Rags and Riches: Relative prices, non-homothetic preferences and inequality in India*

Ingvild Almås[†] Anders Kjelsrud[‡]

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Abstract

It is well known that consumption patterns change with income. Relative price changes would therefore affect rich and poor consumers differently. Yet, the standard price indices are not income-specific, and hence, they cannot account for such differences. In this paper, we study consumption inequality in India, while fully allowing for non-homotheticity. We show that the relative price changes during most of the period from 1993 to 2012 were pro-poor, in the sense that they favored the poor relative to the rich. As a result, we also find that conventional measures significantly overstate the rise in real consumption inequality during this period. The main lesson from our study is the importance of accounting for non-homotheticity when measuring inequality. The price index literature has, as of yet, paid relatively little attention to this. In our application, however, it turns out that the allowance for non-homotheticity is quantitatively much more important than much discussed adjustments, such as those for substitution in consumption.

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[†]IIES, Stockholm University and Norwegian School of Economics, email: `ingvild.almas@iies.su.se`

[‡]Statistics Norway and University of Oslo, email: `gkj@ssb.no`

1 Introduction

It is well known that consumption patterns change with economic affluence, i.e. that preferences are non-homothetic. Relative price changes will hence affect people differently even if all face the same set of prices (Muellbauer, 1974). Yet, the conventional price indices are not income-specific, and they will therefore mask these differences.[1] This is likely to be a problem of first-order importance when discussing distributions and inequality, but it might also be a problem for other types of analysis as it is not transparent whose cost of living the standard indices represent (see e.g. Beatty & Crossley, 2012). For example, the typical consumer price index formulae would, due to the aggregation technique used, generate price indices that represent a relatively rich consumer, and this "representative" individual will be increasingly rich when the level of inequality rises.

In this paper, we study consumption inequality and expenditure-specific cost of living in India during the period 1993–94 to 2011–12. We show that the changes in relative prices in most of this period were pro-poor, meaning that they favored the poor rather than the rich. We also show that these relative price changes have a large impact on measured inequality. Standard measures suggest that inequality rose quite steeply during our study period (Cain *et al.*, 2010; Datt & Ravallion, 2009; The World Bank, 2011).[2] However, about one third of the increase between 1993–94 and 2004–05 disappears when we apply our expenditure-specific cost of living adjustment. For the years after 2004–05, we find that the relative price changes were pro-rich and that the standard measures therefore somewhat understate the rise in inequality. Much of these patterns can be explained by changes in the relative prices of food grains versus the relative prices of different non-food items. In our data we find that the budget share devoted to food grains falls as people become richer, whereas the budget share devoted to non-food goods increases. The cost of living of the rich therefore rises relatively to that of the poor when non-food prices increase more than grain prices. This is exactly what happened during the period from the mid 1990s to the mid 2000s, and the opposite of what happened during the subsequent period.

Overall, we also find that the conventional inequality measures overstate the *variance* in inequality over time. We cannot, however, conclude that this is a general bias of measures relying on homothetic preferences. Yet, there are plausible scenarios in which these measures will exhibit such a bias. For example, we could imagine societies where the poor are producing and consuming necessities, while the rich are producing and consuming luxury goods in addition to necessities. In such societies, relative increases (decreases) in the prices of luxury goods would lead to higher (lower) nominal inequality as the relative wages of the rich rise (fall). The effect on real inequality would be smaller, however, because the cost of living of the rich also would rise relative to that of the poor. Since the conventional measures do not account for this they will overstate the variance in real inequality. We provide some empirical evidence for such a systematic relationship between income and cost of living effects following from relative price changes, by comparing how poor rural farmers and others are affected by prices of food grains.

The standard price indices have other biases beside those induced by relying on homothetic preferences. For example, the fixed basket approaches, such as the Laspeyres, the Paasche and the classical Geary methods – the latter underlies the Penn World Table – fail to incorporate substitution, as the assumed consumer basket is held fixed in comparisons involving different relative price levels. A large part of the price index literature is about how to avoid this problem (Akmal, 2005; Diewert, 1978; Feenstra *et al.*, 2012; Neary, 2004). In our empirical investigation, we make an effort to disentangle the biases caused by not adjusting for substitution and the biases caused by implicitly relying on homothetic preferences. This is done by comparing our estimates, which incorporate both substitution and non-homotheticity, with inequality measures derived through the Geary index, which does not allow for either of the two, and with measures derived through an index that allows for substitution but that relies on homothetic preferences. This comparison suggests that substitution alone has a very limited quantitative importance in our application – the differences between our estimates and the traditional fixed basket approaches are driven almost entirely by the allowance for non-homotheticity in our estimates.

We implement our analysis with household data collected by the National Sample Survey Organisation (NSS). This is the standard source for household expenditure comparisons in India. Using these survey data, we construct expenditure-specific cost of living indices in three main steps. In the first step, we calculate unit values and use those as measures of item prices (Deaton, 2008; Deaton & Dupriez, 2011; Deaton & Tarozzi, 2005). In the second step, we characterize consumer preferences. This is necessary in order to account for non-homotheticity. It is also necessary in order to incorporate substitution in consumption. As a way of recovering preferences, we estimate the Quadratic Almost Ideal Demand System (Banks *et al.*, 1997), using 11 aggregate consumption groups and percentiles of the expenditure distributions within each state, sector (urban and rural) and time period as the unit of observation.[3] In the third and final step, we make use of the estimated price and income responses to compute money metric utilities and use those to calculate expenditure specific cost of living. From this it is straightforward to compute measures of real inequality. To evaluate the robustness of our measures, we repeat the procedure for a series of alternative specifications. All these alternative setups provide similar inequality trends as our main estimates, and all confirm that the allowance for non-homotheticity is quantitatively much more important than the allowance for substitution.

Our paper illustrates how conventional inequality measures are biased, depending on the particular patterns of relative price changes. We are not the first to discuss this type of bias. Some papers have, for example, proposed solutions on how to weight individual cost of living to obtain one aggregated "social cost of living index" (Crossley & Pendakur, 2010; Muellbauer, 1976; Pollak, 1980, 1981). More recently, other papers have directly discussed how price changes within countries affect different income groups (Cravino & Levchenko, 2016; Faber, 2014; Handbury, 2013; Moretti, 2013; Sakai *et al.*, 2017). Mishra & Ray (2011), Nicholas *et al.* (2010) and Pendakur (2002) investigate real consumption inequality in India, Australia and Canada, respectively, correcting for cost of living differences by indices closely related to ours. These authors also calculate money metric utility using the cost function. However, the other standard indices are not derived in any of the papers and they do not make an attempt to adjust for cost of living differences across geographical areas. Hence, they cannot nail down how important the adjustment for non-homotheticity is compared to other adjustments. One of the contributions of our paper is to calculate cost of living deflators across time and space using standard indices and thus separate the bias stemming from the assumption of homothethic preferences from other types of biases.

The rest of the paper is organized as follows. In Section 2 we describe the construction of the different cost of living indices used in the empirical investigation. In Section 3 we present the data and discuss the implementation of our methods. We present our main findings in Section 4. In Section 5 we discuss the robustness checks, whereas concluding remarks are given in Section 6.

2 Non-homothetic preferences and cost of living

This section gives an overview of the different cost of living indices used in the analysis. For brevity, we use the notation "unit" for a unique state in a specific time period and sector (urban or rural). Throughout, there are n commodities indexed $i = 1, \ldots, n$, and m units indexed $j = 1, \ldots, m$. For each unit, there is a price vector p^j and a corresponding per capita quantity vector q^j. The total quantity consumed in a unit is given by the vector Q^j. Per capita nominal consumption in unit j is given by $z_j = p^j q^j$.

The Geary index, also known as the Geary–Khamis index, is based on the idea of evaluating quantities, not by actual prices, but by a vector of average prices, π. The real per capita consumption level of unit j, evaluated in this way, could be written as:

$$I_j^{cons} = \pi q^j, \tag{1}$$

and the corresponding cost of living index as:

$$P_j^{cons} = \frac{p^j q^j}{\pi q^j}. \tag{2}$$

So far, this is similar to any conventional consumer price index. Therefore, we label this index by "cons", for "consumption index". As actual quantities are evaluated at the reference prices, this index does not take into account substitution in consumption. That is, the index does not adjust for the fact that the consumers would have chosen a different consumption basket if faced with the reference prices instead of the actual prices in their unit. The failure of the standard indices, such as the Geary index, to account for substitution has spurred a literature on more structural cost of living indices, sometimes referred to as "the economic approach" to price index measurement (Akmal, 2005; Neary, 2004).[4] This approach requires the estimation of preferences and is based on evaluating money metric utilities, $m(\pi, p^j, z_j)$. The real consumption level of unit j in this system could be denoted by:

$$I_j^{exp\text{-}h} = m(\pi, p^j, z_j) = e(\pi, v(p^j, z_j)), \tag{3}$$

where $e(.)$ and $v(.)$ are the expenditure function and the indirect utility function, respectively (that are specified once preferences have been estimated, more on this later). The cost of living index of unit j could now be written as:

$$P_j^{exp\text{-}h} = \frac{e(p^j, v(p^j, z_j))}{e(\pi, v(p^j, z_j))}. \tag{4}$$

The system allows for substitution in consumption, but does not allow for non-homotheticity. For this reason, we use the labelling "exp-h" for "expenditure homothetic", where the expenditure part refers to the computation through the expenditure function. If relative prices differ, and if the consumption basket changes with real income, there is no unique cost of living for every individual within a unit. The cost of living will not only depend on prices, but also on income. Indices of the form in (4) cannot be applied even if we are only interested in the average cost of living in each unit, since there is no representative consumer when preferences are non-homothetic.

To fully allow for non-homotheticity, we construct a final real consumption index as:

$$I_j^{exp\text{-}nh} = L_j^{-1} \sum_{l=1}^{L_j} e(\pi, v(p^j, z_{jl})), \tag{5}$$

where z_{jl} denotes per capita nominal consumption for individual l in unit j. The equation sums the money metric utilities for all individuals, $l = 1, \ldots, L_j$, in each unit. We label this extension by "exp-nh", for "expenditure non-homothetic", as it fully allows for non-homothetic preferences. The disaggregated nature of this index allows us to compute every individual's real consumption level from $e(\pi, v(p^j, z_{jl}))$ or, equivalently, by adjusting their nominal consumption level using the income-specific cost of living index:

$$P_{jl}^{exp\text{-}nh} = \frac{e(p^j, v(p^j, z_{jl}))}{e(\pi, v(p^j, z_{jl}))}. \tag{6}$$

The implementation of the above expenditure indices requires a procedure to determine the reference price vector and a characterization of preferences. Below we discuss both of these in turn.

In our main set of calculations, we determine the reference prices for all three indices in a Geary-like fashion. The Geary approach implicitly identifies reference prices by requiring that total consumption of each good should have the same overall value whether evaluated at the reference prices or at each unit's own prices divided by the unit's estimated cost of living. For the consumption index, this could be stated as follows:

$$\sum_{j=1}^{m} \pi_i Q_{ij} = \sum_{j=1}^{m} \frac{p_{ij} Q_{ij}}{P_j^{cons}}, \quad \text{for all } i = 1, \ldots, n. \tag{7}$$

These n linear equations in π determine the n reference prices (up to a normalization). Neary (2004) suggests a procedure to calculate similar types of reference prices in money metric cost of living indices. The procedure calculates the reference price vector π as in the classical Geary calculation, but multiplies the reference prices with virtual instead of actual quantities. The virtual quantities are those that would have been consumed if the reference prices had been the actual prices. This procedure enables us to account for substitution. By Shepard's lemma, these quantities could be identified through the Hicksian demand functions. Thus, for the expenditure homothetic index, we could determine the reference prices by the following equations:

$$\sum_{j=1}^{m} \pi_i H_i(\pi, u_j) = \sum_{j=1}^{m} \frac{p_{ij} Q_{ij}}{P_j^{exp\text{-}h}}, \quad \text{for all } i = 1, \ldots, n, \tag{8}$$

where $H_i(\pi, u_j)$ is the total amount of virtual quantities of item i that would have been consumed in unit j at prices π. To take account of the within-unit distribution of expenditures, we can write the corresponding equations for the expenditure non-homothetic index as (Almås & Sørensen, 2012):

$$\sum_{j=1}^{m} \pi_i \sum_{l=1}^{N_j} h_i(\pi, u_{jl}) = \sum_{j=1}^{m} p_{ij} \sum_{l=1}^{N_j} \frac{q_{ijl}}{P_{jl}^{exp\text{-}nh}}, \quad \text{for all } i = 1, \ldots, n. \tag{9}$$

These two sets of nonlinear equations determine the reference prices in the two expenditure based systems, just as the (linear) equations in (7) determine the reference prices of the Geary system. In the robustness section, we propose yet two alternative procedures to determine the reference prices. All our main results are invariant to the use of these alternative procedures.

To recover the necessary preference parameters, we estimate the Quadratic Almost Ideal Demand System (QUAIDS) due to Banks *et al.* (1997). The QUAIDS is consistent with utility maximization and the budget share equation for good i can be expressed in the following flexible form:

$$\omega_{ij} = \alpha_i + \sum_{h=1}^{n} \gamma_{ih} \ln p_{hj} + \beta_i \ln y_j + \frac{\lambda_i}{\beta(p^j)} (\ln y_j)^2, \tag{10}$$

where $\ln y_j = \ln z_j - \ln \alpha(p^j)$, z_j is nominal per capita expenditure, and $\alpha(p^j)$ and $\beta(p^j)$ are price indices that depend on the parameters.[5] Moreover, the log expenditure function in the QUAIDS could be expressed as:[6]

$$\ln e(p_j, u_j) = \ln \alpha(p^j) + \frac{u_j \beta(p^j)}{1 - u_j \lambda(p^j)}. \tag{11}$$

The next section describes the data and the computation of the above cost of living indices.

3 Data and implementation

3.1 Data and price estimates

Our analysis is based on the nationwide household surveys collected by the National Sample Survey Organization (NSS). The NSS conducts household expenditure surveys every year, but the large surveys which can be used for state-level analysis are typically quinquennial. We use the five most recent such survey rounds, conducted in 1993–94, 1999–00, 2004–05, 2009–10 and 2011–12. We limit the analysis to the 17 states labelled as "major" by the NSS. These states account for almost the entire Indian population.[7] Table 1 provides summary statistics of the sample of large states. As can be seen, the sample size in each survey varies from around 80000 to about 100000.

[Table 1 here]

The household surveys include information on consumption expenditure for a wide range of items. However, to ease the estimation of the demand system, we aggregate all consumption items into 11 groups. These are: *Cereal and cereal substitutes; Pulses and pulse products; Milk and milk products; Edible oil, fruits, egg, fish and meat; Vegetables; Sugar, salt and spices; Beverages, pan, tobacco and intoxicants; Fuel and light; Clothing; Bedding and footwear* and *Miscellaneous non-food.* The demand system estimation requires prices for each of these consumption groups, separately for every unit in the analysis. We obtain these prices by calculating household-specific unit values directly from the NSS data. This is possible since the surveys include information on quantities and expenditure for the different consumption items. In all, we are able to obtain such estimates for 155 consumption items. We drop items that either do not appear in every survey round, or that are reported in incompatible units across survey rounds. Having obtained household level unit values, we compute median unit values within each unit. We next aggregate to the 11 consumption groups using the weighted country-product-dummy method due to Rao (1990).[8] We provide more details on this aggregation in Appendix A.

Clearly, unit values are only proxies for prices. One advantage of using unit values in our setting is that they could be calculated from a large set of observations (in contrast to retail prices, which are often based on fairly small samples). Another advantage is that the unit values are linked to actual transactions as opposed to price quotations. Still, one potential concern is that there may be quality differences in the reported consumption goods. We therefore provide a robustness check where we try to correct the unit values for item quality. It is comforting that our results are robust to the use of these alternative price measures.

The last consumption group (*Miscellaneous non-food*) consists of goods for which we are not able to compute unit values. This is due to the fact that the NSS does not collect information on quantities for these items. If this consumption group was equally important for rich and poor households, we could reasonably have estimated our model without it. However, the data clearly suggest that the budget share devoted to these non-food items increases with total expenditure.[9] Thus, the consumption group could potentially be an important source of cost of living differences between the rich and the poor. Therefore, we proceed in a similar manner as Deaton (2008) and impute prices using information from the official state- and sector-wise consumer price indices (CPIs). These CPIs consist of several sub-indices, such that it is possible to construct an index for goods corresponding to our residual group. Yet, the CPIs cannot provide estimates of price *levels* across space. We therefore proceed by setting the price level of miscellaneous non-food goods in the first time period equal to the price level of food items in the same state and sector. For later periods we impute prices such that we match the relative inflation rate vis-à-vis food items observed in the CPIs. Appendix A describes this procedure in more detail.

The Public Distribution System (PDS) in India is a public scheme centered on providing quotas of subsidized food grains (mainly rice and wheat) to eligible households. The NSS values the consumption of these subsidized goods at the actual prices people pay. However, because the program has strict restrictions on quantity, it is best seen as providing implicit income transfers (Dreze & Khera, 2013; Himanshu & Sen, 2013; Khera, 2011). In the analysis we therefore value consumption of PDS rice and wheat at the median market prices in each unit.[10] In the robustness section we show that our main findings are unaffected by this adjustment. The level of inequality changes somewhat, however.

3.2 Estimation of demand system

We estimate the 11 goods QUAIDS demand system based on the budget share formulation shown in Equation (10). The system is identified through spatial and inter-temporal variation in prices and household consumption levels, and under the assumption of homogenous preferences. This latter assumption is clearly somewhat restrictive, but we nonetheless allow for more heterogeneity, namely in terms of cost of living across groups of households, than any standard analysis of inequality. Future research should aim at also addressing heterogenous tastes. In the estimation, we use data on 100 expenditure level groups from every unit (mean per capita expenditure and budget shares for each group), and a Seemingly Unrelated Regressions system (SUR) estimated by Maximum Likelihood. By using group data instead of individual household data, we implicitly assume that preferences are homothetic within each of the expenditure groups. We consider the within-group variance in total expenditure to be small enough such that this aggregation is unproblematic. Moreover, the assumption of normally distributed error terms is more likely to hold with grouped data (Aasness & Rødseth, 1983).

We impose homogeneity and negativity of the substitution matrix in the estimation. The homogeneity restriction is imposed simply by excluding the eleventh budget share equation and by normalizing all prices relative to this last consumption group. The negativity restriction on the Slutsky matrix is more challenging. We follow an approach first suggested by Lau (1978) and later applied by Moschini (1998), which is based on imposing negativity at a *single* data point. Thus, we cannot be sure that the restriction holds throughout. It is more likely to be violated in points far away from the point where negativity was imposed. Like Neary (2004), we impose negativity at the sample means. By an appropriate scaling of the data, the substitution terms in the Slutsky matrix at this point reduce to a simple function of parameters only (see Appendix C in Neary (2004) for a discussion). Finally, we do not directly estimate on the Slutsky matrix, but rather on the Cholesky decomposition of its mean values.

Yet, even after imposing these restrictions, there are still 85 parameters to be estimated, most of them appearing in every budget share equation. We follow Blundell & Robin (1999) in estimating the parameters in an iterative manner. This is done by placing restrictions on the price responsiveness in the demand system, setting the last n-k-1 rows of the Cholesky decomposition equal to zero. This gives a "semi-flexible" system of rank k, with a smaller number of parameters to be estimated. We gradually increase the allowed price responsiveness by increasing the rank, using the estimated coefficients from the preceding values of k as starting values. We keep increasing the rank until the likelihood function no longer improves, which happens at $k = 8$.

To obtain elasticities we first differentiate Equation (10) and obtain:

$$\mu_i = \frac{\partial \omega_i}{\partial \ln y} = \beta_i + \frac{2\lambda_i}{\beta(p)} \ln y. \tag{12}$$

We then calculate the budget elasticity as:

$$e_i = \frac{\mu_i}{\omega_i} + 1. \tag{13}$$

Table 2 presents estimates for two of the key parameters in these expressions. Standard errors, derived through bootstrapping, are shown in parentheses.[11] Since the budget share equations are non-linear, the elasticities will vary with total expenditure. From the table it can still be seen that *Cereal and cereal substitutes* and *Miscellaneous non-food* are the two consumption groups for which the budget shares vary the most with total expenditure. The budget share for cereals falls in total expenditure – at least for low levels of expenditure – whereas the budget share for miscellaneous non-food increases for all expenditure levels.

[Table 2 here]

4 Empirical findings

4.1 Main findings

The estimation procedure described above provides all parameters needed to compute the expenditure function given in Equation (11). This, combined with consumption group prices, is sufficient to calculate cost of living and real consumption inequality.

Table 3 displays population weighted all-India cost of living measures by the rural and the urban sector, relative to the first time period (1993–94). The differences across the consumption index and the two expenditure indices are fairly small for this aggregated statistic. However, the aggregated numbers in the table mask important differences *within* units. Figure 1 provides an illustration of this. The figure compares the cost of living for households in the bottom two and upper two expenditure percentiles relative to the average in each unit. A number above (below) unity therefore indicates that households in the particular groups experienced higher (lower) increases in their cost of living as compared to other households. The figure thus suggests that the period from 1993–94 to 2004–05 can be characterized as pro-poor, in the sense that the cost of living increased relatively more for the rich than for the poor. Whereas the cost of living in this period increased by almost 100 percent on average for the richest one percent in each unit, it rose by roughly 80 percent on average for the poorest one percent. The overall relative price changes during the subsequent period are pro-rich, and the effect is therefore somewhat dampened when we consider the whole period up until 2011–12.

[Table 3 here]

[Figure 1 here]

The figure only provides a snapshot of the distribution, however. We now proceed to investigate the full expenditure distribution, by computing inequality estimates directly from the household data. In this section, we focus on one particular measure, namely the Theil index. In the appendix we present two other standard inequality measures, the Gini index and mean relative deviation, and show that our main findings are robust to the use of these alternative measures (Table B1). We also present inequality estimates broken down to state level (Table B2).

Figure 2 displays trends in consumption inequality.[12] The first column in the figure presents inequality numbers for the rural and the urban sectors combined, whereas the second and third columns show inequality estimates for the two sectors separately. The consumption and the expenditure homothetic cost of living numbers reveal close to similar inequality estimates for all three samples.[13] Thus, the allowance for substitution in consumption does not seem to be of any quantitative importance in this application. The expenditure non-homothetic estimates deviate more substantially. In particular, these estimates suggest a more moderate increase in inequality over the period 1993–94 to 2004–05, once again indicating that the changes in relative prices were pro-poor. The opposite is true for the next five-year period, and the homothetic indices underestimate the increase in inequality. This is especially noticeable in the rural sector where these estimates suggest a decrease in inequality, whereas the estimates that allow for non-homotheticity reveal a modest increase.

[Figure 2 here]

We produce and present standard errors for the various inequality numbers through bootstrapping (see Table B1). These standard errors capture the uncertainty related to the estimated demand model, and as the parameters of the demand system are relatively precisely estimated the standard errors of the inequality measures are correspondingly small. All the inequality trends and levels presented in Figure 2 are therefore significantly different from each other.[14]

4.2 Discussion

How do we explain the above findings? One advantage of using the Theil index is that we can easily study inequality across different groups of households, as the index is decomposable. Figure 3 displays three measures of between-group inequality. The first column presents inequality in average consumption across rural and urban areas, the second presents inequality across states, while the third column presents inequality in average consumption across all units, i.e. across states and rural and urban areas. The overall pattern suggests that all of these inequalities have risen steadily during our study period. However, the estimates in the figure are almost invariant to the choice of cost of living index, and hence, the between-group inequalities cannot explain why the non-homothetic inequality measure differs from the two others.

[Figure 3 here]

The differences in measured inequality are instead due to cost of living variation *within* units. From Table 2 we can see that *Cereals* and *Miscellaneous non-foods* are the consumption groups for which the budget shares change the most with total consumption: the budget share of cereals decreases as households become richer, whereas the budget share of miscellaneous non-food increases. It turns out that differences between the homothetic and the non-homothetic inequality measures map the changes in the relative prices of these two consumption groups. Figure 4 plots the percentage changes in prices of non-food goods relative to prices of cereals. A value above zero therefore indicates that non-food prices increased relatively more. The figure also presents changes in the homothetic inequality measure relative to changes in the non-homothetic measure, and thus a value above zero now means that the homothetic measure increased relatively more. By comparing the two lines, we see that the homothetic estimates overvalue (undervalue) inequality during periods when the prices of non-food goods increased relatively more (less) than the prices of cereals. The reason is that these measures fail to account for the relative greater importance of non-food goods for the rich and the relative greater importance of cereals for the poor. We find the same pattern for the inequality estimates at the state level, as can be seen from the regression coefficients in Table 4. In order to compare changes over equally long time spells, we exclude the latest survey round in these regressions (the results are not sensitive to this).

[Figure 4 here]

We also find that the non-homothetic inequality numbers, especially those for the rural sector, vary less over time compared to the homothetic inequality estimates. Hence, the differential trends in cost of living seem to offset some of the factors causing changes in nominal inequality. We cannot conclude, however, that this finding is directly generalizable to other settings. Yet, we could think of plausible scenarios for which the same finding will occur. Imagine, for example, a society where the rich are engaged in producing non-food luxury goods, while the poor are producing food and necessities. Relative increases in the prices of non-food goods would, in such a society, lead to higher nominal inequality since the relative wages of the rich would rise. But as the rich consume relatively more non-food luxury goods, their cost of living would also rise relatively more and thus dampen the increase in real inequality. The differences in the consumption patterns of rich and poor will, similarly, dampen decreases in inequality when food prices rise relative to non-food prices.

It is out of the scope of this paper to fully investigate whether income and cost of living effects are systematically related in such a way in practice. However, we here provide an illustrative example based on data for rural crop producers. These crop producing households are on average 30 to 40 percent poorer than other households and their population share was around 50 percent in 1993–94, falling gradually to about 30 percent in 2011–12. When crop prices rise less than other prices, we would expect the nominal incomes of these rural farmers, and hence also their total expenditure, to fall further behind those of other households. We investigate this by regressing changes in relative expenditure levels of crop producers and other households on changes in relative prices of miscellaneous non-food goods and cereals. Column (1) in Table 5 presents such a regression at state level. As can be seen, the estimated coefficient is negative and significant, meaning that crop producers tend to become poorer (richer) compared to others when prices of non-food goods increase (decrease) relative to prices of cereals. Since crop producers on average are substantially poorer than others this effect will thus push in the direction of increasing (decreasing) nominal inequality.

However, exactly because crop producers are poor, they also tend to spend relatively little on non-food consumption items. Their cost of living will therefore be less affected than that of the richer households when the prices of these goods change. The conventional measures fail to account for this differential effect, and hence, they will tend to exaggerate changes in inequality that are caused by such price changes. This is shown in the rest of Table 5. The coefficients in Column (2) show that changes in the homothetic inequality measure are positively associated with changes in relative non-food/cereal prices, meaning that inequality increases when the prices of miscellaneous non-foods rise relative to the prices of cereals. The association is positive also when we use the non-homothetic inequality measure, but as can be seen from Column (3), the correlation is much weaker and not statistically significant.

[Table 4 here]

[Table 5 here]

5 Robustness

In this section, we present four types of robustness checks. All these alternative specifications provide similar trends in real consumption inequality as in our main analysis. Moreover, for all specifications, we find that the allowance for non-homotheticity is quantitatively much more important than the allowance for substitution in consumption. For brevity we mainly focus on the combined inequality estimates. All the robustness results also hold for the rural and urban estimates.

5.1 Alternative reference prices

As a first robustness check, we compute the cost of living indices using two alternative sets of reference prices. First, we adopt the procedure suggested by Barnett *et al.* (2009), and later implemented by Feenstra *et al.* (2012). This procedure is based on using *every* unit's price vector as a reference, and then taking a geometric mean of all such comparisons. For brevity, we refer to these references as "Diewert prices". Using the Diewert prices as a base price vector, we could express the real consumption level of unit j derived through the consumption index as:

$$I_j^{cons} = \prod_s^m (p^s q^j)^{\frac{1}{m}}. \tag{14}$$

The expenditure homothetic index becomes:

$$I_j^{exp\text{-}h} = \prod_s^m e(p^s, v(p^j, z_j))^{\frac{1}{m}}, \tag{15}$$

whereas the expenditure non-homothetic index can be written as:

$$I_j^{exp\text{-}nh} = \prod_s^m \left(L^{-1} \sum_l e(p^s, v(p^j, z_{jl})) \right)^{\frac{1}{m}}. \tag{16}$$

As a second set of alternative reference prices, we simply use all unit prices as references, instead of taking the geometric mean. As most methods of calculating reference prices would produce some average of the price vectors of the individual units, this procedure should be seen as extremely flexible. However, for most applications, it is not very convenient, as it gives the same number of real consumption estimates for each unit as for the total number of units.

Figure 5 plots the trends in inequality using the different reference price vectors. The left column shows the expenditure non-homothetic Theil index, whereas the middle and the right columns plot the difference between these numbers and the inequality estimates derived through the consumption index and the expenditure homothetic index, respectively. The solid lines, labeled "Geary ref.", are based on the Geary reference prices (as are the inequality estimates presented in the main analysis), while the dotted lines, labeled "Diewert ref.", are based on the Diewert reference prices. Finally, the light grey lines use the price vectors of all units as references. As can be seen from all three panels, the choice between the Geary and the Diewert reference prices does not affect the subsequent inequality estimates (they are indistinguishable in the graphs). We obtain somewhat different inequality numbers when we use each unit's price vector as a reference, but the trends in inequality, as well as the difference between the inequality measures, are still not substantially affected.

[Figure 5 here]

5.2 Quality-adjusted unit values

In the main analysis, we use median unit values as proxies for prices. Even though we are able to compute these unit values at a fine level of goods disaggregation, we cannot be certain that the consumption items are perfectly homogeneous. This could be problematic, as households' reported unit values will be affected by the quality of the underlying goods. The median unit values will provide biased estimates of the true price differences if households from different regions systematically purchase goods of different quality. Deaton *et al.* (2004) suggest a regression-based method to correct for this possible bias. They start out by assuming that variation in the reported unit values stems from a mixture of differences in quality and true prices:

$$ln\ uv_{il} = ln\ p_{ij} + ln\ \varphi_{il}, \tag{17}$$

where uv_{il} is the unit value of item i reported by household l, p_{ij} is the true item price in unit j (at some base quality level common for all units), while φ_{il} is the quality of the item consumed by household l. A convenient assumption is that quality can be represented as a log-linear function of real consumption:

$$ln\ uv_{il} = ln\ p_{ij} + b_i ln\ y_l + \gamma X, \tag{18}$$

where y_l is the real consumption level of household l, and X is a vector of other possible household covariates. The b_i-coefficient can be interpreted as the elasticity of quality with respect to total expenditure. From this it can be seen that the quality-bias in the unit values is a function of the real consumption level and the quality elasticity. The procedure proposed in Deaton *et al.* (2004) only partially removes this bias, since it replaces real per capita expenditure with nominal per capita expenditure. Provided that cost of living differs across regions and over time, the quality-adjusted prices will therefore include a bias which depends on the expenditure elasticity and the overall price level in each unit. More particularly, the estimated item prices in a unit would be more biased if the cost of living in the unit deviates significantly from the average. Provided that the expenditure elasticity is positive, we can also infer that the procedure would underestimate spatial cost of living differences across units, as it undervalues item prices in high-cost areas and overvalues item prices in low-cost areas. By the same logic, we can infer that the procedure would underestimate increases in cost of living over time – provided that the overall cost of living rises – since it overestimates item prices in early time periods and underestimates item prices in later time periods.

The bias could be avoided by replacing nominal expenditure by real expenditure in Equation (18). The main challenge is that we need the unbiased item prices to derive an estimate of the overall cost of living in each unit. We therefore propose an iterative method. In the first step, we estimate the following regression, separately for every item i, using nominal per capita expenditure values as in Deaton *et al.* (2004):

$$ln\ uv_{il} = \sum_j d_j D_j + bln z_{lj} + \gamma X, \tag{19}$$

where D_j is a dummy variable for each unit, z_{lj} is the nominal expenditure level of household l living in unit j and X is a vector of household covariates (the number of household members below 16 years of age, the number of household members above 16 years of age and the age of the household head). We identify the price component from the dummy variables. The bias in the subsequent price measure of item i can now be expressed as:

$$ln\ p_{ij} - ln\ \hat{p_{ij,1}} = b_i ln(\overline{e(\pi, v(p^j, z_{jl}))}) - \hat{b}_i ln \overline{z_{lj}}, \tag{20}$$

where $\overline{e(\pi, v(p^j, z_{jl}))}$ and $\overline{z_{lj}}$ display the mean real and nominal expenditure levels, respectively, in unit j relative to some base. The subscript of $\hat{p}_{ij,1}$ denotes that this is our first estimate of p_{ij}. Next, we use these proxies of the item prices to estimate aggregated consumption group prices, and then to compute our non-homothetic cost of living index as described in Section 2. Having obtained these overall cost of living measures, we re-run the regression from Equation (19), again separately for each item i, but now using real expenditure instead of nominal expenditure:

$$ln\ uv_{il} = \sum_j d_j D_j + bln(e(\hat{\pi_1}, v(\hat{p_1^j}, z_{jl}))) + \gamma X. \tag{21}$$

From this estimation, we are able to extract a new set of item price measures. The bias in this price estimate of item i can be expressed as:

$$ln\ p_{ij} - ln\ \hat{p_{ij,2}} = b_i ln(\overline{e(\pi, v(p^j, z_{jl}))}) - \hat{b}_i ln(\overline{e(\hat{\pi_1}, v(\hat{p_1^j}, z_{jl}))}). \tag{22}$$

The absolute size of the bias in $ln\ \hat{p}_{ij,2}$ is smaller than the bias in $ln\ \hat{p}_{ij,1}$, provided that:

$$\left| b_i ln(\overline{e(\pi, v(p^j, z_{jl}))}) - \hat{b}_i ln(\overline{e(\hat{\pi_1}, v(\hat{p_1^j}, z_{jl}))}) \right| < \left| b_i ln(\overline{e(\pi, v(p^j, z_{jl}))}) - \hat{b}_i ln\overline{z_{lj}} \right|. \tag{23}$$

Hence, if this requirement is fulfilled, we could repeat the procedure and the solution should eventually converge.

Table B3 in the appendix presents unit value estimates for the eight most important items in terms of average budget shares. All numbers in the table are shown as population weighted averages. The first row for each good shows the median unit values (that is, the population weighted average of the median unit values within each unit), whereas the second row presents quality adjusted numbers based on the methodology in Deaton *et al.* (2004). The following five rows show the unit value estimates from the five succeeding iterations in our proposed procedure. The numbers in parenthesis display the b-coefficients from the item-specific regressions. These coefficients would be zero if the consumption items were completely homogeneous. For items such as sugar and edible oil, which are likely to be rather homogeneous, we see that the coefficients indeed are almost zero. Thus, the biases in the median unit values are likely to be small. However, goods within consumption headings such as "garments" are clearly more heterogeneous, and the median unit values are therefore likely to be more severely biased.

Figures B1 and B2 present the price trends for the different groups of unit values. The figures show that the adjustment of Deaton *et al.* (2004) gives rise to lower price increases than what is suggested by the median unit values. This is as expected, given positive b-coefficients and increases in overall cost of living over time. The price estimates from our iteration procedure are generally somewhere in between the two other price estimates, although much closer to the median unit values.

Figure 6 presents the trends in inequality, using both median unit values and quality adjusted unit values. Given that the quality adjustment has a relatively small impact on the unit values, it is not very surprising that these measures are rather similar. The middle and the right panels display the difference between the non-homothetic numbers and the consumption and the expenditure homothetic estimates, respectively. As can be seen, the differences between these estimates are not affected by the use of quality adjusted unit values.

[Figure 6 here]

5.3 Equivalence scaling and demographics

As a third robustness check, we repeat the whole analysis using equivalence scaling. The key difference between these estimates and those in the main analysis is the composition of households in the expenditure groups used for the estimation of the demand system and for the calculation of the cost of living indices. Various equivalence scales have been proposed in the literature. We use the standard OECD scale of 1982. This scale gives a weight of 1 to the first adult in the household, a weight of 0.7 to the rest of the adults in the household, and a weight of 0.5 to each child in the household. We define a child as an individual aged below 16. The resulting inequality estimates are presented in Figure 7. The use of equivalence scales reduces the level of inequality somewhat, as can be seen from the left panel. Still, the trends in inequality, as well as the differences between the various estimates, are almost identical to our main estimates.

Relative prices may affect people differently not only because preferences are non-homothetic, but also because people live in households with different compositions. To test more directly whether our results are driven by differences in family composition, we conduct the whole analysis for 11 subsamples. All households in each of these subsamples have an identical composition of adults and children. Table B4 in the appendix shows the number of households in each of these subsamples. Since we need a reasonable number of observations within each unit, we pick subsamples with at least 3000 observations in each survey round. Still, there are too few observations within each of these to construct percentiles for every unit. We therefore base the estimation of the QUAIDS, and the subsequent cost of living measures, on 20 expenditure groups instead of 100 as in the main analysis. Figure B3 and B4 in the appendix display cost of living for the bottom two and upper two expenditure groups, relative to the average, for the rural and the urban sector, respectively. As can be seen from these figures, the trends are very similar across all of these subsamples, which suggests that our estimated trends in inequality and cost of living are not driven by differences in family composition.[15]

[Figure 7 here]

5.4 The Public Distribution System (PDS)

In the main analysis, we value the consumption of subsidized goods through the PDS at local market prices. As a fourth robustness check, we now estimate cost of living and inequality while evaluating these goods at the actual prices paid. This robustness check is interesting in its own right, as it tells us something about the distributional impact of the public scheme.

Table B5 in the appendix presents some background statistics of the PDS. The first two columns show the share of households consuming any PDS rice and PDS wheat, respectively, while the next two columns display the average per capita quantities consumed among these households. As can be seen, the average quantities are fairly stable over time, while the coverage of households – especially in rural areas – has increased substantially. Columns (5) to (8) display the (average) median unit values for subsidized PDS items and corresponding market items. The PDS prices have been close to constant over time, whereas the market prices have increased roughly threefold – meaning that the value of having access to the scheme has risen substantially over time. This, together with the increase in coverage, means that the choice of how to treat PDS consumption will be more important for the later survey rounds. The two final columns present the fraction of households with PDS consumption of either rice or wheat that also consume the same goods from the regular market. As can be seen, the majority of the PDS households purchase additional quantities of rice or wheat from the regular market.

Figure 8 shows how the inequality estimates change when we evaluate the PDS items at actual prices paid. As the program is (at least intentionally) targeted towards the poor, it is not surprising that the inequality numbers rise somewhat as compared to those presented in the main analysis.[16] However, the trends and the differences between the three sets of inequality estimates are very similar.

[Figure 8 here]

6 Concluding remarks

In this paper, we study relative price changes and real consumption inequality in India during the period 1993–94 to 2011–12. We find that in periods when the price of necessities decreased relative to that of other goods (1993–94 to 2004–05 and 2009–10 to 2011–12), traditional indices overestimate the increase in inequality whereas the opposite is true for the period when the prices of necessities increased relative to other goods (2004–05 to 2009–10). Much of these patterns can be explained by relative changes in the prices of cereals and different non-food goods. We also show that the adjustment for non-homotheticity is quantitatively much more important than the adjustment for substitution in consumption, despite the greater attention given to the substitution bias in the price index literature. These findings are robust to various robustness checks.

The main lesson from our study is the importance of accounting for non-homotheticity when measuring inequality. The quantitative importance is quite clearly going to be smaller in analyses that do not directly depend on the full distribution of consumers. Yet, the use of conventional price indices may give rise to misleading conclusions also in such analyses, as it is often unclear whose cost of living the standard price indices represent. This is particularly problematic during periods when relative consumption prices change markedly.

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Notes

[1]See Feenstra *et al.* (2015) for an overview of standard price indices used for comparisons of income/consumption.

[2]There is much less evidence on the trend in income inequality. As one of the few exceptions, Banerjee & Piketty (2005) present trends in top incomes and wages for the period 1922–2000 using individual tax return data. Goel (2017) provides evidence of increased wage inequality between skill groups in India.

[3]The number of consumption groups that we use is similar to in many other applications, e.g., the number of goods corresponds to that of the Penn World Table basic headings. Our findings are robust to categorizing goods in different ways. We have tested several groupings and our findings hold up.

[4]See also Almås (2012), Costa (2001) and Hamilton (2001) for related approaches.

[5]The price indices are defined as follows: $\ln \alpha(p^j) \equiv \alpha_0 + \sum_i \alpha_i \ln p_{ij} + \frac{1}{2}\sum_i \sum_h \gamma_{ih} \ln p_{ij} \ln p_{hj}$ and $\ln \beta(p^j) \equiv \sum_i \beta_i \ln p_{ij}$.

[6]$\lambda(p^j) \equiv \sum_i \lambda_i \ln p_{ij}$.

[7]According to the Indian Census, the 17 major states accounted for 96 percent of the population in 1991, 95 percent in 2001 and 94 percent in 2011. Note also that as Jharkhand and Chhattisgarh were carved out of Bihar and Madhya Pradesh in 2000, they do not appear in the household surveys before 2004–05. They do, however, appear as regions in Bihar and Madhya Pradesh such that it is possible to single them out. Therefore, we proceed by using the post-partition state boarders.

[8]The weighted country-product-dummy method is a modification of the unweighted version first suggested by Summers (1973).

[9]As there is significant consumption growth during over study period, the importance of the non-food group is also likely to change over time. The average budget share of miscellaneous non-food increases from 17 percent in 1993–94 to 25 percent in 2011–12 in the rural sector, and from 17 percent to 24 percent in the urban sector.

[10]Our way of valuing PDS goods is reasonable since most households consuming either rice or wheat through the PDS make additional purchases of the same goods in the regular market. See also Column (9) and (10) in Table B5). Hence, the marginal prices faced by households do not change.

[11]We conduct the bootstrapping as follows. We start with the sample of 100 expenditure groups for each unit. Then, we draw observations from this sample, with replacement, such that we match the original number of observations. We do this 1000 times, and estimate the demand system for each of these samples. Finally, we construct standard errors using the large set of estimated parameters. We execute the procedure using the Abel Cluster,

owned by the University of Oslo and the Norwegian metacenter for High Performance Computing (NOTUR).

[12]We remove the 0.1 percent poorest and the 0.1 percent richest households in each unit. This exclusion is done because we are afraid that some of the extreme outliers are due to measurement errors. Our main findings are invariant to the inclusion/exclusion of these households.

[13]Note that the NSS survey from 1999–00 is not fully compatible with the other survey rounds, due to some inconsistencies in the recall periods used. See Deaton & Kozel (2005) for a detailed discussion on this. The level of inequality in 1999–00 might therefore not be comparable with the levels in the other years. Still, we have no reasons to expect that the inconsistency in recall period affects the differences between our three real expenditure measures.

[14]We have tested both the differences in means in each time period, and the differences-in-differences between each of the time periods.

[15]The inequality numbers for each of these subsamples are less interesting, since they are based on completely different populations than those in our main analysis.

[16]For evidence on how the PDS affects measures of poverty, see Dreze & Khera (2013) and Himanshu & Sen (2013).

Tables

Table 1: Summary statistics from the NSS

	1993–94	**1999–00**	**2004–05**	**2009–10**	**2011–12**
	(1)	(2)	(3)	(4)	(5)
Demographics					
Household size (#)	5.99	6.23	5.98	5.68	5.54
Children below 16 years of age (#)	2.33	2.54	2.34	2.05	1.93
Adults (#)	3.66	3.69	3.64	3.63	3.61
Occupations					
Self-employed non-agriculture (share)	0.19	0.20	0.23	0.23	0.24
Agriculture, self-employed and labor (share)	0.52	0.52	0.49	0.45	0.42
Other					
Monthly per capita expenditure (Rs.)	326	564	698	1172	1601
Rural (share)	0.76	0.75	0.76	0.74	0.72
Observations (#)	97965	100954	99788	80386	80409

Note: All variables are weighted by the population multipliers provided by the NSS.

Table 2: Parameters from the estimated QUAIDS

	β		λ	
Cereal and cereal substitutes	-0.1224	(0.0011)	0.0308	(0.0014)
Pulses and pulse products	-0.0111	(0.0002)	-0.0024	(0.0002)
Milk and milk products	0.0201	(0.0009)	-0.0293	(0.0009)
Edible oil, fruits, egg, fish and meat	-0.0086	(0.0005)	-0.0105	(0.0005)
Vegetables	-0.0213	(0.0003)	-0.0008	(0.0006)
Sugar, salt and spices	-0.0136	(0.0002)	-0.0033	(0.0003)
Beverages, pan, tobacco and intoxicants	0.0150	(0.0007)	-0.0026	(0.0009)
Fuel and light	-0.0213	(0.0004)	-0.0030	(0.0008)
Clothing	-0.0083	(0.0002)	-0.0020	(0.0004)
Bedding and footwear	0.0021	(0.0001)	-0.0020	(0.0001)
Miscellaneous non-food	0.1693	(0.0010)	0.0252	(0.0020)

Note: The table displays two of the key parameters from the estimation of the QUAIDS demand system. Standard errors are shown in the parentheses.

Table 3: All-India cost of living relative to 1993–94

	Consumption Index	**Expenditure Index**			
		Homothetic		Non-homothetic	
	(1)	(2)		(3)	
Rural					
1993–94	100.0	100.0	(0.00)	100.0	(0.00)
1999–00	158.8	158.4	(0.03)	158.0	(0.02)
2004–05	184.6	184.7	(0.07)	183.5	(0.06)
2009–10	280.0	281.1	(0.07)	281.5	(0.06)
2011–12	329.0	329.9	(0.08)	328.5	(0.08)
Urban					
1993–94	100.0	100.0	(0.00)	100.0	(0.00)
1999–00	156.6	156.5	(0.02)	156.6	(0.01)
2004–05	188.9	186.6	(0.07)	185.6	(0.06)
2009–10	286.2	285.0	(0.06)	285.4	(0.04)
2011–12	341.4	340.0	(0.09)	338.1	(0.08)

Note: All numbers are population weighted, using the multipliers provided by the NSS. The non-homothetic indices are normalized such that they give the same cost of living for all expenditure groups *within* each unit in the first period. Standard errors are shown in the parentheses.

Table 4: Percentage changes in relative prices and inequality

Dep.var: %-changes in relative inequality (homothetic over non-homothetic	**Combined** (1)	**Rural** (2)	**Urban** (3)
%-changes in relative prices	0.225***	0.216***	0.233***
(miscellaneous non-foods over cereals)	(0.031)	(0.043)	(0.038)
Constant	0.996***	0.995***	1.001***
	(0.006)	(0.008)	(0.005)
R^2	0.523	0.336	0.584
N	51	51	51

Note: The regressions are based on the same variables that are used in Figure 4, but at state level. All numbers are population weighted, using the multipliers provided by the NSS. Robust standard errors are shown in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Expenditure ratios vs. relative prices

Dep. var.: %-changes in:	**Relative exp. crops vs others** (1)	**Theil Exp-h.** (2)	**Theil Exp-nh.** (3)
%-changes in relative prices	-0.103**	0.430***	0.182
(miscellaneous non-foods over cereals)	(0.049)	(0.130)	(0.132)
Constant	-0.026**	0.095***	0.099***
	(0.010)	(0.021)	(0.023)
Observations	51	51	51
R^2	0.062	0.196	0.043

Note: The table is based on data at the state level. The regression shown in the first column uses the percentage change in the ratio of average per capita expenditure of rural crop producers over average per capita expenditure of other households as the dependent variable. The dependent variables in the second and third columns are the percentage change in the homethetic and in the non-homethetic inequality measure, respectively. The independent variable in all three regressions is the percentage change in relative prices of miscellaneous non-food goods over cereals. Robust standard errors are shown in the parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A1: Unit values and CPI price estimates

	$\mathbf{UV_{food}}$ (1)	$\mathbf{CPI_{food}}$ (2)	$\mathbf{CPI_{m.n\text{-}f}}$ (3)	$\frac{\mathbf{CPI_{food}}}{\mathbf{CPI_{m.n\text{-}f}}}$ (4)
Rural				
1993–94	1.00	1.00	1.00	1.00
1999–00	1.56	1.51	1.65	1.10
2004–05	1.72	1.60	1.95	1.22
2009–10	2.91	2.61	2.64	1.01
2011–12	3.28	2.90	3.09	1.06
Urban				
1993–94	1.00	1.00	1.00	1.00
1999–00	1.55	1.61	1.69	1.05
2004–05	1.69	1.80	2.22	1.24
2009–10	2.88	2.95	3.21	1.09
2011–12	3.30	3.36	3.78	1.13

Note: "UV_{food}" presents the unit value food index, "CPI_{food}" presents the CPI food index, "$CPI_{m.n\text{-}f}$" presents the CPI sub-index that corresponds to our residual consumption group, whereas $\frac{CPI_{food}}{CPI_{m.n\text{-}f}}$ displays the ratio of "CPI_{food}" over "$CPI_{m.n\text{-}f}$".

TABLE B1: Inequality estimates

	Theil			Gini			Mean relative deviation		
	Cons	Exp-h	Exp-nh	Cons	Exp-h	Exp-nh	Cons	Exp-h	Exp-nh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Combined									
1993–94	0.14572	0.14598	0.14592	0.28356	0.28381	0.28382	0.13032	0.13058	0.13057
		(0.00001)	(0.00001)		(0.00001)	(0.00001)		(0.00001)	(0.00001)
1999–00	0.15844	0.15892	0.15574	0.29524	0.29579	0.29283	0.14041	0.14093	0.13806
		(0.00003)	(0.00003)		(0.00002)	(0.00003)		(0.00002)	(0.00003)
2004–05	0.20176	0.20461	0.19283	0.32473	0.32700	0.31871	0.17069	0.17301	0.16415
		(0.00002)	(0.00009)		(0.00001)	(0.00006)		(0.00001)	(0.00006)
2009–10	0.20476	0.20628	0.20491	0.32588	0.32711	0.32662	0.17169	0.17299	0.17231
		(0.00002)	(0.00011)		(0.00001)	(0.00007)		(0.00002)	(0.00007)
2011–12	0.21499	0.21522	0.20785	0.33516	0.33531	0.32988	0.18152	0.18169	0.17558
		(0.00002)	(0.00007)		(0.00002)	(0.00005)		(0.00002)	(0.00006)
Rural									
1993–94	0.11730	0.11724	0.11745	0.25655	0.25657	0.25680	0.13032	0.13058	0.13057
		(0.00001)	(0.00001)		(0.00001)	(0.00001)		(0.00074)	(0.00074)
1999–00	0.11970	0.12026	0.11663	0.25997	0.26065	0.25679	0.14041	0.14093	0.13806
		(0.00001)	(0.00003)		(0.00002)	(0.00003)		(0.00099)	(0.00100)
2004–05	0.14814	0.14893	0.14100	0.27945	0.28025	0.27311	0.17069	0.17301	0.16415
		(0.00002)	(0.00005)		(0.00001)	(0.00005)		(0.00142)	(0.00134)
2009–10	0.14105	0.14068	0.14208	0.27500	0.27477	0.27549	0.17169	0.17299	0.17231
		(0.00004)	(0.00007)		(0.00003)	(0.00007)		(0.00161)	(0.00156)
2011–12	0.15344	0.15252	0.14805	0.28683	0.28599	0.28106	0.18152	0.18169	0.17558
		(0.00005)	(0.00008)		(0.00005)	(0.00008)		(0.00156)	(0.00151)
Urban									
1993–94	0.16850	0.16877	0.16857	0.30914	0.30941	0.30927	0.13032	0.13058	0.13057
		(0.00001)	(0.00001)		(0.00000)	(0.00000)		(0.00076)	(0.00076)
1999–00	0.18367	0.18382	0.18255	0.32404	0.32421	0.32356	0.14041	0.14093	0.13806
		(0.00001)	(0.00005)		(0.00001)	(0.00004)		(0.00088)	(0.00095)
2004–05	0.22988	0.23052	0.21488	0.35807	0.35863	0.34778	0.17069	0.17301	0.16415
		(0.00001)	(0.00014)		(0.00001)	(0.00008)		(0.00110)	(0.00098)
2009–10	0.24020	0.24022	0.23571	0.36257	0.36285	0.36025	0.17169	0.17299	0.17231
		(0.00002)	(0.00017)		(0.00001)	(0.00010)		(0.00127)	(0.00120)
2011–12	0.23985	0.24009	0.23017	0.36222	0.36263	0.35582	0.18152	0.18169	0.17558
		(0.00001)	(0.00009)		(0.00001)	(0.00006)		(0.00098)	(0.00092)

Note: "Cons" denotes the consumption index; "Exp-h" denotes the expenditure homothetic index, and "Exp-nh" denotes the expenditure non-homothetic index. The mean relative deviation inequality measure is derived as the difference in the logarithms of the arithmetic mean and the geometric mean. The numbers in the parenthesis display standard deviations derived through bootstrapping. We derive these by running 1000 replications of the estimation of the QUAIDS model, and by computing the subsequent inequality measures for all these replications.

Table B2: Theil index by states and sectors

	1993–94			1999–00			2004–05			2009–10			2011–12		
	Cons	Exp-h	Exp-nh	Cons	Exp-h	Exp-nh	Cons	Exp-h	Exp-nh	Cons	Exp-h	Exp-nh	Cons	Exp-h	Exp-nh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Rural															
Andhra Pradesh	0.110	0.110	0.110	0.096	0.096	0.093	0.122	0.122	0.119	0.127	0.127	0.129	0.101	0.101	0.096
Assam	0.049	0.049	0.049	0.068	0.068	0.070	0.061	0.061	0.056	0.079	0.079	0.080	0.079	0.079	0.080
Bihar	0.074	0.074	0.074	0.070	0.070	0.071	0.063	0.063	0.061	0.077	0.077	0.079	0.070	0.070	0.070
Chhattisgarh	0.070	0.070	0.070	0.095	0.095	0.088	0.125	0.125	0.115	0.080	0.080	0.080	0.094	0.094	0.091
Gujarat	0.079	0.079	0.079	0.092	0.092	0.090	0.115	0.115	0.108	0.111	0.111	0.110	0.114	0.114	0.110
Haryana	0.119	0.119	0.119	0.101	0.101	0.089	0.213	0.213	0.186	0.128	0.128	0.127	0.105	0.105	0.097
Jharkhand	0.079	0.079	0.079	0.096	0.096	0.098	0.076	0.076	0.070	0.071	0.071	0.073	0.083	0.083	0.086
Karnataka	0.097	0.097	0.097	0.100	0.100	0.101	0.114	0.114	0.108	0.092	0.092	0.099	0.133	0.133	0.133
Kerala	0.133	0.133	0.133	0.122	0.122	0.126	0.187	0.187	0.186	0.187	0.187	0.197	0.191	0.191	0.197
Madhya Pradesh	0.105	0.105	0.105	0.107	0.107	0.095	0.113	0.113	0.108	0.132	0.132	0.130	0.123	0.123	0.120
Maharashtra	0.124	0.124	0.124	0.115	0.115	0.118	0.146	0.146	0.141	0.101	0.101	0.101	0.120	0.120	0.109
Odisha	0.096	0.096	0.096	0.098	0.098	0.097	0.123	0.123	0.116	0.098	0.098	0.100	0.087	0.087	0.086
Punjab	0.099	0.099	0.099	0.099	0.099	0.098	0.135	0.135	0.130	0.131	0.131	0.134	0.123	0.123	0.122
Rajasthan	0.088	0.088	0.088	0.077	0.077	0.079	0.087	0.087	0.080	0.085	0.085	0.093	0.091	0.091	0.096
Tamil Nadu	0.141	0.141	0.141	0.118	0.118	0.109	0.120	0.120	0.108	0.102	0.102	0.105	0.133	0.133	0.129
Uttar Pradesh	0.113	0.113	0.113	0.109	0.109	0.097	0.115	0.115	0.103	0.097	0.097	0.093	0.118	0.118	0.099
West Bengal	0.089	0.089	0.089	0.082	0.082	0.075	0.126	0.126	0.108	0.089	0.089	0.081	0.098	0.098	0.085
Urban															
Andhra Pradesh	0.156	0.156	0.156	0.158	0.158	0.153	0.224	0.224	0.200	0.208	0.208	0.204	0.169	0.169	0.156
Assam	0.135	0.135	0.135	0.160	0.160	0.165	0.160	0.160	0.148	0.186	0.186	0.182	0.218	0.218	0.210
Bihar	0.137	0.137	0.137	0.158	0.158	0.154	0.177	0.177	0.154	0.184	0.184	0.163	0.137	0.137	0.120
Chhattisgarh	0.131	0.131	0.131	0.148	0.148	0.148	0.246	0.246	0.228	0.146	0.146	0.140	0.272	0.272	0.247
Gujarat	0.128	0.128	0.128	0.149	0.149	0.143	0.171	0.171	0.150	0.167	0.167	0.152	0.151	0.151	0.121
Haryana	0.123	0.123	0.123	0.145	0.145	0.141	0.207	0.207	0.198	0.230	0.230	0.234	0.271	0.271	0.265
Jharkhand	0.169	0.169	0.169	0.213	0.213	0.214	0.194	0.194	0.191	0.202	0.202	0.195	0.209	0.209	0.194
Karnataka	0.157	0.157	0.157	0.171	0.171	0.172	0.234	0.234	0.218	0.231	0.231	0.219	0.288	0.288	0.273
Kerala	0.167	0.167	0.167	0.171	0.171	0.173	0.267	0.267	0.251	0.244	0.244	0.234	0.269	0.269	0.247
Madhya Pradesh	0.166	0.166	0.166	0.166	0.166	0.164	0.233	0.233	0.216	0.246	0.246	0.251	0.263	0.263	0.280
Maharashtra	0.190	0.190	0.190	0.206	0.206	0.211	0.236	0.236	0.226	0.254	0.254	0.253	0.237	0.237	0.233
Odisha	0.142	0.142	0.142	0.156	0.156	0.156	0.198	0.198	0.187	0.268	0.268	0.274	0.210	0.210	0.211
Punjab	0.115	0.115	0.115	0.153	0.153	0.150	0.196	0.196	0.180	0.230	0.230	0.223	0.169	0.169	0.157
Rajasthan	0.131	0.131	0.131	0.136	0.136	0.130	0.186	0.186	0.165	0.176	0.176	0.161	0.179	0.179	0.154
Tamil Nadu	0.176	0.176	0.176	0.167	0.167	0.165	0.217	0.217	0.202	0.166	0.166	0.159	0.173	0.173	0.164
Uttar Pradesh	0.166	0.166	0.166	0.199	0.199	0.200	0.234	0.234	0.229	0.307	0.307	0.323	0.313	0.313	0.318
West Bengal	0.189	0.189	0.189	0.169	0.169	0.160	0.232	0.232	0.202	0.278	0.278	0.260	0.260	0.260	0.247

Note: "Cons" denotes the consumption index; "Exp-h' denotes the expenditure homothetic index, and "Exp-nh' denotes the expenditure non-homothetic index.

Table B3: Unit values: medians, "Deaton et al. (2004)-adjustment" and our iteration procedure

		Rural					Urban				
	($\hat{b}$)	1993–94	1999–00	2004–05	2009–10	2011–12	1993–94	1999–00	2004–05	2009–10	2011–12
Rice											
UV Median		6.9	11.1	10.9	18.4	20.7	7.7	12.4	12.1	21.5	23.7
$\hat{p}_1$ (Deaton et al. (2004))	(0.191)	8.7	12.5	12.1	18.5	19.2	9.3	13.5	13.0	20.2	21.0
$\hat{p}_2$	(0.194)	7.6	11.8	11.7	19.1	20.4	8.2	12.9	12.8	21.3	22.6
$\hat{p}_3$	(0.194)	7.4	11.7	11.6	19.3	20.6	8.1	12.8	12.8	21.5	22.9
$\hat{p}_4$	(0.194)	7.4	11.7	11.6	19.3	20.6	8.1	12.8	12.8	21.5	22.9
$\hat{p}_5$	(0.194)	7.4	11.7	11.6	19.3	20.6	8.1	12.8	12.8	21.5	22.9
$\hat{p}_6$	(0.194)	7.4	11.7	11.6	19.3	20.6	8.1	12.8	12.8	21.5	22.9
Wheat											
UV Median		5.1	9.2	9.8	16.1	17.0	5.7	9.9	10.5	17.2	18.3
$\hat{p}_1$ (Deaton et al. (2004))	(0.072)	5.4	9.2	9.8	15.9	16.2	5.8	9.9	10.5	16.8	17.5
$\hat{p}_2$	(0.073)	5.1	8.9	9.7	16.1	16.6	5.5	9.7	10.5	17.1	18.0
$\hat{p}_3$	(0.073)	5.1	8.9	9.7	16.2	16.6	5.5	9.7	10.5	17.1	18.1
$\hat{p}_4$	(0.073)	5.1	8.9	9.7	16.2	16.6	5.5	9.7	10.5	17.2	18.1
$\hat{p}_5$	(0.073)	5.1	8.9	9.7	16.2	16.6	5.5	9.7	10.5	17.2	18.1
$\hat{p}_6$	(0.073)	5.1	8.9	9.7	16.2	16.6	5.5	9.7	10.5	17.2	18.1
Milk											
UV Median		6.6	10.6	11.6	19.0	25.1	8.0	12.3	13.7	20.9	27.0
$\hat{p}_1$ (Deaton et al. (2004))	(0.074)	7.1	11.0	12.4	18.5	23.7	8.3	12.3	13.9	20.0	25.5
$\hat{p}_2$	(0.075)	6.8	10.7	12.2	18.7	24.2	7.9	12.1	13.8	20.5	26.3
$\hat{p}_3$	(0.075)	6.7	10.7	12.2	18.8	24.3	7.9	12.1	13.8	20.5	26.4
$\hat{p}_4$	(0.075)	6.7	10.7	12.2	18.8	24.3	7.9	12.1	13.8	20.5	26.4
$\hat{p}_5$	(0.075)	6.7	10.7	12.2	18.8	24.3	7.9	12.1	13.8	20.5	26.4
$\hat{p}_6$	(0.075)	6.7	10.7	12.2	18.8	24.3	7.9	12.1	13.8	20.5	26.4
Fish, prawn											
UV Median		24.2	38.8	47.2	75.5	95.6	29.2	40.6	47.9	80.2	101.6
$\hat{p}_1$ (Deaton et al. (2004))	(0.191)	29.4	42.5	49.5	72.3	89.2	33.4	43.5	50.6	75.7	90.5
$\hat{p}_2$	(0.194)	25.7	40.0	48.0	74.8	94.7	29.7	41.5	49.8	79.7	97.6
$\hat{p}_3$	(0.194)	25.3	39.7	47.9	75.3	95.5	29.3	41.3	49.8	80.4	98.8
$\hat{p}_4$	(0.193)	25.3	39.7	47.9	75.3	95.6	29.2	41.3	49.8	80.5	98.9
$\hat{p}_5$	(0.193)	25.3	39.7	47.9	75.3	95.6	29.2	41.3	49.8	80.5	98.9
$\hat{p}_6$	(0.193)	25.3	39.7	47.9	75.3	95.6	29.2	41.3	49.8	80.5	99.0
Mustard oil											
UV Median		32.4	41.4	56.4	65.4	84.0	33.2	43.1	60.6	68.7	82.9
$\hat{p}_1$ (Deaton et al. (2004))	(0.004)	32.1	40.9	55.7	61.3	85.0	31.4	42.2	60.7	69.4	83.8
$\hat{p}_2$	(0.004)	32.0	40.8	55.7	61.3	85.1	31.3	42.1	60.7	69.5	84.0
$\hat{p}_3$	(0.004)	32.0	40.8	55.7	61.4	85.2	31.3	42.1	60.7	69.5	84.0
$\hat{p}_4$	(0.004)	32.0	40.8	55.7	61.4	85.2	31.3	42.1	60.7	69.5	84.0
$\hat{p}_5$	(0.004)	32.0	40.8	55.7	61.4	85.2	31.3	42.1	60.7	69.5	84.0
$\hat{p}_6$	(0.004)	32.0	40.8	55.7	61.4	85.2	31.3	42.1	60.7	69.5	84.0
Sugar											
UV Median		12.9	16.6	18.8	34.8	32.8	12.8	16.5	18.6	34.5	32.8
$\hat{p}_1$ (Deaton et al. (2004))	(0.003)	13.2	16.5	18.6	34.7	32.8	13.1	16.4	18.7	34.5	32.7
$\hat{p}_2$	(0.003)	13.1	16.5	18.6	34.8	32.9	13.1	16.4	18.6	34.5	32.8
$\hat{p}_3$	(0.003)	13.1	16.5	18.6	34.8	32.9	13.1	16.4	18.6	34.5	32.8
$\hat{p}_4$	(0.003)	13.1	16.5	18.6	34.8	32.9	13.1	16.4	18.6	34.5	32.8
$\hat{p}_5$	(0.003)	13.1	16.5	18.6	34.8	32.9	13.1	16.4	18.6	34.5	32.8
$\hat{p}_6$	(0.003)	13.1	16.5	18.6	34.8	32.9	13.1	16.4	18.6	34.5	32.8
Firewood and chips											
UV Median		0.6	1.0	1.1	2.0	2.7	0.9	1.3	1.4	2.5	3.4
$\hat{p}_1$ (Deaton et al. (2004))	(0.097)	0.7	1.1	1.3	2.0	2.6	0.9	1.4	1.7	2.4	3.2
$\hat{p}_2$	(0.099)	0.7	1.0	1.3	2.0	2.7	0.9	1.3	1.7	2.5	3.3
$\hat{p}_3$	(0.099)	0.7	1.0	1.3	2.0	2.7	0.9	1.3	1.7	2.5	3.3
$\hat{p}_4$	(0.099)	0.7	1.0	1.3	2.0	2.7	0.9	1.3	1.7	2.5	3.4
$\hat{p}_5$	(0.099)	0.7	1.0	1.3	2.0	2.7	0.9	1.3	1.7	2.5	3.4
$\hat{p}_6$	(0.099)	0.7	1.0	1.3	2.0	2.7	0.9	1.3	1.7	2.5	3.4
Ready-made garments											
UV Median		49.4	91.9	108.2	181.1	183.0	67.7	127.0	137.5	234.8	229.4
$\hat{p}_1$ (Deaton et al. (2004))	(0.473)	87.0	124.0	136.3	179.9	152.7	98.6	140.9	146.1	195.1	167.0
$\hat{p}_2$	(0.480)	62.3	106.6	125.7	196.1	176.5	73.2	125.3	140.5	222.1	201.8
$\hat{p}_3$	(0.479)	60.1	105.2	125.0	199.0	180.5	70.9	124.0	140.5	226.6	207.7
$\hat{p}_4$	(0.479)	59.8	105.0	124.9	199.3	181.0	70.6	123.9	140.4	227.2	208.4
$\hat{p}_5$	(0.479)	59.8	105.0	124.9	199.3	181.0	70.6	123.9	140.4	227.3	208.5
$\hat{p}_6$	(0.479)	59.8	105.0	124.9	199.3	181.1	70.5	123.9	140.4	227.3	208.5

Note: The table shows different item price estimates. "UV Median" shows the average over median unit values within each unit, whereas $\hat{p}_i$ shows the price estimates from the ith iteration of the procedure explained in Section 5.2. $\hat{b}$ present the quality-expenditure elasticity from each of these iterations (see Equation (19)).

Table B4: Number of observations by household composition, NSS

	1993–94	1999–00	2004–05	2009–10	2011–12
	(1)	(2)	(3)	(4)	(5)
Total	97.965	100.954	99.788	80.386	80.409
One adult and no children	6.166	6.052	5.620	4.683	4.613
Two adults and no children	8.432	7.887	8.567	7.988	8.078
Two adults and one child	6.329	6.412	6.300	5.339	5.614
Two adults and two children	9.015	9.971	10.182	8.726	8.695
Two adults and three children	6.851	7.212	6.684	4.492	4.189
Three adults and no children	5.259	5.162	5.626	5.451	5.814
Three adults and one child	4.075	4.458	4.447	3.915	4.173
Three adults and two children	4.458	4.537	4.688	3.857	3.647
Four adults and no children	4.656	4.762	5.373	5.270	5.439
Four adults and one child	3.708	3.966	3.952	3.769	3.934
Four adults and two children	3.407	3.321	3.694	3.181	3.149

Note: The table shows the number of households within each of the subsamples used in the robustness check in Section 5.3.

Table B5: Summary statistics of the PDS

	Share of HHs		Avg pc q PDS		UV market		UV PDS		PDS HHs w market	
	Rice	Wheat	Rice	Wheat	Rice	Wheat	Rice	Wheat	Rice	Wheat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rural										
1993–94	0.21	0.01	3	2	7	4	5	5	0.76	0.06
1999–00	0.29	0.16	3	1	11	9	5	4	0.86	0.44
2004–05	0.22	0.11	4	3	11	9	6	5	0.74	0.32
2009–10	0.37	0.28	4	2	18	15	5	6	0.80	0.49
2011–12	0.43	0.34	4	2	20	16	6	7	0.81	0.54
Urban										
1993–94	0.25	0.01	3	2	8	5	5	5	0.80	0.09
1999–00	0.21	0.16	3	2	12	10	7	6	0.88	0.42
2004–05	0.14	0.07	4	2	12	11	6	5	0.80	0.39
2009–10	0.22	0.20	4	2	23	17	4	6	0.87	0.49
2011–12	0.25	0.22	3	2	24	19	6	7	0.85	0.52

Note: "Share of HHs" displays the share of all households with any consumption of PDS rice and wheat, respectively. "Avg pc q PDS" presents the average per capita quantity (in kilograms) for households with any PDS consumption. "UV market" and "UV PDS" show the average state and sector-specific median unit value for market purchases and PDS purchases, respectively. Finally, "PDS HHs w market" shows the fraction of households with any PDS consumption that report purchases of the same item in the market.

Figures

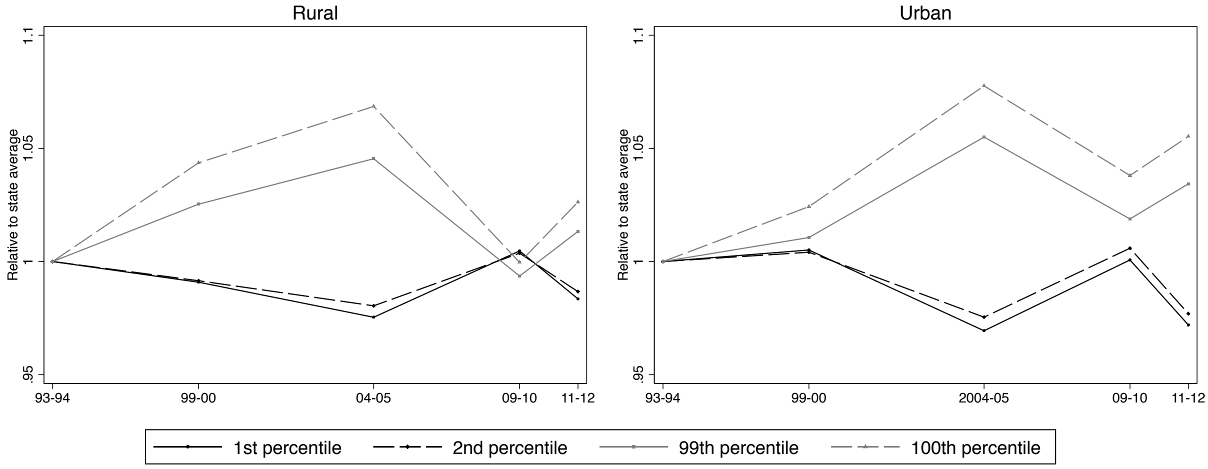

Figure 1: Relative increases in cost of living
Note: The figure shows how the cost of living of the two bottom and the two upper expenditure percentiles in each unit change relative to the average. A value above (below) unity therefore indicates that the particular expenditure group experienced a relatively large (small) increase in cost of living.

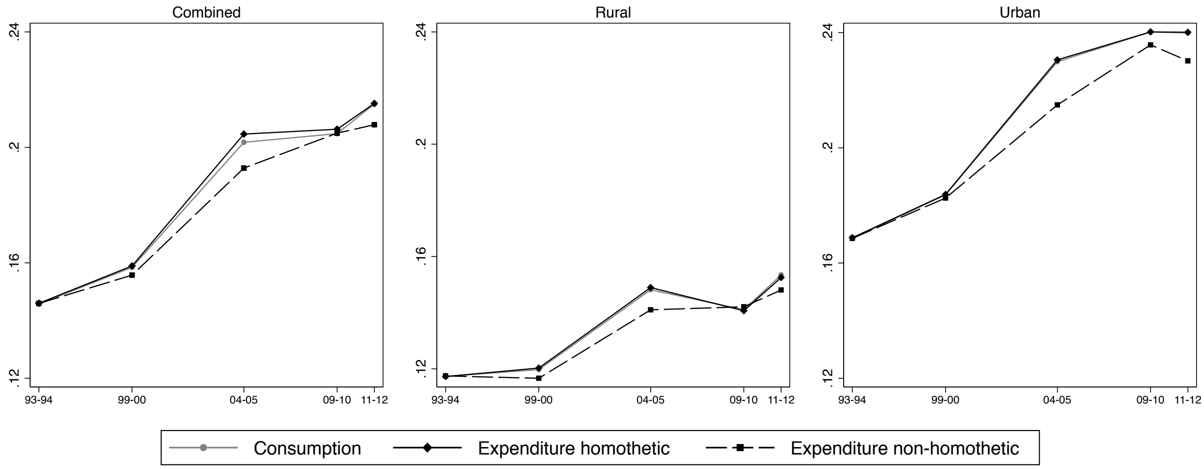

Figure 2: Trends in consumption inequality (Theil)
Note: The figure presents measures of real consumption inequality using the different cost of living indices. The left panel presents inequality for the rural and the urban sector combined, whereas the middle and the right panel display inequality separately for the two sectors.

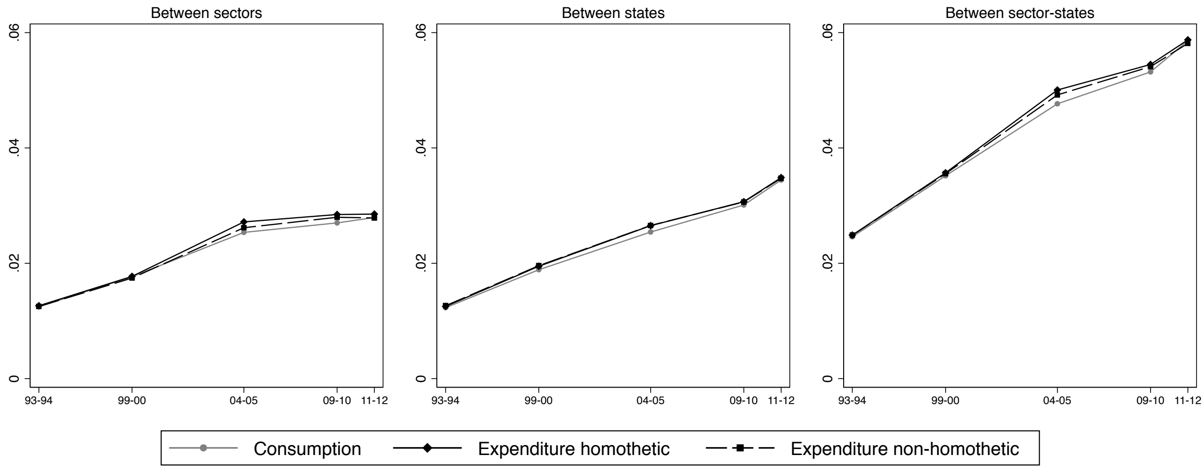

Figure 3: Decomposition of consumption inequality (Theil)
Note: The figure presents between-group inequality using the different cost of living indices. "Sectors" shows inequality in average real consumption between the rural and the urban sector, "States" shows inequality in averages between states (rural and urban sector combined), whereas "Sector-states" presents inequality between every state and sector (what we call "units").

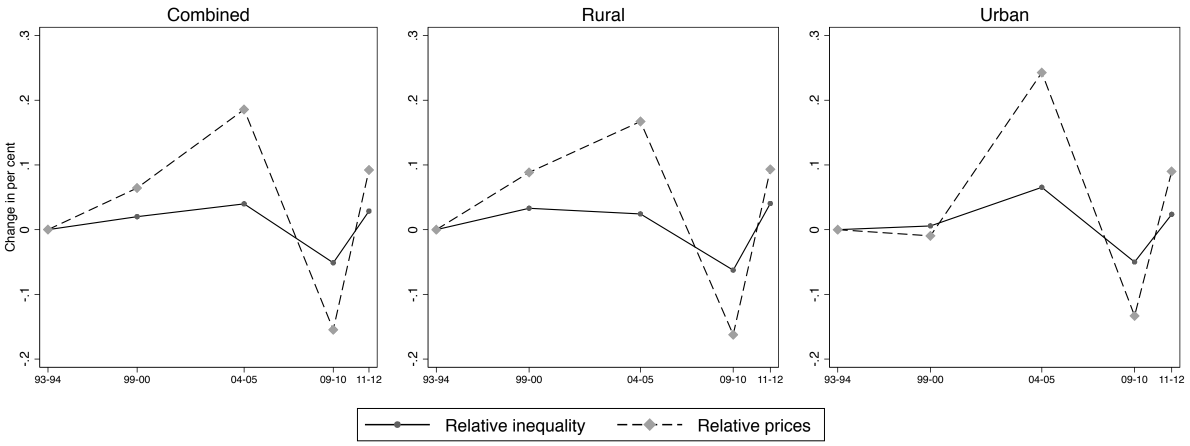

Figure 4: Percentage changes in relative prices and inequality
Note: "Relative prices" shows the percentage changes in the price ratio miscellaneous non-foods goods over cereals. A value above (below) zero therefore means that the non-food prices increased relatively more (less). "Relative inequality" shows the percentage changes in the ratio of the homothetic Theil index over the non-homothetic Theil index. Here a value above (below) zero means that the homothetic measure increased relatively more (less). All numbers are population weighted, using the multipliers provided by the NSS.

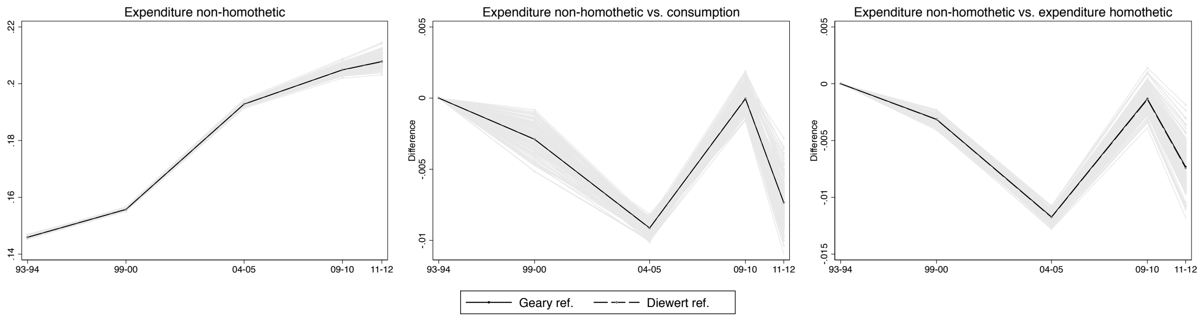

FIGURE 5: Consumption inequality (Theil) using alternative reference prices
Note: The left panel shows trends in inequality using the different reference price vectors and the expenditure non-homothetic cost of living index. The middle panel shows the absolute differences between these estimates and those derived through the consumption index, whereas the right panel presents the absolute differences versus the estimates derived through the expenditure homothetic index.

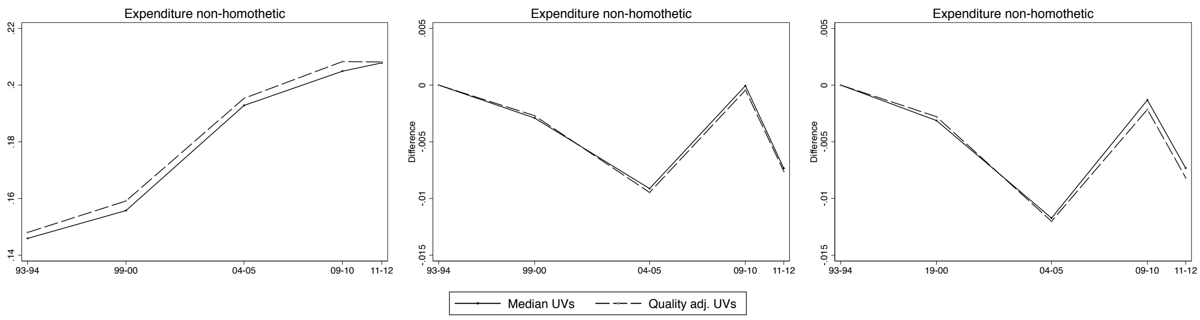

FIGURE 6: Consumption inequality (Theil) using quality-adjusted unit values
Note: The left panel shows trends in inequality using the expenditure non-homothetic cost of living index based on the median unit values and the quality-adjusted unit values. The middle panel shows the absolute differences between these estimates and those derived through the consumption index, whereas the right panel presents the absolute differences versus the inequality estimates derived through the expenditure homothetic index.

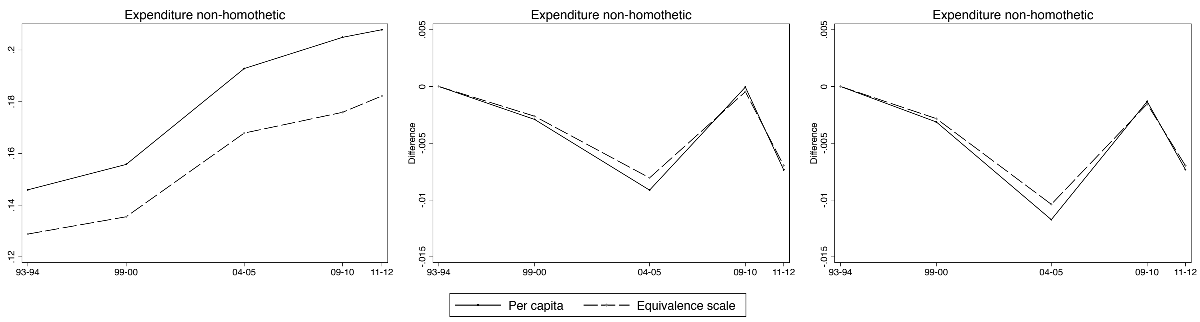

FIGURE 7: Consumption inequality (Theil) using different equivalence scales
Note: The left panel shows trends in inequality using the expenditure non-homothetic cost of living index based on per capita expenditure and equivalence scaled expenditure. The middle panel shows the absolute differences between these estimates and those derived through the consumption index, whereas the right panel presents the absolute differences versus the inequality estimates derived through the expenditure homothetic index.

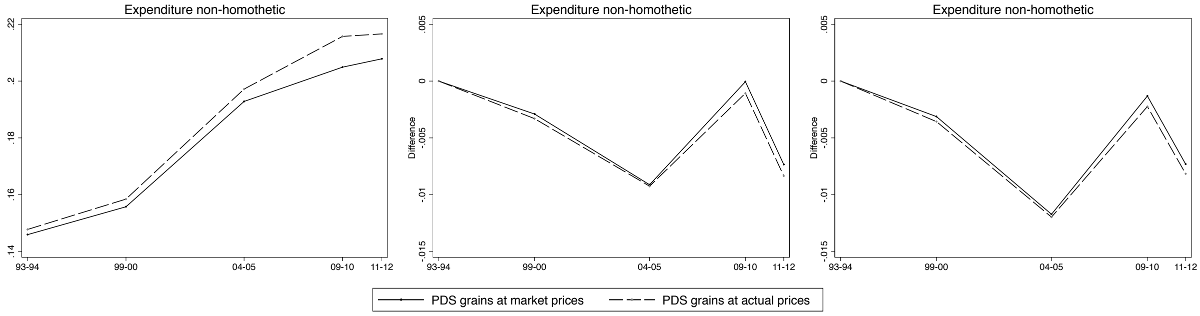

FIGURE 8: Consumption inequality (Theil) using actual prices to value items from the PDS
Note: The left panel shows trends in inequality using the expenditure non-homothetic cost of living index based on different valuations of PDS items. The middle panel shows the absolute differences between these estimates and those derived through the consumption index, whereas the right panel presents the absolute differences versus the inequality estimates derived through the expenditure homothetic index.

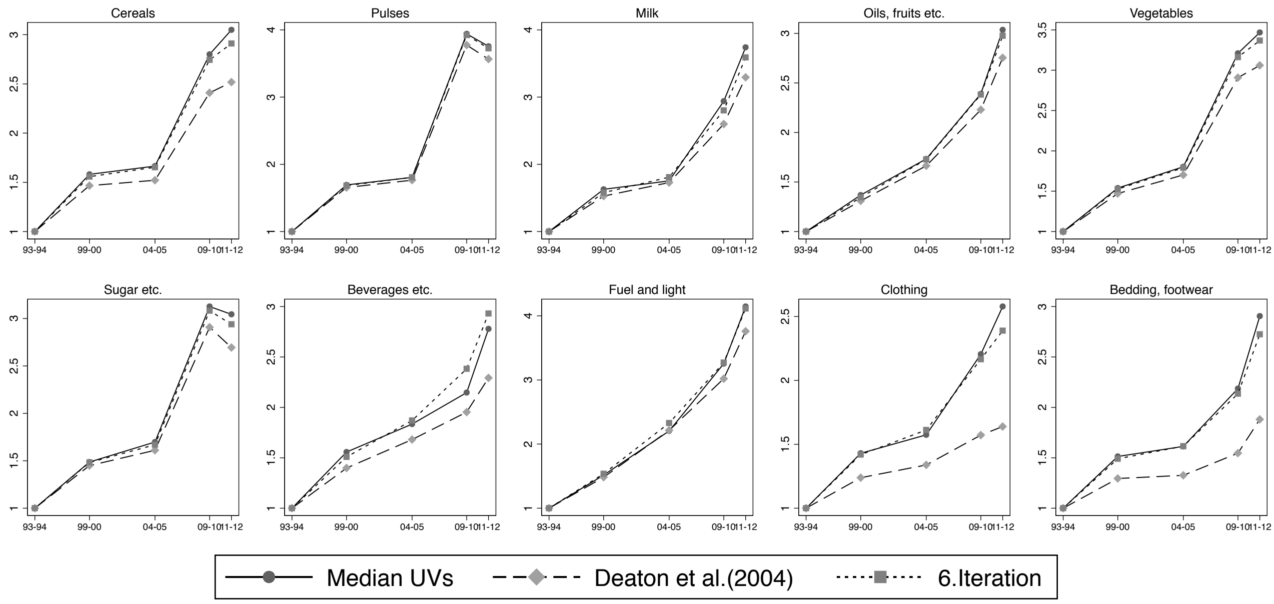

FIGURE B1: Trends in consumption group prices, Rural areas
Note: The figure shows price trends for the 10 unit value consumption groups. "Median UVs" shows trends using median unit values within each unit, "Deaton et al. (2004)" shows trends using the quality adjustment suggested by Deaton and co-authors, whereas "6.Iteration" displays the price trends when using the price estimates from the 6th iteration in our proposed procedure ($\hat{p}_6$).

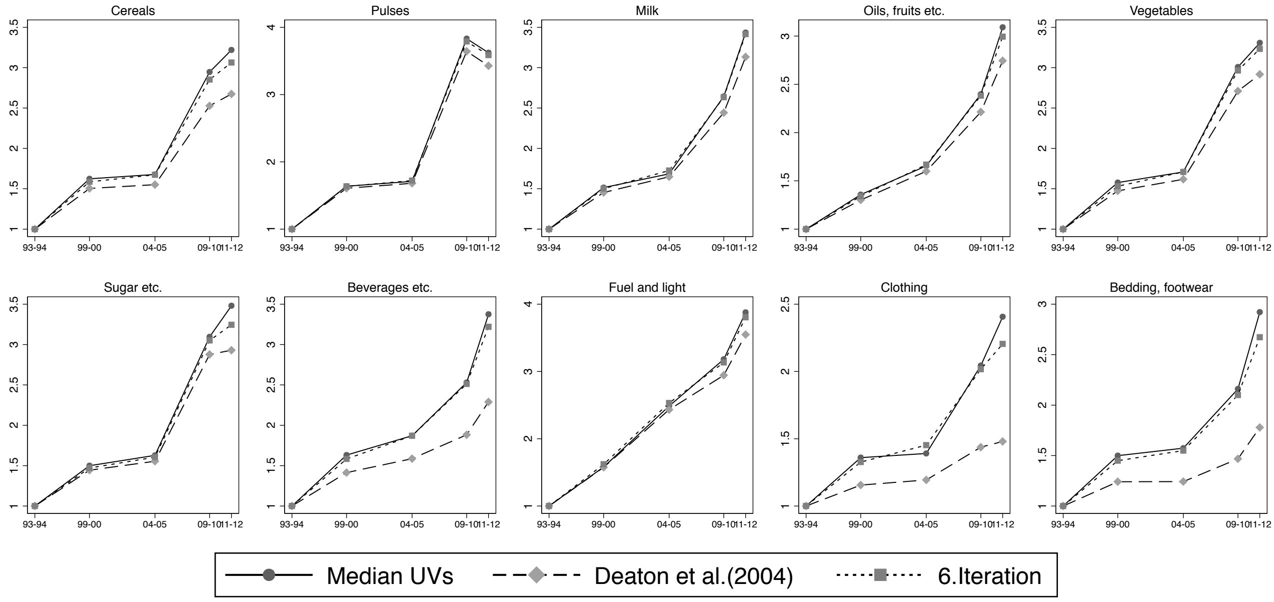

FIGURE B2: Trends in consumption group prices, Urban areas

Note: The figure shows price trends for the 10 unit value consumption groups. "Median UVs" shows trends using median unit values within each unit, "Deaton et al. (2004)" shows trends using the quality adjustment suggested by Deaton and co-authors, whereas "6.Iteration" displays the price trends when using the price estimates from the 6th iteration in our proposed procedure ($\hat{p}_6$).

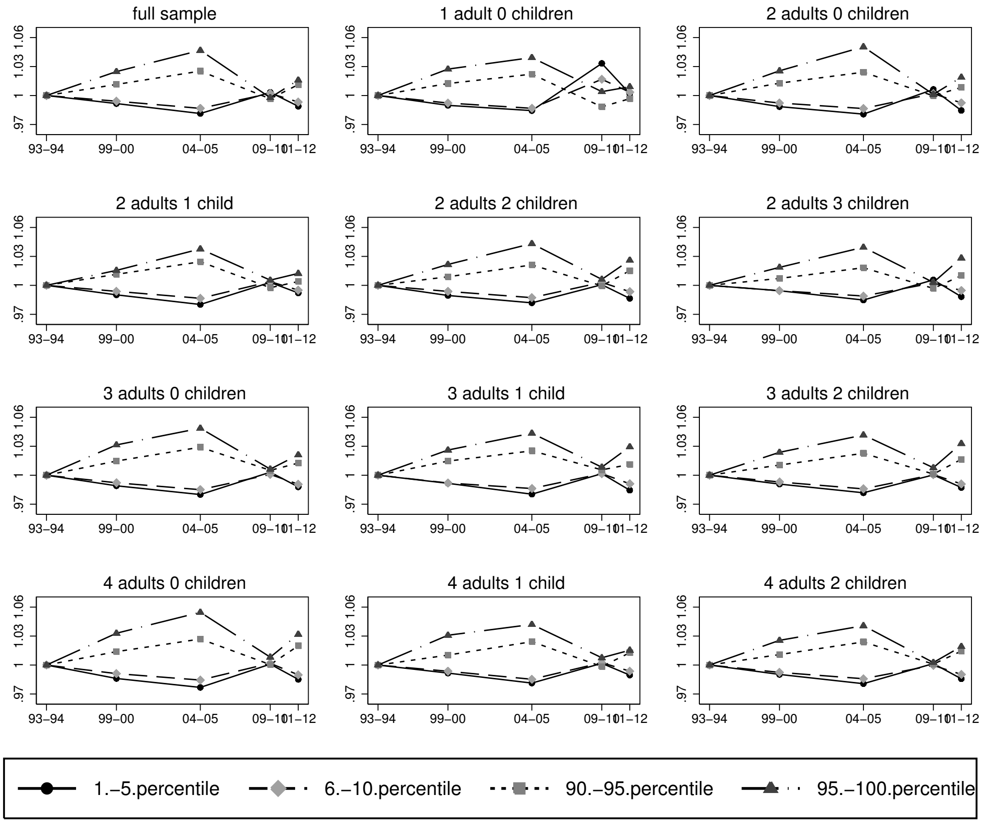

Figure B3: Relative increases in cost of living, Rural

Note: The figure shows the relative increase in cost of living for some selected expenditure groups, relative to the average of all expenditure groups. Each panel represents a subsample consisting of families with similar household composition.

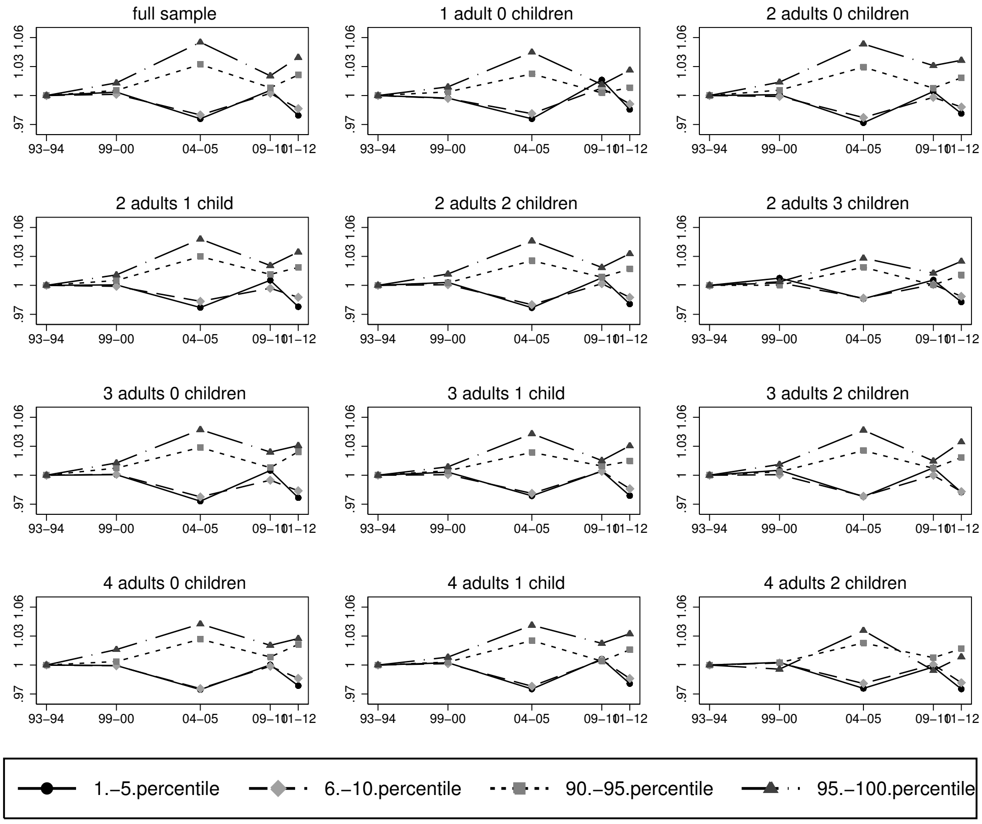

Figure B4: Relative increases in cost of living, Urban

Note: The figure shows the relative increase in cost of living for some selected expenditure groups, relative to the average of all expenditure groups. Each panel represents a subsample consisting of families with similar household composition.

Appendix A Aggregation and imputation of prices for miscellaneous non-food

This section explains in detail how we construct the consumption group price measures. Having obtained the median unit values for each unit (states-sectors), we aggregate the item level estimates to consumption groups. This aggregation is done using the weighted country-product-dummy method (WCPD) due to Rao (1990). The procedure is based on a set of regressions, where the logarithm of the item prices is regressed on a set of dummy variables using weighted least squares. We thus run the following regression, separately for every consumption group:

$$ln\ \hat{p}_{ij} = \sum_j \alpha_j D_j + \sum_i b_i D_i, \tag{24}$$

where D_j is a dummy variable for each unit, and D_i is a dummy variable for every item i in each consumption group. We use the item-wise average budget shares in each unit as weights. Finally, the aggregate price estimates for the consumption group are found directly from the dummy coefficients as:

$$ln\ \hat{p}_j = \alpha_j. \tag{25}$$

The last consumption group (*Miscellaneous non-food*) consists of goods for which we are unable to compute unit values as there is no straightforward way of imputing prices for this residual group. Yet, it seems most natural to use the official state-specific consumer price index (see also Deaton, 2008). We proceed as follows: we first calculate a unit-specific food price index using the price estimates from all food items and the WCPD method. We display the all-India values of this food price index in Table A1, relative to the first time period and separate for the rural and the urban sector. The second column in the table shows the corresponding numbers from the *Consumer Price Index for Industrial Workers* (CPIIW) for the urban sector, and the *Consumer Price Index for Agricultural Labourers* (CPIAL) for the rural sector. These numbers are derived as the weighted average of the state-specific indices. In the third column, we show the CPI sub-index that corresponds to our *Miscellaneous non-food* consumption group. For the rural sector, this CPI sub-index exactly matches our residual consumption group. The urban CPI, however, has two sub-indices for the goods in our residual group. For urban areas we therefore use a weighted average of the *Miscellaneous non-food* and the *Housing* CPI sub-indices.

Finally, the fourth column in the table presents the ratio of columns (3) and (4). We use this ratio to scale our residual group. This seems like a reasonable procedure, especially since our unit value food indices follow roughly the same trends as the CPI food indices. For the first period, we set the prices of the *Miscellaneous non-food* group in each unit equal to their values for the unit value food index. For later periods, we impute values equal to the same food index multiplied by the relative inflation rates displayed in the fourth column of the table.

[Table A1 here]

Appendix B Extra tables and figures

[Table B1 here]

[Table B2 here]

[Table B3 here]

[Table B4 here]

[Table B5 here]

[Figure B1 here]

[Figure B2 here]

[Figure B3 here]

[Figure B4 here]