CES) in a spatial econometric framework. Given that India has recently introduced inflation targeting as its monetary policy framework, a study of regional and disaggregate inflation is crucial in affording insight into the components of inflation and push-and-pull factors. To the best of the authors' knowledge, a regional analysis of disaggregated food inflation in India using NSSO data has not been attempted so far.

Methodology and Data Sources

This descriptive and empirical analysis uses four variables:
(i) region-wise inflation of each of the commodities selected from 2004–05 to 2011–12 (yi);
(ii) region-wise monthly per capita consumption expenditure (MPCE) for 2011–12 (dd);
(iii) region-wise average rainfall during the period of study (2004–05 to 2011–12)(ss); and
(iv) the CAGR of inflation derived from the NSSO–CES data and CPI–IW data.

The study employs annual data on regional prices of consumption items, derived from the 61st round on CES of the NSS (covering data in 2004–05) and 68th (covering data in 2011–12). The NSSO definition for the 61st and 68th rounds of consumption expenditure was adopted to define a region. A total of 61 consumption items for the 79 regions (rural and urban areas) were selected for the descriptive studies (Appendix Table 1). The inflation rate of a particular consumption item in a particular region from 2004–05 to 2011–12 was then calculated as the log percentage change in the value per unit of that item from 2004–05 to 2011–12. The NSSO collects and publishes unit-level data for more than 350 consumption items for the entire country in its quinquennials on consumer expenditure. These data are collected in terms of quantity of a particular item consumed and its value. Prices can, therefore, be derived by dividing the quantity consumed with the value of the item for each household. This gives the unit values of price of that item for that household. However, this unit value suffers from problems such as measurement error, quality preferences of the household, and household composition effect (Deaton 1988), which give an upward bias in the unit value data. The unit value so derived was filtered following Cox and Wohlgenant (1986), and the price of an item for a given region for a given commodity was derived as the average price of that commodity for all the households in a given NSSO region.

The centre-wise CPI–IW data can be obtained from the annual reports on CPI–IW, published by the Labour Bureau of India. The CAGR was then estimated as follows:

$$\text{CAGR} = [(\text{Price in 2011–12/Price in 2004–05})^{1/6} - 1]$$

From the NSSO 68th round of CES unit quantity file, the MPCE per region was calculated as follows:

$$\text{MPCE per region} = \frac{\text{Total quantity of each item consumed by all households}}{\text{total number of people in all households}}$$

Data on rainfall was collected from the official website of the meteorological department of the Government of India, and the average rainfall of each region was calculated as follows:

$$\text{Average rainfall of a region} = \frac{\text{Total rainfall in six years (2004 to 2011)}}{\text{number of years}}$$

Kernel Density Plot

Since the main aim is to study the behaviour of inflation of select food items across the 79 NSSO regions, a study of the distribution of the inflation data would give meaningful insights. An attempt is made to estimate the non-parametric kernel densities of inflation of each item selected and map the probability distributions. Kernel densities are smoothened representations of the probability distribution, and the choice of point of origin does not affect the kernel density. A non-parametric kernel estimate can be derived as follows:

$$\hat{f}(y) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{y - y_i}{h}\right) \quad \text{... (1)}$$

where $K(x)$ is the kernel, a nonnegative function that integrates to 1 (as shown in equation 2) in order for $\hat{f}(y)$ to conserve the properties of a density function.

$$\int_{-\infty}^{\infty} K(x)dx = 1 \quad \text{... (2)}$$

From among a range of kernel functions that exist in literature, the Gaussian kernel is used here (Ahamada and Flachaire 2010):

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \quad \text{... (3)}$$

In equation (1), h is known as the smoothing parameter or the bandwidth, which has to be as small as possible. Thus, the kernel estimation requires the specification of the kernel $K(x)$ and the smoothing parameter h. Kernel estimation suffers from the drawback of becoming noisy in the tails of the distribution. This problem can, however, be mitigated by broadening the kernel (Hatekar and Raju 2013).

Spatial Autocorrelation/Moran's *I*

Moran's I values would give the spatial autocorrelations among the inflation rates of commodities under study at the level of NSS regions. Spatial autocorrelation is the correlation among values of a single variable strictly attributable to its relatively close locational position on a two-dimensional surface, introducing a deviation from the independent observations assumption of classical statistics (Griffith 2009a, 2009b). Moran's I is the most common measure of spatial autocorrelation. Positive spatial autocorrelation occurs when similar values (high/low) of a variable are clustered together, and negative values occur when dissimilar values are clustered in space (Shaban 2006). Moran's I is estimated as follows:

$$I = \left(\frac{n}{S_o}\right)\sum_{I=1}^{N}\sum_{J=1}^{N} w_{ij}x_i x_j \Big/ \sum_{i=1}^{n} x_i^2 \quad \text{... (4)}$$

where n is the number of observations, w_{ij} is the element in the spatial weight matrix w corresponding to the region (i, j), observations x_i and x_j are deviations from mean values for regions i and j, respectively, and s_o is the normalising factor equal to the sum of the elements of the weight matrix, that is, $s_o = \sum_i\sum_j w_{ij}$. The spatial weight matrix is constructed based on a local neighbourhood around each geographical unit. In the present case, these weights are row-standardised, with zeroes on the diagonal and some nonzero values off the diagonal. With a null hypothesis of no global spatial autocorrelation, the expected value of I is given as follows:

$$E(I) = -\frac{1}{N-1} \quad \text{... (5)}$$

If the computed I is larger than the expected value, then the overall distribution of variable y can be seen as being characterised by positive spatial autocorrelation, and if the computed I is smaller than the expected value, the overall distribution of y is characterised by no spatial autocorrelation. Moran's I ranges between –1 to +1, positive values of I showing a very strong spatial correlation and vice versa (Hatekar and Raju 2013).

Beta (β) Convergence

For testing convergence in price, the usual β convergence has been used. The β convergence is the partial correlation between growth in prices over time (of the region being considered) and its initial level (Young et al 2013). If β is significant and negative, there is β convergence, that is, prices are converging. Herein, the Barro and

Sala-i-Martin (1991) model for measuring the β convergence is employed:

$$\ln(y_{it} / y_{it-7}) = \alpha - \beta \ln y_{it-7} + u_i \quad \ldots (6)$$

where y_{it} is the variable (price) whose convergence is being measured, $i = 1, 2, 3 \ldots$ is the region unit being considered. Since the data span is 2004–05 to 2011–12, β convergence of prices during these seven years was estimated (Appendix Table 2).

The β convergence, as measured from equation (6), is the regression of inflation on initial prices. This implies that if β is negative and significant, an inverse relation exists between current inflation and initial prices. In other words, regions with initial low prices will experience higher current inflation, implying heterogeneity in regional inflation due to convergence of prices.

Spatial Regression Techniques

The factors of regional variations in inflation for a select basket of food items may include spatial spillovers that arise from its own region characteristics (LeSage and Fischer 2008) and other spatial dependence. Studies on regional growth observe that the impact of initial growth fades away and only spatial or regional characteristics remain in the long run (LeSage 1997). It seems reasonable to assume the same for regional inflation as space plays an important role in determining prices in a given region. Also, ordinary least squares (OLS) regressions assume that the observations should be independent of each other for the estimated β coefficients to be efficient. The presence of spatial information, if ignored, yields regression residuals that contain spatial information which do not become white noise processes. Several studies use spatial econometric techniques to model regional prices (Majumder et al 2013; Patnaik 2016). Working on the same lines, spatial regression techniques are employed herein to empirically estimate the determinants of inflation of the basket of items selected for the study. Most researchers follow the method of general to specific modelling, by starting with estimating an OLS model and then testing whether the model needs to be extended for spatial interactions (Yesilyurt and Elhorst 2014).

The most basic spatial regression models can be classified broadly into the spatial lag model/spatial autoregressive model and the spatial error model. The Lagrange multiplier test for spatial dependence is used in cross-section, following Anselin (2001), to choose between the two models. In spatial lag models, a spatially lagged dependent variable—similar to the inclusion of a serially autoregressive term for the dependent variable in the time series context (Anselin 2001)—is added as an explanatory variable to the regression equation. Formally, the model is

$$y = \rho W_y + X\beta + \varepsilon \quad \ldots (7)$$

where y is an $N \times 1$ vector of dependent variables. In the present case, it is the inflation rate of each of the items selected for the study. W_y is the corresponding spatially lagged dependent variable for the weights matrix W, X an $N \times K$ matrix of explanatory variables (in the present case, the average rainfall of the 79 regions and the average MPCE of the 79 regions), ε is the $N \times 1$ vector of error term such that $\varepsilon \sim N(0; \sigma^2_\varepsilon)$ and ρ is the spatial autoregressive parameter (Anselin 2001). The matrix W is an $N \times N$ non-stochastic, nonnegative spatial weight matrix.

The elements of W are used to specify the spatial dependence structure among the observations (as explained for Moran's I above). The W_y variable vector captures spatial dependence in y, with the scalar parameter ρ providing a measure of influence on the inflation rate of a region of related regions' inflation rates i (LeSage 1997). This parameter must take on values less than 1 and, in the context of inflation, it can either be negative or positive.

As against the spatial lag model, the spatial error model specifies a spatial process for the error as follows:

$$y = X\beta + \varepsilon \quad \ldots (8)$$

and

$$\varepsilon = \lambda W\varepsilon + \xi \quad \ldots (9)$$

where λ is the spatial autoregressive component for the error lag $W\varepsilon$. ξ is an uncorrelated homoscedastic error term. Rest of the parameters and variables are the same as in equation (7). Choosing between the two models is done using the Lagrange multiplier test (Anselin 2001).

Disaggregate Food Inflation of India

The study has used the log percentage change in the value per unit of an item in the NSSO regions from the 61st and 68th rounds to derive the rate of change in prices, that is, the aggregate inflation during 2004–05 to 2011–12. Out of the 350+ items for which price data are available for both these rounds, 61 everyday consumption items common to both rounds were selected for the descriptive analysis (Appendix Table 1). Descriptive statistics such as skewness, kurtosis, and Moran's I (Appendix Tables 2 and 3) and non-parametric methods such as kernel density plots (Appendix 1, Figures 1–61) have been used.

During the seven-year span, the rate of inflation increased over 100% for all commodities on average. Region-wise, the highest and lowest inflation rates are varying with respect to the commodities; as a result, it is not possible to figure out whether a region is the costliest or cheapest with respect to all commodities. This will be possible only if price indices are constructed for these regions, which is beyond the scope of the present study.

Most of the inflation data are skewed (Appendix Tables 2 and 3). While negative skewness can be observed in the case of five items in rural areas and three items in urban areas, they are positively skewed for the rest of the items. This means that in the case of most items, there are thick tails on the right side of the distribution, that is, in a number of regions, the rate of inflation is greater than the modal value of inflation. Similarly, in the case of 12 items in rural areas and 13 items in urban areas, the kurtosis is greater than 3. This again points at the prevalence of thick tails of the distribution, implying variation of inflation across regions.

The kernel density plots (Appendix 1, Figures 1 to 61) represent the kernel density of inflation of the 61 selected items across the 79 NSSO regions. The x-axis corresponds to the range of inflation across the NSSO regions, and the y-axis corresponds to the probability of occurrence of these inflation values across the 79 regions. It is clear that the kernel density plots are leptokurtic. This implies that the probabilities in the tails of the distribution are greater, clearly implying huge variations in the inflation figures of the same commodity across regions.

The mode of most of the distribution is approximately within the range of 80 to 150. This supports the argument that prices rose 80%–150% during the six years that the rate of inflation was measured. Most of the distributions are unimodal, which defines the left and the right of the distribution. The kernel density plots stand as testimony to the information contained in the kurtosis. Thick tails of the kernel density plots imply that the extreme values are dominant and that there is a huge variation in the inflation of the same item across regions.

Similarly, the Moran's I values are significant in the case of 13 items in rural areas and nine items in urban areas, implying spatial correlation among these inflation rates. It can be inferred that the spatial autocorrelation coefficient is very small (0.14–0.34). However, all the significant Moran's I values are positive, implying clustering of high–high or low–low values of inflation. Significant spatial autocorrelations only in the case of 22 items (rural + urban) clearly implies that inflation clustering is not happening in the case of 39 items, which clearly implies divergence in the rates of inflation.

According to the law of one price, when prices converge, inflation diverges. All these items were tested for β convergence, following Barro and Sala-i-Martin (1991). Usually, β convergence is used to study income convergence in the long run; it is expected that in the case of prices, six years can be treated as a sufficiently long period for convergence. While estimating the price convergence in the case of the 61 items (rural and urban) (Appendix Tables 2 and 3), spatial effects are considered, but these do not, in most cases, influence the convergence process. The OLS estimates of the β coefficients are derived from the convergence equation (equation 6). The β convergence is significant at conventional levels, with the required negative sign in the case of 21 items in rural areas and 11 items in urban areas out of the 61 items (rural and urban) considered (Appendix Table 2, for rural areas and Appendix Table 3, for urban areas). By the law of one price, price convergence leads to inflation divergence in most commodities. In many cases, the negative and significant β values are as high as 0.6 in many cases.

CPI–IW Data vs NSSO Unit Level Data

The NSSO publishes unit-level data on the total quantity of a particular item consumed by a household, and on the total value of consumption of a particular item, but it does not give the actual prices. The prices of the items studied herein have been derived as outlined in the discussion on data sources. Since the prices—and, therefore, inflation—have been derived, it would be interesting to compare them with the centre-wise (CPI–IW) price data published by the Labour Bureau of India. The CAGR of unit cost of items as per NSS–CES is compared with the CAGR of the centre-wise CPI–IW for the period 2004–05 to 2011–12.

The CPI–IW provides disaggregate price data on food items broadly classified as cereals and products, pulses and products, milk and products, and spices and condiments. The base year of the CPI–IW data for the year 2004–05 was 1982; it was 2001 for the year 2011–12. The base year for the CPI–IW data for 2004–05 was converted to 2001 using the method of splicing, so that the base years of CPI–IW 2004–05 and 2011–12 are the same and their prices are comparable. A total of 37 centres common to the NSS–CES data and the CPI–IW data were selected for this comparison. Appendix Tables 6A to 6E contain the details of the broad commodity-wise/centre-wise CAGR using the NSS–CES and CPI–IW data set). The CAGR of CPI–IW and the CAGR NSS–CES behaved more or less similarly, except for some upward bias in the prices measured using the NSS–CES data.

In the case of cereals and products, the CAGR of CPI–IW was the highest in Jabalpur, followed by Nashik and Rourkela. The NSS–CAGR values were also found to be on similar lines. Similarly, in the case of pulses and products, the centre with the highest CAGR is Surat, followed by Nagpur and Rourkela. Rourkela has a very high CAGR for both cereals and pulses. Again, in the case of oil and products, Bhilai occupies the top slot for the highest CAGR, followed by Rajkot and Surat. In the case of milk, the three costliest centres seem to be Salem, Visakhapatnam, and Warangal. In the case of spices and condiments, Madurai, Guwahati, and Chennai appear to have the highest CAGR (Appendix Tables 6A to 6E). The same three cities appear to be the costliest with respect to both price measures, with some shuffling of rank.

The rate of inflation at the disaggregate level is not uniform across regions or commodities. An attempt is made to empirically understand the factors of the rate of inflation of food items, using the inflation data of 79 regions of India, as defined by the 61st and 68th rounds of CAGR of NSSO–CES, for the commodities listed in Appendix Tables 4 (for rural areas) and 5 (for urban areas). To map the variation in rural and urban areas, inflation has been used of only those food items for which data are available for both rural and urban areas (Appendix Table 7). Therefore, the items used in this part of the analysis are different from those used in the descriptive statistics.

The MPCE and average rainfall data have been derived for 2011–12; therefore, the inflation rate also has to be for the same year, and the CAGR of the NSSO–CES data is used as a proxy for inflation in 2011–12. Spatial regressions were run for food items with inflation (CAGR) of food items as the dependent variable and average MPCE (proxy for demand-side factors) of the NSS region and average rainfall (proxy for supply-side factors) as the explanatory variables (equations 7–9). The significant spatial coefficients allow for the inference that regional inflation rates are influenced by idiosyncratic factors, which are captured by using spatial regressions. Studies on food inflation include international food prices, minimum support prices, and rural wages as factors of inflation (Malhotra and Maloo 2017); since regional-level data on these variables are not available, only demand and supply are used as factors of food inflation.

Results

Spatial effects are significant in the case of 11 of the 12 items considered in the rural areas and in 10 out of 12 items in urban areas, the spatial regression results show (Appendix Table 4, for rural areas and Appendix Table 5, for urban areas). The spatial weight coefficient exceeds 0.5 in five items in rural areas and seven items in urban areas. Strong spatial/regional effects influence the inflation of a particular region in both rural and urban areas. For all items, the Lagrange multiplier test chose the spatial lag model, which implies that the inflation of neighbouring regions strongly impacts the inflation of any item. Rainfall is not a significant determinant of inflation in rural areas in most cases, but it is a significant determinant of inflation for six items in urban areas. Wherever significant, its coefficient has a negative sign, implying an inverse relation between rainfall and inflation.

The MPCE is significant for nine items and positive in most of the cases in rural areas, whereas it is significant for five items in urban areas, but the sign of the coefficient is negative for three items. Item-wise, the inflation of wheat depends majorly on regional factors in urban areas, whereas only about 10% variation in inflation can be attributed to regional factors in rural areas. The inflation of bread depends upon regional, supply-side, and demand-side factors in rural areas, but the most important determinant of inflation is demand for bread. However, in urban areas, the inflation of bread depends only upon regional factors.

The inflation of processed food items such as biscuits and noodles depends on regional and demand-side factors in rural areas, whereas in urban areas even supply-side factors influence this inflation. The sign of the coefficient of MPCE is negative, implying increased production due to the rising demand. The inflation of pulses is a demand-side phenomenon in both rural and urban areas. However, in urban areas, the coefficient of MPCE of pulses has a negative sign, which is contrary to the law of demand (as demand increases, the price should also increase). The negative sign points at the government's policy of importing pulses when there is excess demand, which ultimately results in pushing prices downwards and, therefore, inflation. The spatial weight coefficient of pulses is very high (0.9493) in rural areas, implying very sharp regional effects on the inflation; however, in urban areas, it is 0.079, which is less than the coefficient of MPCE (–1.0817). Thus, the demand for pulses in urban areas is the most important factor of inflation.

The inflation of sugar depends on all the explanatory variables in both rural and urban areas. Demand-side factors are major determinants of sugar inflation in rural areas, but regional factors dominate sugar inflation in urban areas. In the case of vegetables, regional factors are important determinants of inflation in both urban and rural areas; however, supply-side factors impact inflation in urban areas, while demand-side factors influence inflation in rural areas. A similar behaviour can be noticed for fruits.

In the case of spices and beverages, again, the contrast in behaviour between rural and urban areas can be found: demand-side factors push up inflation in rural areas, whereas supply-side factors dominate in urban areas.

Conclusions

Based on the growth rate in prices of food items over the period of six years, one may conclude that food inflation in India was very persistent at the disaggregate level. This is contrary to the common belief that food inflation is a temporary phenomenon. The rate of inflation was not constant across regions or commodities, contrary to the traditional belief that local inflation should be no different from national inflation.

Although all food items were found to be pushing up food inflation, some items such as pulses, eggs, and vegetables are the major drivers. Only stabilisation policies or other demand management policies would fail to arrest the inflation triggered by such items. Aggressive supply-side policies such as improving the production of these items may help.

The significant spatial effects on inflation rates clearly imply that idiosyncratic factors dominate the regional inflation of food items in India, and that demand and supply conditions in adjoining areas and, therefore, their rate of inflation have a major impact on regional inflation.

Rainfall is a major determinant of regional inflation of food items in urban areas. Urban food inflation is a supply-side phenomenon. India lacks adequate irrigation facilities; therefore, agriculture is exclusively dependent on the monsoons.

In rural areas, inflation of most of the food items studied depended either on idiosyncratic factors or on demand-side factors (increase in MPCE). A number of studies (Goyal and Baikar 2014) point to the impact of rising rural wages (as a result of the implementation of the MGNREGA) on rural inflation in India. The results of the empirical analysis clearly validate the argument that rising rural wages have led to an increased demand of food items in rural areas which, in turn, pushes up food inflation in rural areas. Shifts in consumption pattern, such as the adoption of protein-rich food items, are pushing up inflation in protein-rich food items.

In India, local inflation differs from aggregate inflation because idiosyncratic factors vary across regions and commodities and factors of food inflation vary from rural to urban areas. Regional inflation can be controlled by a mix of macroeconomic policies and local effort. Coordinated and complementary monetary and fiscal policies can be used to address the demand and supply bottlenecks that are important push factors of inflation. Such an approach would help the inflation-targeting central bank (the Reserve Bank of India) make accurate inflation forecasts in the short to medium run and tame the dragon called inflation. The regional or local administration needs to address idiosyncratic factors that push up inflation and implement effective market regulations, improve governance, and reduce the cost of production and transportation.

REFERENCES

Ahamada, I and E Flachaire (2010): *Non-Parametric Econometrics*, Oxford, UK: Oxford University Press.

Anand, R, D Ding and V Tulin (2014): "Food Inflation in India: The Role for Monetary Policy," IMF Working Paper WP/14/178, International Monetary Fund, Washington, DC, USA.

Anselin, L (2001): "Spatial Econometrics," *A Companion to Theoretical Econometrics*, Baltagi B (ed), US: Blackwell Publishing Ltd, pp 310–30.

Barro, R J and X Sala-i-Martin (1991): "Convergence across States and Regions," *Brookings Papers Economic Activity*, Vol 22, No 1, pp 107–82.

Beck, G, K Hubrich and M Marcellino (2009): "Regional Inflation Dynamics within and across Euro Area Countries and a Comparison with the US Economic Policy," *Economic Policy*, Vol 24, No 57, pp 142–84.

Bhattacharya, R and A Sen Gupta (2015): "Food Inflation in India: Causes and Consequences," NIPFP Working Paper No 2015–151.

Clark, G L (1984): "Does Inflation Vary between Cities?" *Environment and Planning*, Vol 16, No 4, pp 513–27.

Cox, T L and M K Wohlgenant (1986): "Prices and Quality Effects in Cross-sectional Demand Analysis," *American Journal of Agricultural Economics*, Vol 68, No 4, pp 908–19.

Darbha, G and U R Patel (2012): "Dynamics of Inflation 'Herding': Decoding India's Inflationary Process," Brookings Global Economy and Development Working Paper No 48.

Deaton, A (1988): "Quality, Quantity and Spatial Variation of Price," *American Economic Review*, Vol 78, No 3, pp 418–30.

Deaton, A and O Dupriez (2011): "Spatial Price Differences within Large Countries," Working Paper 1321, Woodrow Wilson School of Public and International Affairs, Princeton University.

Goyal, A and A Baikar (2014): "Psychology, Cyclicality or Social Programs: Rural Wage and Inflation Dynamics in India," Working Paper 14, Indira Gandhi Institute of Development Research.

Griffith, D A (2009a): "Modeling Spatial Autocorrelations in Spatial Interaction Data: Empirical Evidences from 2002 Germany Journey to Work Flows," *Journal of Geographical Systems*, Vol 11, No 2, pp 117–40.

— (2009b): "Spatial Autocorrelation in Spatial Interaction," *Complexity and Spatial Networks*, Berlin, Heidelberg: Springer, pp 221–37.

Guha, A and A Tripathi (2014): "Link between Food Price Inflation and Rural Wage Dynamics," *Economic & Political Weekly*, Vol 49, Nos 26 and 27, pp 66–73.

Hatekar, N and S Raju (2013): "Inequality, Income Distribution and Growth in Maharashtra," *Economic & Political Weekly*, Vol 48, No 39, pp 75–81.

LeSage, J P (1997): "Regression Analysis of Spatial Data," *The Journal of Regional Analysis and Policy*, Vol 27, No 2, pp 83–94.

LeSage, J P and M M Fischer (2008): "Spatial Growth Regressions: Model Specification, Estimation and Interpretation," *Spatial Economic Analysis*, Vol 3, No 3, pp 275–304.

Majumder, A, R Ray and K Sinha (2013): "Temporal Comparisons of Prices, Expenditure and Growth in India: A State-wise Analysis," *Indian Growth and Development Review*, Vol 6, No 2, pp 195–211.

— (2014): "Spatial Comparison of Prices and Expenditure in a Heterogenous Country: Methodology with Applications for India," *Macroeconomic Dynamics*, Vol 19, No 5, pp 931–89.

Malhotra, A and M Maloo (2017): "Understanding Food Inflation in India: A Machine Learning Approach," arXiv:1701.08789.

Marques, H, G Pino and J de D Tena (2009): "Regional Inflation Dynamics Using Space–Time Models," CRENoS WP 9–15, 30 November.

Mohanty, D (2011): "Changing Inflation Dynamics in India," Speech at the Motilal Nehru National Institute of Technology, Allahabad.

Nair, S R and L M Eapen (2012): "Food Price Inflation in India (2008 to 2010)," *Economic & Political Weekly*, Vol 47, No 20, pp 46–54.

Osorio, C and F Unsal (2011): "Inflation Dynamics in Asia," *Inflation Dynamics in Asia: Causes, Changes, and Spillovers from China*, Vol 11, No 257, pp 1–20.

Özgör, G (2013): "Unemployment Persistence and Inflation Convergence: Evidence from Regions of Turkey," *Regional and Sectoral Economic Studies*, Vol 13, No 1, pp 55–64.

Patnaik, A (2016): "Inflation Differential and Inflation Targeting in India," *Prajnan*, Vol 45, No 1, pp 9–24.

Pino, G, J de D Tena and A Espasa (2016): "Geographical Disaggregation of Sectoral Inflation: Econometric Modelling of the Euro Area and Spanish Economies," *Applied Economics*, Vol 48, No 9, pp 799–815.

Raj, J and S Mishra (2011): "Measures of Core Inflation in India: An Empirical Evaluation," Working Paper (DEPR), 16/2011, Reserve Bank of India.

Shaban, A (2006): "Regional Structures, Growth and Convergence of Income in Maharashtra," *Economic & Political Weekly*, Vol 41, No 18 (6–12 May), pp 1803–15.

Walsh, C E (2010): *Transparency, the Opacity Bias, and Optimal Flexible Inflation Targeting* (No 10–17), Working Papers, Santa Cruz Institute for International Economics.

Yesilyurt, F and P J Elhorst (2014): "A Regional Analysis of Inflation Dynamics in Turkey," *Annals of Regional Science*, Vol 52, No 1, pp 1–17.

Young, A, M Higgins and D Levy (2013): "Heterogeneous Convergence," *Economics Letters*, Vol 120, No 2, pp 238–41.

Zaffaroni, P (2004): "Contemporaneous Aggregation of Linear Dynamic Models in Large Economies," *Journal of Econometrics*, Vol 120, No 1, pp 75–102.

Appendix

Table 1: Everyday Consumption Items

Code	Item
x1	Bread..Bakery..R
x2	Rice..Other.Sources..U
x3	Suji.Rawa.R
x4	Wheat.Atta..Other.Sources..R
x5	Rice..Other.Sources..R
x6	cereal.subtotal.R
x7	cereal.subtotal.U
x8	cereal.substitute.R
x9	moong.R
x10	moong.U
x11	masur.U
x12	urd.R
x13	milk.liquid.R
x14	salt.R
x15	salt.U
x16	sugar.othersources.R
x17	sugar.othersources.U
x18	Eggs.R
x19	Eggs.U
x20	Goat.Meat.Mutton.R
x21	Potato.R
x22	Potato.U
x23	Onion.R
x24	Onion.U
x25	Tomato.R
x26	Tomato.U
x27	Brinjal.R
x28	Brinjal.U
x29	Palak.other.leafy.vegetables.R
x30	Green.Chillies.R
x31	Green.Chillies.U
x32	Lady.s.Finger.R
x33	Lady.s.Finger.U
x34	Cauliflower.R
x35	Cauliflower.U
x36	Cabbage.R
x37	Cabbage.U
x38	Peas.R
x39	Lemon.R
x40	Other.Vegetables.R
x41	Other.Vegetables.U
x42	Banana.R
x43	Banana.U
x44	Apple.R
x45	Apple.U
x46	Grapes.R
x47	Grapes.U
x48	Fruits.DryR
x49	Ginger.R
x50	Garlic.R
x51	Garlic.U
x52	Turmeric.R
x53	Turmeric.U
x54	Dry.Chillies.U
x55	Other.Spices.R
x56	Other.Spices.U
x57	Tea.Cups.R
x58	Tea.Cups.U
x59	Tea.Leaf.R
x60	Tea.Leaf.U
x61	bidi-R

Table 2: Descriptive Statistics, Moran's *I*, and *β* Convergence Results of the Inflation of Food Items for Rural Areas

Code	Item	Skewness	Kurtosis	Mean	Moran's *I*	*β* Coefficient
x1	Bread..Bakery..R	0.7054	1.762705	99.2995	−0.107	0.5955
x3	Suji.Rawa.R	−0.17657	1.040784	85.41937	0.07253	0.03962
x4	Wheat.Atta.. Other.Sources..R	0.339773	0.158315	73.95419	0.233076***	0.18194***
x5	Rice.. Other.Sources..R	0.456097	1.824064	85.63497	0.151871	−0.07889
x6	cereal.subtotal.R	0.353958	0.353332	64.18275	0.088042	−0.26886
x8	cereal. substitute.R	1.73163	1.931733	95.95006	0.039184	−0.3917
x9	moong.R	2.452197	11.03521	142.2324	0.100998	−0.07652
x12	urd.R	−0.1727	0.953916	135.5023	0.273343***	−0.3316
x13	milk.liquid.R	−0.19764	0.065917	102.9065	0.336795***	−0.5606***
x14	salt.R	−0.25475	0.316417	131.0099	0.282757***	−0.6688***
x16	sugar. other sources.R	2.361083	10.48541	78.10446	0.245685***	0.4618***
x18	Eggs.R	−0.20303	2.425278	95.52045	−0.12055	−0.3904***
x20	Goat.Meat. Mutton.R	6.95245	56.78347	135.8074	0.024928	0.1026
x21	Potato.R	2.043018	7.54309	63.59326	0.125426	0.2676*
x23	Onion.R	0.180333	−0.52926	92.38323	0.020912	−0.1852
x25	Tomato.R	0.704856	1.426701	87.72078	0.262328***	−0.3544***
x27	Brinjal.R	0.325824	0.335816	112.5086	−0.00302	−0.4351***
x29	Palak.other.leafy. vegetables.R	0.163543	0.479707	147.0729	0.015169	−0.4252***
x30	Green.Chillies.R	6.629993	50.31393	351.6409	0.17383***	−0.4322***
x32	Lady.s.Finger.R	0.002227	2.2373	123.7458	0.311321***	−0.3861***
x34	Cauliflower.R	0.550578	0.889288	91.74982	−0.00667	−0.18162**
x36	Cabbage.R	0.552523	0.721324	102.2043	0.0414	−0.11054
x38	Peas.R	1.252597	2.605258	99.80226	0.3421***	−0.1953
x39	Lemon.R	3.453166	20.90191	149.4814	0.086523	−0.2405
x40	Other. Vegetables.R	4.794901	29.34417	281.6309	0.016483	−0.3223***
x42	Banana.R	1.089979	3.333481	120.959	0.176663***	−0.06889
x44	Apple.R	7.546914	63.44714	168.4545	−0.02338	−0.4561***
x46	Grapes.R	8.211091	70.42262	157.794	−0.03607	−0.4565**
x48	Fruits.DryR	3.902106	16.51557	877.6562	0.109818	−0.3746***
x49	Ginger.R	7.547528	62.79458	45.58603	−0.04166	−1.5619***
x50	Garlic.R	0.505788	0.059214	137.5574	0.037323	−0.3627***
x51	Garlic.U	1.105376	2.042284	139.4551	0.182329***	−0.3905***
x52	Turmeric.R	−0.72802	0.780846	191.2921	0.153292**	−0.4894***
x55	Other.Spices.R	1.00692	0.82451	93.33382	0.151871**	−0.4434
x57	Tea.Cups.R	7.77582	65.41257	141.9475	−0.04016	−0.22556*
x59	Tea.Leaf.R	0.416259	0.599696	58.91264	0.100998	−0.1329
x61	bidi-R	4.875905	32.67971	127.6649	−0.02138	−0.18005

1 Item definitions are as per NSSO definitions.
2 "U" implies urban areas and "R" implies rural areas.
3 *** implies significance at 1% level, ** implies significance at 5% level, and * is significance at 10% level.

Table 3: Descriptive Statistics, Moran's *I*, and *β* Convergence Results of the Inflation of Food Items for Urban Areas

Code	Item	Skewness	Kurtosis	Mean	Moran's *I*	*β* Coefficient
x2	Rice..Other. Sources..U	−0.04218	1.096142	86.22431	−0.10061	−0.02378
x7	cereal.subtotal.U	−0.24722	1.149093	71.13896	−0.0094	0.01605
x10	moong.U	0.243045	0.859557	138.4805	0.291785***	−0.3358***
x11	masur.U	0.518483	0.208081	108.0084	0.097884	−0.3882*
x15	salt.U	6.754877	54.24255	112.1008	−0.01075	−0.1858
x17	sugar. othersources.U	0.862767	1.28876	78.25169	0.233562***	0.1102
x19	Eggs.U	1.403615	3.222989	102.6831	0.006138	−0.168
x22	Potato.U	0.731786	1.400201	60.23569	0.290825	0.1886
x24	Onion.U	5.025562	32.15526	91.55237	−0.00224	−0.2497**
x26	Tomato.U	3.268516	20.22576	80.2336	0.201822***	−0.4036***
x28	Brinjal.U	1.134193	1.293066	278.1076	0.298334***	0.5618
x31	Green.Chillies.U	5.252032	31.43115	280.682	−0.0225	−0.4177***
x33	Lady.s.Finger.U	2.550889	11.17119	124.4589	0.175996***	−0.2888***
x35	Cauliflower.U	0.634586	1.242599	90.80656	−0.03578	−0.252*
x37	Cabbage.U	1.579423	5.262969	104.0147	0.023089	−0.3873***
x41	Other. Vegetables.U	8.455342	73.6145	425.7904	0.001251	−0.1934
x43	Banana.U	0.066715	0.20884	117.1379	0.159864**	−0.06071
x45	Apple.U	1.968496	8.240857	239.3132	−0.00249	0.04395
x47	Grapes.U	8.0042	67.66711	197.9119	0.007881	−0.2102
x51	Garlic.U	1.105376	2.042284	139.4551	0.182329***	−0.3905***
x53	Turmeric.U	0.141711	0.948001	183.4096	0.191694***	−0.3742***
x54	Dry.Chillies.U	−0.2478	0.668784	124.2206	0.204658***	−0.3878***
x56	Other.Spices.U	1.13379	1.804824	95.47608	0.14667**	−0.5055***
x58	Tea.Cups.U	1.689223	4.147637	122.9859	0.121018	0.2271
x60	Tea.Leaf.U	6.114951	47.33875	64.02251	−0.03322	−0.11504

1 Item definitions are as per NSSO definitions.
2 "U" implies urban areas and "R" implies rural areas.
3 *** implies significance at 1% level, ** implies significance at 5% level, and * implies significance at 10% level.

Table 4: Determinants of Food Inflation—Spatial Regression Results for Rural Areas

Food Item	Spatial Weight Coefficient	P-value	Rainfall	P-value	MPCE	P-value
Wheat	–0.108	0.07	–	–	–	–
Rice	–	–	–	–	–	–
Suji	0.17	0.02	–	–	–	–
Bread	–0.390	0.01	–0.0026	0.015	5.97	0.002
Processed food	0.4944	0.10	–	–	0.0160	0.001
Pulses	0.9493	0.001	–	–	1.250	0.001
Salt	0.0616	0.02	–	–	1.2388	0.001
Sugar	0.150	0.035	–0.001	0.009	1.2388	0.001
Vegetables	0.1218	0.003	–	–	0.6157	0.00
Fruits	0.1639	0.000	–	–	3.714	0.02
Spices	0.477	0.001	–	–	0.0332	0.001
Beverages	0.9493	0.000	–	–	0.0076	0.0002

Table 5: Determinants of Food Inflation—Spatial Regression Results for Urban Areas

Food Item	Spatial Weight Coefficient	P-value	Rainfall	P-value	MPCE	P-value
Wheat	0.85	0.00	–	–	–0.0018	0.0055
Rice	–	–	–	–	–	–
Suji	–	–	–	–	–	–
Bread	0.91	0.001	–	–	–	–
Processed food	0.17	0.00	–0.0075	0.07	–0.0113	0.000
Pulses	0.079	0.0001	–	–	–1.0817	0.00
Salt	0.95	0.001	–	–	–	–
Sugar	0.98	0.01	–0.009	0.05	0.060	0.00
Vegetables	0.341	0.003	–0.024	0.003	–	–
Fruits	0.8512	0.01	–0.119	0.001	0.0003	0.004
Spices	0.561	0.01	–0.078	0.01	–	–
Beverages	0.95	0.001	–0.0015	0.001	–	–

Table 6A: CAGR Cereals—Centre-wise CPI Data vs NSS Data, 2005–12

Centre	Cereals-CPI	Cereals-NSS
Guntur	7.339495	8.598
Hyderabad	7.115598	6.5215
Visakhapatnam	9.143242	6.2689
Warangal	9.899733	10.3315
Guwahati	6.749672	6.9743
Munger	9.237178	8.4587
Bhilai	10.87597	8.0685
Ahmedabad	9.112331	8.2205
Rajkot	7.532338	6.4618
Surat	10.14076	9.9714
Vadodara	8.365406	9.9714
Faridabad	9.212908	8.1868
Srinagar	2.88801	6.5429
Ranchi	9.929167	5.1628
Bengluru	9.249137	11.0659
Belgaum	10.21858	5.8338
Bhopal	9.988349	8.1612
Indore	8.794462	6.2286
Jabalpur	12.60268	11.5297
Mumbai	9.110958	10.3186
Nagpur	10.35624	7.2047
Nashik	11.02393	13.9797
Pune	9.64011	6.2184
Rourkela	11.16756	11.9585
Ludhiana	10.16266	4.6764
Ajmer	9.085449	6.062976
Jaipur	9.320123	6.062976
Chennai	8.225741	4.6167
Coimbatore	7.666269	9.474
Madurai	9.532887	5.4088
Salem	5.813898	9.474
Agra	7.875857	1.8783
Kanpur	8.754875	4.3093
Varanasi	9.31787	7.459
Darjeeling	10.30727	9.0755
Howrah	6.932893	9.0755
Kolkata	7.090908	6.846

Table 6B: CAGR Pulses—Centre-wise CPI Data vs NSS Data, 2005–12

Centre	Pulses-CPI	Pulses-NSS
Guntur	12.39035647	12.2161
Hyderabad	12.45454981	13.8669
Visakhapatnam	11.58369987	12.8988
Warangal	12.06943621	12.2705
Guwahati	11.91127037	12.4226
Munger	10.85850004	12.7075
Bhilai	13.43982417	11.713
Ahmedabad	12.45213188	11.5587
Rajkot	13.06136723	11.6663
Surat	14.1329549	13.453
Vadodara	10.49592561	13.453
Faridabad	12.27704718	11.5485
Srinagar	10.14968392	12.282
Ranchi	11.10359287	11.7464
Bengluru	11.63426994	13.9264
Belgaum	12.46982594	13.9353
Bhopal	12.83089094	10.8879
Indore	12.35939209	13.312
Jabalpur	11.86635965	13.2859
Mumbai	12.90793821	10.8184
Nagpur	13.8343733	14.1265
Nashik	13.30576789	14.3585
Pune	12.96284357	13.444
Rourkela	13.78207641	15.1445
Ludhiana	13.28112785	7.479
Ajmer	12.13238414	10.57934
Jaipur	13.04062389	10.57934
Chennai	11.21393804	11.42
Coimbatore	12.30046735	13.9958
Madurai	11.43602186	10.0795
Salem	12.33277297	13.9958
Agra	10.79997738	12.2978
Kanpur	12.09984194	10.7385
Varanasi	11.03402333	12.1021
Darjeeling	12.26591084	13.8538
Howrah	12.09333638	13.8538
Kolkata	12.31948279	12.8391

Table 6C: CAGR Oil—Centre-wise CPI Data vs NSS Data, 2005–12

Centre	Oil-CPI	Oil-NSS
Guntur	12.87609	9.3052
Hyderabad	10.59393	10.9556
Visakhapatnam	6.43834	12.037
Warangal	11.89516	13.9523
Guwahati	8.122984	5.676
Munger	9.013507	0.6645
Bhilai	13.23038	15.8434
Ahmedabad	11.12392	58.9101
Rajkot	13.05684	13.873
Surat	12.95559	13.8514
Vadodara	12.28059	12.8514
Faridabad	8.546664	6.865
Srinagar	7.034287	5.3951
Ranchi	8.701776	11.6395
Bengaluru	8.681613	13.782
Belgaum	9.630173	7.514
Bhopal	7.69187	10.0396
Indore	12.28499	12.9535
Jabalpur	6.520433	9.5537
Mumbai	12.91106	12.2578
Nagpur	10.42559	12.6039
Nashik	12.21771	13.3329
Pune	12.4425	13.3227
Rourkela	9.492343	2.7539
Ludhiana	7.67872	9.7153
Ajmer	9.930846	11.61542
Jaipur	10.22318	13.61542
Chennai	8.74243	6.3344
Coimbatore	12.57182	10.4
Madurai	10.93154	11.7612
Salem	8.600121	10.4
Agra	9.288253	11.6871
Kanpur	9.791852	19.6275
Varanasi	9.040547	11.8671
Darjeeling	7.825081	5.3004
Howrah	10.31563	7.3004
Kolkata	10.32761	8.9023

Table 6D: CAGR Milk—Centre-wise CPI Data vs NSS Data, 2005–12

Centre	Milk-CPI	Milk-NSS
Guntur	10.02362	12.5424
Hyderabad	14.24995	12.68
Visakhapatnam	15.36559	16.3759
Warangal	14.77089	11.7511
Guwahati	12.36007	12.5239
Munger	9.236482	10.4417
Bhilai	10.45758	11.3166
Ahmedabad	11.3958	12.3824
Rajkot	13.45592	13.1036
Surat	11.7651	9.659
Vadodara	12.14944	9.659
Faridabad	11.3934	9.5553
Srinagar	8.065233	10.6226
Ranchi	10.22174	10.5259
Bengaluru	9.973287	9.4528
Belgaum	10.49388	7.0731
Bhopal	11.73833	9.1972
Indore	11.14332	12.6986
Jabalpur	11.84838	11.0885
Mumbai	6.790784	8.9181
Nagpur	12.24633	11.7414
Nashik	7.818343	8.209
Pune	11.18119	13.5854
Rourkela	9.076704	7.878
Ludhiana	12.14044	10.6406
Ajmer	12.34244	11.60441
Jaipur	11.6869	10.60441
Chennai	11.8583	12.938
Coimbatore	10.60506	12.2094
Madurai	10.84664	12.0352
Salem	17.15092	16.2094
Agra	10.40727	10.0251
Kanpur	10.45205	12.3494
Varanasi	11.3156	10.6493
Darjeeling	6.35701	5.784
Howrah	8.509889	9.784
Kolkata	8.789943	10.8313

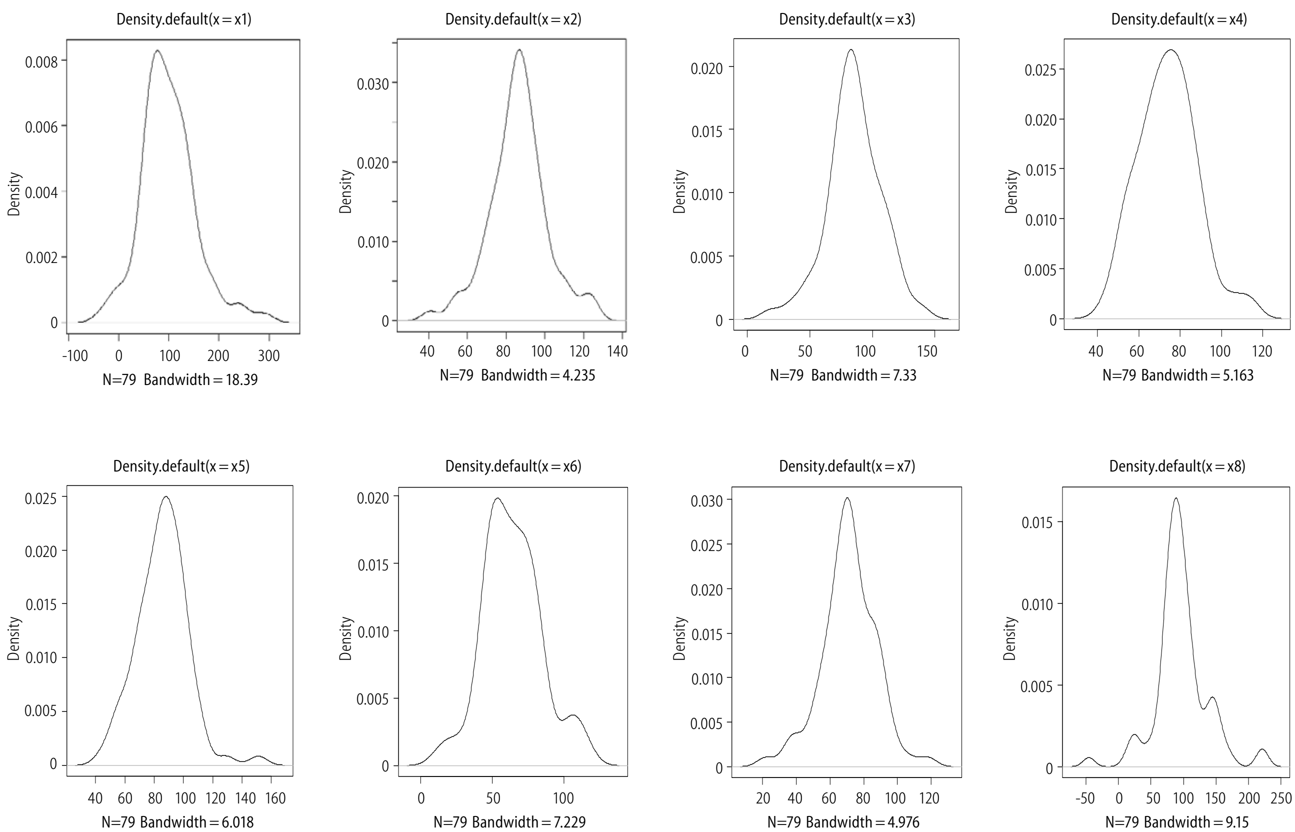
Table 6E: CAGR Species—Centre-wise CPI Data vs NSS Data, 2005–12

Centre	Spices-CPI	Spices-NSS
Guntur	9.722429	12.1536
Hyderabad	9.986958	12.5854
Visakhapatnam	9.852017	14.9181
Warangal	11.09163	12.2375
Guwahati	12.68995	14.6577
Munger	8.547166	10.0226
Bhilai	10.2139	11.1828
Ahmedabad	9.9674	6.612
Rajkot	6.861244	9.2441
Surat	8.860591	9.5557
Vadodara	7.673715	9.5557
Faridabad	8.495404	10.4511
Srinagar	11.05295	13.5092
Ranchi	7.393529	9.367
Bengluru	10.0725	11.9403
Belgaum	7.271564	6.8312
Bhopal	9.342885	6.4331
Indore	10.30306	11.3728
Jabalpur	9.043363	11.559
Mumbai	8.872709	10.8622
Nagpur	10.45306	12.9383
Nashik	9.223718	8.849
Pune	6.862866	8.0875
Rourkela	8.992845	11.8099
Ludhiana	10.06353	9.7231
Ajmer	10.82157	9.573606
Jaipur	9.848442	9.573606
Chennai	12.37097	12.2595
Coimbatore	11.60655	12.1992
Madurai	13.31767	12.4078
Salem	9.772056	11.1992
Agra	7.711407	9.7533
Kanpur	10.23402	11.6965
Varanasi	8.492653	10.3242
Darjeeling	11.7163	13.9172
Howrah	11.41417	12.9172
Kolkata	10.18648	11.8975

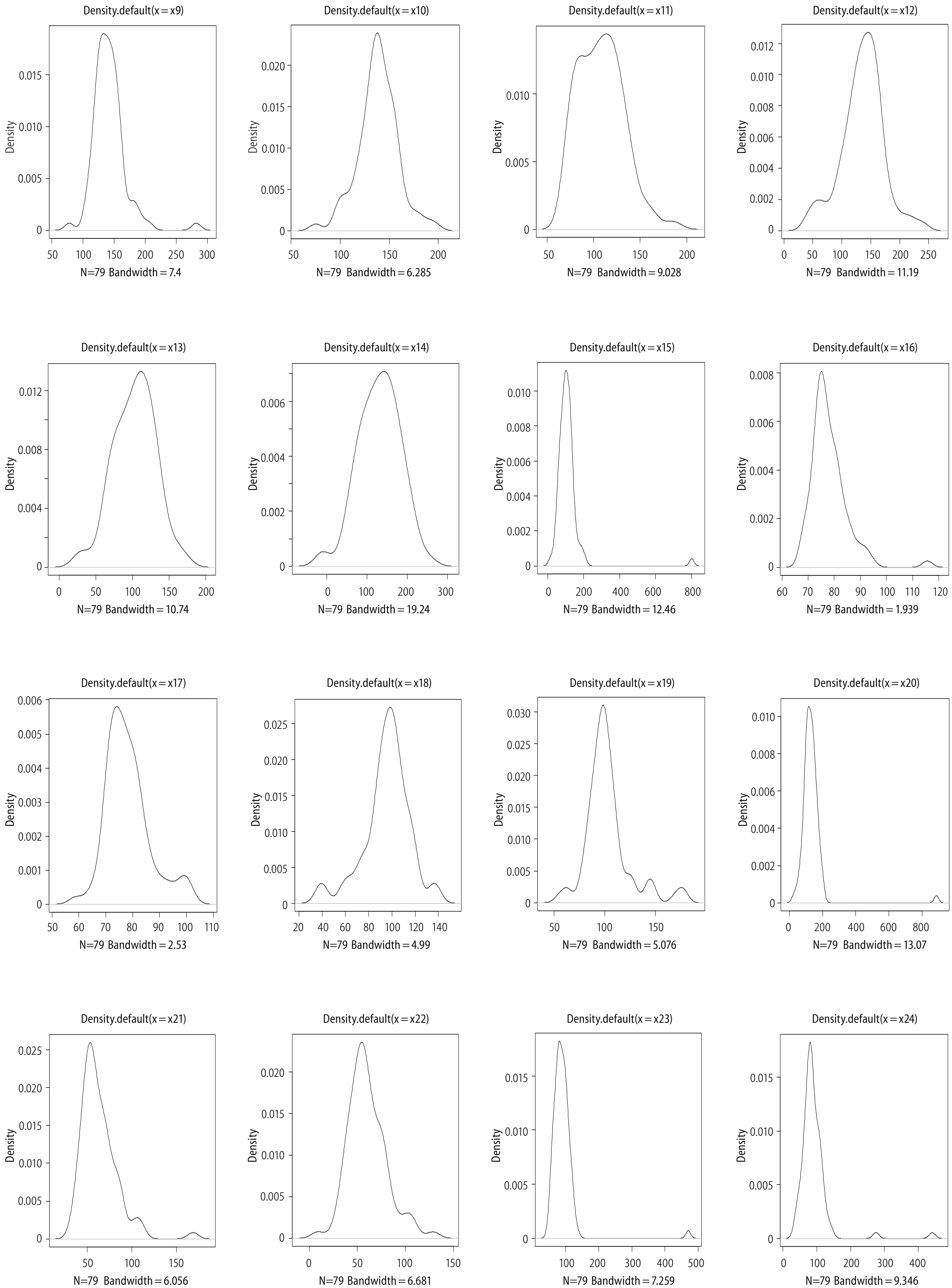
Table 7

	Food item
1	Wheat
2	Rice
3	Suji
4	Bread
5	Processed food
6	Milk
7	Salt
8	Sugar
9	Vegetables
10	Fruits
11	Spices
12	Pulses
13	Beverages

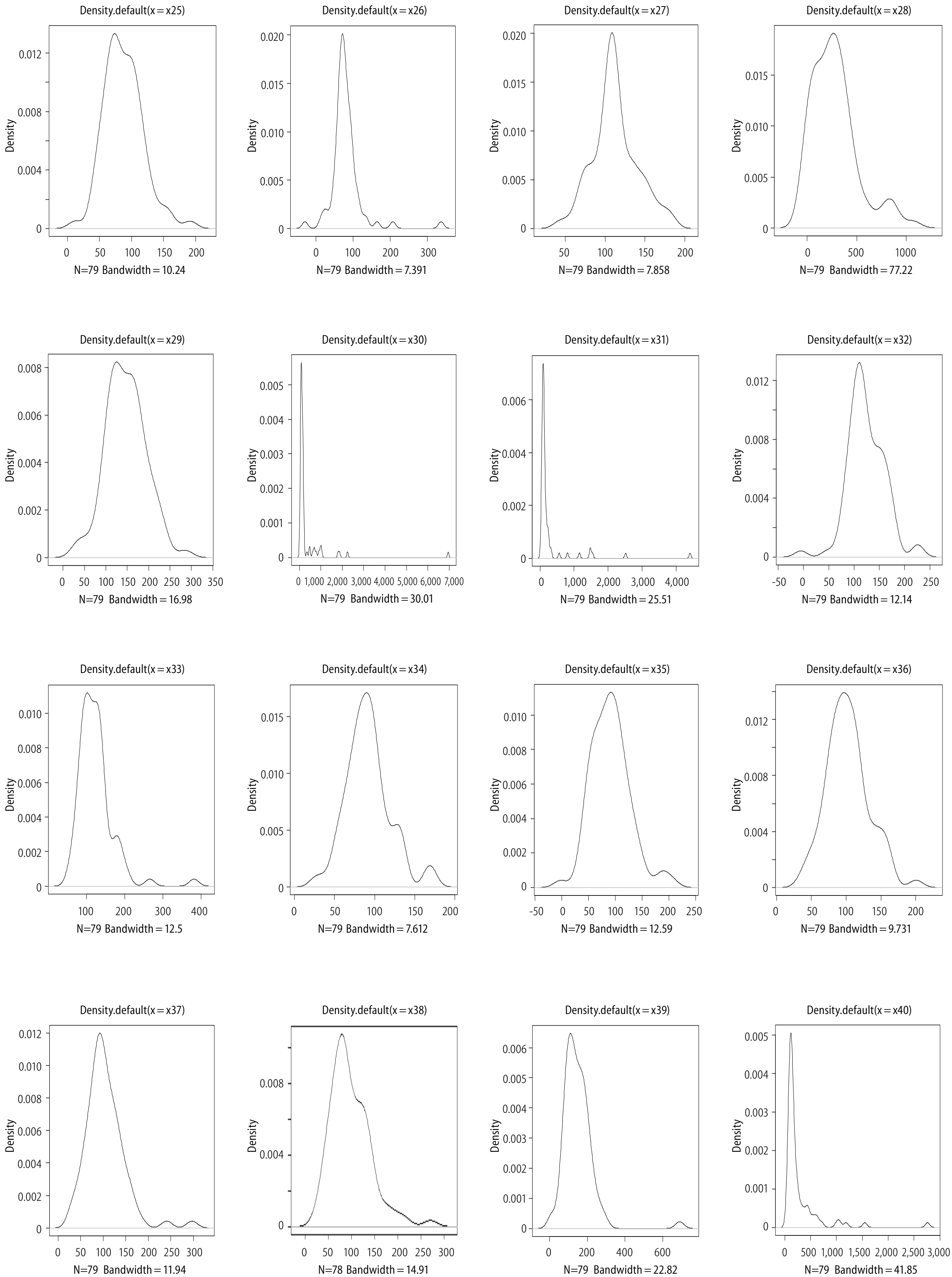
Appendix 1: Distributions



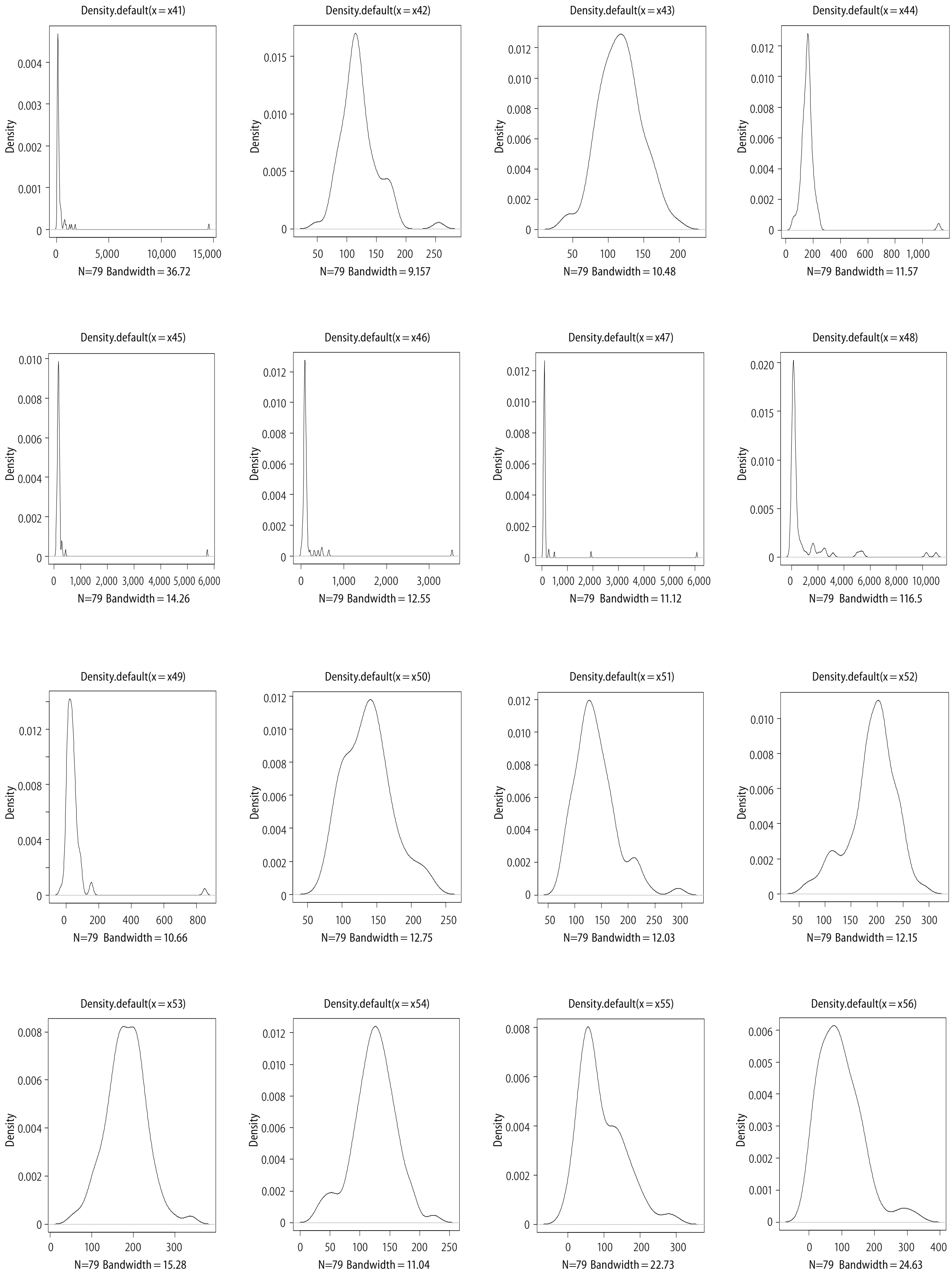
Appendix: Distributions *(Continued)*



Appendix: Distributions *(Continued)*



Appendix: Distributions *(Continued)*



Appendix: Distributions *(Continued)*