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A FRAMEWORK FOR THE SIMULTANEOUS MEASUREMENT OF SPATIAL VARIATION AND TEMPORAL MOVEMENT IN PRICES IN A HETEROGENEOUS COUNTRY: THE DYNAMIC HOUSEHOLD REGIONAL PRODUCT DUMMY MODEL

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This paper contributes to the growing literature on spatial prices in large heterogeneous countries. While the literatures on spatial variation and temporal movement in prices have grown in parallel, this study marks a departure by providing a unified treatment and proposing a comprehensive framework that allows both approaches. The proposed model is based on twin extensions of the household version of the "country product dummy model" by allowing for a dynamic stochastic specification and interdependence of spatial prices of geographically adjacent regions. Tests of temporal stability and regional independence of the estimated spatial prices are proposed and applied in this paper. The paper shows that the introduction of an autoregressive error process of order one, AR(1), improves the efficiency of the estimates of parameters, urban-rural and temporal price indices under certain conditions. The Indian application points to a rich potential for using the proposed framework in cross country comparisons such as the International Comparison Program (ICP) exercises.

JEL Codes: C23, E31, O53

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1. INTRODUCTION

The topic of price measurement has occupied a prominent place in economics reflecting the fact that reliable price information is required widely ranging from micro topics such as inequality and poverty to macro based topics such as real growth rates and real interest rates. It is useful to distinguish between the literatures on the spatial and temporal variation in prices. While the former

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typically refers to the measurement of differences in prices faced by various behavioral units, which may be individuals or provinces or countries, at a point in time, the latter tracks the price changes faced by the same unit over a period of time. While the most prominent example of the measurement of spatial prices is that between countries and takes the form of the periodic exercises of the International Comparison Project (ICP) to estimate the purchasing power parities (PPP) between currencies[1], it is the temporal element in price movement in single country contexts that has attracted the bulk of the attention of the economists. The study by Rao *et al.* (1950) combines the spatial element in price measurement implicit in cross country price comparisons at a point in time with the temporal element in the measurement of inflation over time by proposing an econometric methodology[2] that extrapolates PPPs between and beyond ICP rounds based on information in bench mark years provided by the ICP.

The joint modeling of spatial and temporal prices has not been considered in the price index literature to date. The literatures on spatial and temporal prices have generally moved in parallel, with the spatial studies looking at differences in prices faced by a cross section of units at a single time period, while the temporal studies concentrate on price changes faced by a single unit over time. In case of the measurement of price movements over a long time period for a large, heterogeneous country such as India, the spatial and temporal aspects will interact to record large spatial differences in inflation over time. There was an early recognition of this interaction in the studies on India by Bhattacharya *et al.* (1980), Bhattacharya *et al.* (1988) and Coondoo and Saha (1990). Recent examples of studies that investigate the spatial and temporal aspects of price movements in a unified framework include Hill's (2004) study on the European Union and Almas *et al.*'s (2013) study on India. Hill (2004) proposes "a general taxonomy of panel price index methods" (p. 1379) to compute spatial and temporal price indexes and investigate whether there was convergence in price levels and relative prices across the European Union. Hill's (2004) methodology requires panel data sets which are not often available. As he explains, "One reason why panel comparisons have not received more attention in the index-number literature is the lack of suitable data sets" (p. 1379). In contrast, Almas *et al.* (2013) propose a methodology, that can be implemented on available data sets, for calculating spatial prices in India based on the estimated budget share equation for food specified as a linear function of nominal household expenditure and a set of household specific control variables.

The fact that the literatures on the measurement of the spatial and temporal variation in prices have moved in parallel has meant that there has been an absence of a single unified framework that allows for both sets of calculations. This in turn explains the absence of dynamic specifications in the measurement of spatial price variation[3] within a country, and the absence of allowance of mutual

[1]See, for example, World Bank (1973).

[2]See, also, Ravallion (2005) and Inklaar (2013) for alternative methodologies to predict the PPPs between the ICP rounds.

[3]Exceptions include the cross country study on ICP data by Rambaldi *et al.* (2010) and by Pelagatti (2010) on data from Milan. Both these studies consider the interaction between the temporal and spatial elements in price measurement via stochastic specification of the error structures in the estimating equations, similar to what is done in the present study.

dependence between the regional prices in the measurement of temporal price changes in a country. This study was motivated by the aim to overcome both these limitations by providing a unified framework that simultaneously allows for changes in spatial variation in prices over time and also for dependence between the price movements in adjacent locations that may be due to similarities in preferences between their residents. The proposed framework is based on the Country Product Dummy Model (CPD) that was proposed in the cross country context by Summers (1973) and adapted to the single country, household level context in Coondoo *et al.* (2004). It extends the latter by allowing dependence in price movements between regions and over time. An important departure of the proposed framework from the CPD framework of Summers (1973), and its household adaptation in Coondoo *et al.* (2004), is that it allows the estimated spatial prices to vary over time.

The present study shares the feature of Almas *et al.* (2013) in that both studies use as price information the unit values from the household records in India's National Sample Surveys. However, the motivations and methodologies of the two studies are quite different. The Almas *et al.* (2013) study has the following features: it (i) uses a static framework and was primarily motivated by using the spatial price indices to estimate poverty rates and compare with the official poverty rates in India, (ii) is based on the estimated budget share equation for food preceded by the application of the weighted CPD method of Rao (2005) to aggregate the disaggregated food and non-food prices for the estimation on the way to calculating the spatial price indices, (iii) makes the assumption that "households with the same demographics and occupational characteristics who face the same relative prices spend the same proportion of their income on food", (iv) uses a restricted sample from the NSS data sets consisting of only households with two adults and two children, and finally (v) conducts the study on NSS rounds 61 and 66. In contrast, the present study (i) introduces a dynamic specification that allows the spatial prices to be correlated over time[4] and allows for correlation between prices in adjacent states in India, (ii) is based on a dynamic extension of the household variant of the CPD framework presented in Coondoo *et al.* (2004) to calculate the price indices, (iii) makes no restrictive assumption about budget share on food, (iv) is based on the full NSS sample, and finally, (v) extends the analysis to NSS round 68.

The usefulness of the proposed framework, to be called the "Dynamic Household Regional Product Dummy Model (DHRPD)", is illustrated by applying it to study spatial and temporal variation in prices in India in a comprehensive exercise covering a reasonably long time period that has witnessed many changes. This study builds on the recent evidence contained in Majumder *et al.* (2014, 2015 and 2016c), Chakrabarty *et al.* (2015), that document the spatial price differences in India. While using a demand system based preference consistent method, Majumder *et al.* (2014) provide evidence on the rural urban price differences in India, Majumder *et al.* (2015) document the spatial differences in the temporal movements in prices, and Majumder *et al.* (2016) follows up by showing that the

[4] As a referee pointed out, the methodology of Almas *et al.* (2013) also allows the spatial prices to be correlated over time.

incorporation of the spatial price differences has a significant effect on the comparisons of living standards between the Indian states both contemporaneously and over time[5]. The study by Chakrabarty *et al.* (2015) highlights the importance of jointly modeling the spatial and temporal elements of price movements, especially their interaction, in welfare applications by using them to document the differences between states and regions in India in the movements in both nominal and real expenditure inequality over time. The present study should be viewed as a continuation of this research agenda in the CPD framework by using a time varying model, estimated on a pooled time series of household expenditure surveys, to analyze the spatial price variation in India, both at a point in time and over time. The CPD model, and its household version that is considered in Coondoo *et al.* (2004), are members of the class of stochastic index numbers.[6] As noted by Clements *et al.* (2006), an important advantage of the CPD framework that is shared by the DHRPD model is that it allows the calculation of standard errors of the price indices that is not the case with the fixed weight price indices[7].

This paper has analytical, methodological and empirical interest. The DHRPD model that is introduced here shows that the earlier CPD model can be extended and adapted to incorporate spatial, temporal, dynamic and demographic considerations in a comprehensive, household level study on prices in a large and diverse country such as India. The DHRPD model extends the static HRPD model introduced in Coondoo *et al.* (2004) to measure spatial price variation by allowing time varying spatial prices and allows a formal statistical test of time invariant spatial prices. The proposed framework also allows a test of the assumption that the errors in the price equations are uncorrelated over time. The usefulness of the DHPRD model is strengthened by the result reported later that establishes the presence of serial correlation in the errors, thus, rejecting the static HRPD model. This study confirms the sensitivity of the estimated spatial prices to the stochastic specification, namely, between the DHRPD and HRPD parameter estimates. The proposed framework also allows a test of the regional independence of the errors in the price equation and, as we report later, the incorporation of mutual dependence between the price movements in contiguous states in India has a noticeable impact on the estimated spatial and temporal movements in prices.

Since the proposed DHRPD model is non-linear, the paper proposes a simple two step method of estimation that involves linear estimation at each step. In a significant econometric result with methodological implications, the paper formally shows that the introduction of a dynamic specification, via admitting an autoregressive error structure in the time dimension, increases the efficiency in the temporal estimates of inflation under certain conditions. In contrast, the

[5]These studies are, however, based on a static framework where parameters have been estimated for each time period separately.

[6]See Clements *et al.* (2006) for an excellent review of stochastic index numbers.

[7]Diewert (2005) and Rao (2005) have shown that the weighted CPD method is equivalent to certain fixed weight price indices. Majumder and Ray (2015) have extended that result to establish equivalence between the DHRPD model and some well-known price indices under certain parametric configurations.

paper demonstrates that the introduction of regional co-movement in prices in the spatial context leads to no clear positive efficiency gains in the estimated spatial prices.

The empirical results are also of much interest since the period considered has been a significant one as it includes the period of economic reforms in India that propelled the country into one of the fastest growing countries in the world. In the wider context of the ICP exercise, the results on large spatial variation in prices within the country throw serious doubt on the ICP practice[8] of ignoring the issue of sub national PPPs[9] in the PPP calculations. As the scale of the ICP has grown, it has taken on large and regionally disparate countries with heterogeneous preferences such as Brazil, China and India where the issue of sub-national PPPs is particularly important. The significance of the present results therefore extends far beyond India. Moreover, with the results from several ICP exercises now available, especially from the 2005 and 2011 ICPs, the proposed DHRPD model provides a useful framework for investigating if the PPPs have changed over time and also for testing for the effect of admitting regional dependence in the price structures between neighboring countries, such as the EU nations, on the multilaterally estimated PPPs. The constituent states of the Indian union in the present exercise can be viewed as analogous to the nation states in the ICP exercises.

This study is part of a growing literature on the use of unit values, available from the household surveys, in the context of prices of the consumption items. Examples include McKelvey's (2011) study on Indonesia, Kedir (2005) on Ethiopia, Coondoo *et al.* (2004), Majumder *et al.* (2016) on India, and Majumder *et al.* (2011) on Vietnam. Unit values are a rich source of information on prices since they incorporate consumer preferences as conveyed by the amount actually spent by a household on a unit of an item, besides economies of scale in purchases. Prices based on unit values are able to take into account heterogeneity between households in a manner that is not done by the aggregated price indices used in policy work. This study compares the prices based on unit values with the aggregated price indices and, in keeping with the spirit of this exercise, provides evidence both at the state level and at the level of the whole country.

The rest of the paper is organized as follows. The dynamic household regional product dummy model (DHRPD) and the stochastic specification are introduced in Section 2 along with a description of the procedures for the estimation of spatial and temporal price indices and a test for time invariance of the spatial pattern. Section 3 discusses the sensitivity of the efficiency of the estimated second stage parameters to the alternative stochastic specifications. The dataset is briefly described in Section 4. The results are presented and discussed in Section 5, and the paper concludes in Section 6.

[8]See World Bank (1973).

[9]In addition to the evidence on India referred to earlier, there is now mounting evidence on intra-national price differences in other countries that underline the importance of sub-national PPPs. Examples include Aten and Menezes (2002) on Brazil, Carli (2010) on Italy, Majumder *et al.* (2016) on Indonesia and Vietnam and Mishra and Ray (2014) on Australia.

2. The Dynamic Household Region Product Dummy Model (DHRPD): Speci.cation, Estimation and Testing

Specification:

The basic model is specified as follows:

$$p_{jrht}-\pi_{rt}=\alpha_{jt}+\sum_{i=1}^{4}\delta_{ijt}n_{irht}+\left(\lambda_{jt}+\eta_{jrt}\right)\left(y_{rht}-\pi_{rt}\right)+\varepsilon_{jrht}. \tag{2.1}$$

Here p_{jrht} denotes the natural logarithm of the nominal price/unit value for the *j*-th item *(j=1,2,…,N)* paid by the *h*-th sample household of region *r* (*r=0,1,2,…,R*) at time *t* *(t=1,2,…T)*, y_{rht} denotes the natural logarithm of the nominal per capita income/per capita expenditure (PCE) of the *h*-th sample household in region *r* at time *t;* n_{irht} denotes the number of household members of the *i*-th age-sex category present in the *h*-th sample household in region *r* at time *t*, *i=1,2,3,4* denote adult male, adult female, male child and female child categories, respectively, and ε_{jrht} denotes the random equation disturbance term. α_{jt}, δ_{ijt}, λ_{jt}, η_{jrt} and π_{rt} are the parameters of the model. In principle, π'_{rt}s may be interpreted as *the natural logarithm of the value of a reference basket of items/ commodities purchased at the prices of region r in time t*. The l.h.s. of eq. (2.1) thus measures the logarithm of the price/unit value paid in real terms and $(y_{rht}-\pi_{rt})$ on the r.h.s. of (2.1) measures the logarithm of real PCE. The parameters $(\pi_{rt}-\pi_{0t})$, *r = 1,2,…,R; t=1,2,…,T,* thus denote a set of logarithmic price index numbers for individual regions measuring the regional price level relative to that of the reference *numeraire* region (*r* = 0) at time *t* and the spatial price index is given by the formula $exp(\pi_{rt}-\pi_{0t})$.

Normalizing $\eta_{j0t}=0$ for the numeriare region, λ_{jt} can be interpreted as the elasticity of unit value of item *j* with respect to income in the numeraire region at time *t*, which may in turn be called the *quality elasticity* of item *j* in the numeraire region at time *t* and hence expected to be positive. The term "*quality elasticity*" denotes the change in the unit value of an item due to a change in composition of the item purchased as income changes. Thus, η_{jrt} is the contribution of region *r* to the quality elasticity of item *j* over and above that of the numeriare region at time *t*. In other words, $\left(\lambda_{jt}+\eta_{jrt}\right)$ is the *quality elasticity* of item *j* in region *r* at time *t*. Therefore, $\left(\lambda_{jt}+\eta_{jrt}\right)$ is also expected to be positive.

In the CPD framework the same model can be written as

$$p_{jrht}=\alpha^{*}_{jt}+\phi_{jrt}+\sum_{i=1}^{4}\delta^{*}_{jit}n_{irht}+\left(\lambda^{*}_{jt}+\eta^{*}_{jrt}\right)y_{rht}\ +\varepsilon_{jrht}. \tag{2.2}$$

α^{*}_{jt} captures the pure commodity-time effect, which is the intercept in the numeraire region for item *j* at time *t*, ϕ_{jrt} captures the interaction between time and region and hence $\alpha^{*}_{jt}+\phi_{jrt}$ is the region specific intercept at time *t*. Thus, exp $\left(\phi_{jrt}\right)$ is the price relative of item *j* for region *r* (≠0) with the numeraire region taken as the base. δ^{*}_{jit}'s are the slopes with respect to demographic variables (same for all regions), λ^{*}_{jt} is the overall income slope (slope in the numeraire region) at time *t*, η^{*}_{jrt} captures the differential slope component of each region and hence $\lambda^{*}_{jt}+\eta^{*}_{jrt}$ is the region specific income slope at time *t*. Note that this model (i.e.

equation(2.2)) reduces to the basic CPD model for time t when $\phi_{jrt}=\phi_{jt}$ for all j, t; $\eta^*_{jrt}=0$ for all j, r and t, and $\lambda^*_{jt}=0$ for all j, t. Also, note that the term involving the demographic variables does not affect the basic structure of the CPD model.

Recognizing that equations (2.1) and (2.2) are the same equations, we have

$$\alpha^*_{jt}+\phi_{jrt}=\alpha_{jt}+\left(1-\lambda_{jt}-\eta_{jrt}\right)\pi_{rt} \tag{2.3}$$

$$\delta^*_{jit}=\delta_{ijt}, \quad \lambda^*_{jt}=\lambda_{jt}, \quad \eta^*_{jrt}=\eta_{jrt}. \tag{2.4}$$

Now, observe that (2.1) is a system of equations and is non-linear in parameters. While it may be possible to devise an appropriate non-linear systems approach, such an estimation procedure may turn out to be computationally heavy. Following Coondoo *et al.* (2004), we, therefore, use a two-stage estimation procedure using (2.2). However, while Coondoo *et al.* (2004) is based on a single time period and uses Ordinary Least Squares (OLS) method at both stages, we modify the estimation procedure by using population shares of regions as weights and introduce (i) multiple time periods and an AR(1) structure in the error term and (ii) spatial dependence between contiguous regions along with an AR(1) structure in the error term, which yield the dynamic spatial price indices.

Let us now proceed to describe how this framework can be used to estimate spatial price indices. Following Coondoo *et al.* (2004), we use a two-stage estimation procedure.

We write equation (2.2) (the first stage equation) as

$$\begin{aligned} p_{jrht}= & \sum_{t=1}^{T}\alpha^*_{jt}D_t+\sum_{t=1}^{T}\sum_{i=1}^{4}\delta^*_{jit}D_t n_{irht}+\sum_{t=1}^{T}\sum_{r=1}^{R}\phi_{jrt}D_rD_t+\sum_{t=1}^{T}\lambda^*_{jt}D_t y_{rht} \\ & +\sum_{t=1}^{T}\sum_{r=1}^{R}\eta^*_{jrt}y_{rht}D_rD_t+\varepsilon_{jrht}. \end{aligned} \tag{2.5}$$

D_t is the time dummy that takes a value 1 at time t for all households belonging to time period t, and 0 otherwise and D_r is the region dummy that takes the value 1 for all households in region r and *0* otherwise, for all time periods.

Using its equivalence with (2.1), the relationships in (2.3)–(2.4) and the fact that for the numeraire region we have

$$\alpha^*_{jt}= \alpha_{jt}+\left(1-\lambda_{jt}\right)\pi_{0t}, \tag{2.6}$$

we get

$$\phi_{jrt}=\left(1-\lambda_{jt}-\eta_{jrt}\right)\pi_{rt}-\left(1-\lambda_{jt}\right)\pi_{0t}, \quad r\neq 0. \tag{2.7}$$

Equation (2.7) constitutes the second stage equation.[10]

[10]This equation forms the basis of comparison of the DHRPD model with the Diewert (2005), Rao (2005), and Hill and Syed (2015) systems for measuring price indices. See Majumder and Ray (2015) for derivation of the equivalence conditions.

Equation (2.7) can now be estimated using the following dummy variable regression equation involving the first stage parameter estimates from equation (2.5) [Recall from (2.4) that $\lambda^*_{jt}=\lambda_{jt}, \quad \eta^*_{jrt}=\eta_{jrt}$] :

$$\hat{\phi}_{jrt}=\sum_{t=1}^{T}\sum_{r=1}^{R}\pi_{rt}\left(1-\hat{\lambda}_{jt}-\hat{\eta}_{jrt}\right)D_rD_t-\sum_{t=1}^{T}\pi_{0t}\left(1-\hat{\lambda}_{jt}\right)D_t+u_{jrt}. \quad (2.8)$$

D_r is the region dummy that takes a value of 1 for region *r (=1,2,. . ..,R)* and 0 otherwise. Here u_{jrt} is a composite error term arising out of a linear combination of the errors in the estimated parameters from the first stage regression, thus yielding the regression set up in (2.8).

Also note that $\phi_{j0t}=(1-\lambda_{jt})\pi_{0t}-(1-\lambda_{jt})\pi_{0t}=0$.

This regression equation (2.8) will estimate π_{rt}, *r=0,1,2,. . .,R, t=1,2,. . ..,T.*

Observe that $\pi'_{0t}s$ are over-identified as *R* different estimates of these parameters may be obtained for each *t* by estimating equation (2.8) separately for $r = 1, 2,\ldots, R$. To resolve this over-determinacy of $\pi'_{0t}s$, we propose a pooled estimation, which ensures that unique estimates of π_{0t} are obtained. Also, since we have *R* equations and (*R*+2) unknowns, viz., π_{rt}, *r=0,1,2.,R* and α_{jt} for every *j*, each π_{rt} is a linear function of (every) α_{jt} (which is unidentifiable and hence non-estimable, given the model). In other words, the estimated π_{rt}s will have the α_{jt}s confounded in them thus affecting the magnitude of these estimates. The π_{rt}s estimated for a given data set will contain an additive component which is some kind of an average of the non-estimable α_{jt}'s, say $\bar{\alpha}_t$. However, for a particular time period the spatial indices with respect to the numeraire region 0 will be given by $exp(\pi_{rt}-\pi_{0t})$, where $\bar{\alpha}_t$ will get cancelled because it is confounded in both.

But, for temporal indices some adjustment needs to be made. The temporal index at time t_2 with respect to time t_1 for region *r* will be given by

$$exp(\pi_{rt_2}-\pi_{rt_1}+\bar{\alpha}_{t_2}-\bar{\alpha}_{t_1}). \quad (2.9)$$

To compute the temporal indices, therefore, we have adopted the following procedure. After estimating the parameters, α^*_{jt}, λ_{jt}, π_{0t}, we take the average over *j* on both sides of (2.6). $\bar{\alpha}_t$ is then estimated as

$$\hat{\bar{\alpha}}_t=\hat{\bar{\alpha}}^*_t-\left(1-\hat{\bar{\lambda}}_t\right)\hat{\pi}_{0t}. \quad (2.10)$$

If we allow the disturbances u_{jrt} to be correlated across different time periods, i.e. $E(u_{jrt}u_{jrt'})\neq 0$, for all *t, t'*, then (2.8) becomes the dynamic HRPD model. In the following empirical application, we allow the errors to follow an AR(1) process, i.e. $E(u_{jrt}u_{jrt-s})= \rho^s, \ \rho\neq 0$, for $s\geq 0$. The dynamic HRPD model, therefore, nests the HPRD model if the AR (1) parameter, ρ, equals zero. The dynamic HPRD model can be extended further if we allow the disturbances, u_{jrt}, to be correlated between neighboring regions, i.e. $E(u_{jrt}u_{jvt}) \neq 0$, for all *t*, where *r* and *v* are neighbors. In principle, both extensions can be allowed simultaneously but, to simplify calculations, we have considered them one at a time in this study.

Estimation Steps:

1. In the first stage, equation (2.5) is estimated, for each commodity, on household level observations for each region and time using the least squares method incorporating household level sampling weights. This is the same as estimating the parameters for each time period separately. These regressions yield estimates of α^*_{jt}, δ^*_{jit}, $\phi_{jrt,}$ λ^*_{jt} and η^*_{jrt}.
2. In the second stage, equation (2.8) is estimated on commodity wise observation over region and time using the estimates from stage 1 and using the fact that $\lambda^*_{jt}=\lambda_{jt}$ and $\eta^*_{jrt}=\eta_{jrt}$ (from (2.4)). The following three estimation methods have been used in the second stage estimation:
   i. Ordinary least squares method after adjusting the variables by population shares of the states (weights) in the respective periods.[11] This is same as estimating the π's for each time period separately. This is the HRPD model, or simply the model with time varying spatial price index.
   ii. The above method in a panel framework along with an AR(1) error structure in the time dimension. This is the DHRPD model.
   iii. A maximum likelihood (ML) method[12] for the population share adjusted item-space-time model (system of item equations) with error components that are both spatially and time wise correlated[13]. Here a "neighbor" is an adjacent region with common boundary, with a concurrence value of 1. For non-neighbors, the weights are assigned the value 0. The matrix is then normalized to a row-stochastic weight matrix.[14] If there is a region that shares a border with two others, both have a concurrence value of 1, but the weights are 0.5. This is the DHRPD model with spatial dependence.

Finally, the spatial indices are computed by the formula $exp(\pi_{rt}-\pi_{0t})$and temporal indices by using equations (2.9) and (2.10).[15]

Testing for time invariant spatial price indices:

We want to test $(\pi_{rt}-\pi_{0t})=\delta_r$, say, for all t.

Imposing this restriction in equation (2.7) we have for $r = 1,2,\ldots,R$

$$\phi_{jrt}=\left(1-\lambda_{jt}-\eta_{jrt}\right)(\pi_{0t}+\delta_r)-\left(1-\lambda_{jt}\right)\pi_{0t} \tag{2.11}$$

This yields the restricted model

[11]The weight for All India (Region 0) is 1.

[12]The ML procedure that is used here is in contrast to the generalized moments (GM) estimator employed in panel data models with spatially correlated errors – see, for example, Kelejian and Prucha (1999), Kapoor *et al.* (2007).

[13]Also see Cohen and Morrison Paul (2004) for specification of a system of linear regression equations allowing for serial and spatial error correlation in each equation. However, for a detailed comparison see Appendix C.

[14]See LeSage and Pace (2009). A less restrictive weighting matrix will involve continuous weights that vary inversely with the pair wise geographic distance between the regions. Given the complexity of the estimation procedure, such a general weighting structure is best left for a future study.

[15]Note that in the second stage estimation the dependent variable $\hat{\phi}_{jrt}$ will have standard errors (se) from step 1. One possibility could have been to incorporate (1/se) as weighting factors in the second step. We have, however, not done it here.

$$\phi_{jrt} = \left(1 - \lambda_{jt} - \eta_{jrt}\right)\delta_r - \eta_{jrt}\pi_{0t}.$$

The estimating equation is

$$\hat{\phi}_{jrt} = \sum_{r=1}^{R} \delta_r \left(1 - \hat{\lambda}_{jt} - \hat{\eta}_{jrt}\right) D_r - \sum_{t=1}^{T} \pi_{0t} \hat{\eta}_{jrt} D_t + u_{jrt} \tag{2.12}$$

We can now compare equations (2.8) and (2.12) using F-test or LR test.

3. Sensitivity of the Efficiency of the Estimated Second Stage Parameters, Spatial Indices, Temporal Indices and the Urban-Rural Indices to the Alternative Stochastic Specifications

AR(1) structure in the time dimension: Introducing Price Dynamics in the Temporal Specification:

To illustrate that introduction of AR(1) structure in the time dimension in equation (2.8) increases efficiency of the estimates under certain conditions, we consider models with and without the AR(1) error structure in a panel data set up. We assume that after correcting for the weights (population shares) the error terms are homoscedastic.

In the absence of autocorrelation, with R regions, the variance covariance matrix of u_{jrt} is, therefore, given as

$$\Sigma_0 = \sigma_0^2 I_T \otimes I_{NR}, \tag{3.1}$$

where I_T denotes identity matrix of order $T \times T$ and I_{NR} denotes identity matrix of order $NR \times NR$.

With AR(1) error structure the error can now be written as

$$u_{jrt} = u^*_{jrt} + v_{jt},$$

where u^*_{jrt} is homoscedastic (by our assumption) with variance σ_1^2 and

$$v_{jt} = \rho v_{jt-1} + \varsigma_{jt}.$$

Here ρ is the autocorrelation parameter, $\varsigma_{jt} \sim N\left(0, \sigma_\varsigma^2\right)$, so that $Var\left(v_{jt}\right) = \sigma^2 = \frac{\sigma_\varsigma^2}{(1-\rho^2)}$.

So, the variance-covariance matrix is of the form[16]

$$\Sigma_{AR(1)} = \sigma_1^2 I_T \otimes I_{NR} + \sigma^2 \Theta \otimes I_{NR}, \tag{3.2}$$

where

[16]It may, however, be pointed out that an identification problem may arise for $T = 4$, but only for higher order AR process, as unobserved heterogeneity in the panel would not be distinguishable from genuine higher order dynamics (Arellano, 2003, Ch. 5).

$$\Theta = \begin{pmatrix} 1 & \rho & \cdots & \cdots & \rho^{T-2} & \rho^{T-1} \\ \rho & 1 & \cdots & \cdots & \rho^{T-3} & \rho^{T-2} \\ \rho^2 & \vdots & \ddots & \vdots & & \\ \vdots & \vdots & \vdots & \ddots & \vdots & \\ \rho^{T-2} & \vdots & \vdots & \vdots & 1 & \rho \\ \rho^{T-1} & \rho^{T-2} & \cdots & \cdots & \rho & 1 \end{pmatrix}_{T\times T}. \tag{3.3}$$

Proposition 1. If $\sigma_0^2 > \sigma_1^2 + \sigma^2$ and $\rho \geq 0.25$, then $(\Sigma_0 - \Sigma_{AR(1)})$ is positive definite.[17]

Now, to understand the effect on the spatial and temporal indices, consider the following.

The 2nd stage equation (2.7) can be written as

$$\phi_{jrt} = (1-\lambda_{jt}-\eta_{jrt})\pi_{rt} + (\lambda_{jt}-1)\pi_{0t}, \quad r \neq 0, \tag{3.4}$$

which can be written in the form of partitioned matrix as

$$Y = X_1\Pi + X_2\Pi_0 + \varepsilon,$$

where X_1 is $NRT\times RT$, X_2 is $NRT\times T$, Π is $RT\times 1$ and Π_0 is $T\times 1$, and the stochastic error term, ε, is added to the specification in equation (3.4).

Using formula for partitioned matrices,

$\hat{\Pi}_{RT\times 1} = (X_1'X_1)^{-1}X_1'(Y - X_2\hat{\Pi}_0)$ [These are the regional π's for each time period] and $\hat{\Pi}_{0_{T\times 1}} = (X_2'X_2)^{-1}X_2'(Y - X_1\hat{\Pi})$ [These are the All-India π's for each time period]

These expressions turn out to be

$$\hat{\pi}_{rt} = \frac{\sum_j (1-\lambda_{jt}-\eta_{jrt})(\phi_{jrt} - (\lambda_{jt}-1)\hat{\pi}_{0t})}{\sum_j (1-\lambda_{jt}-\eta_{jrt})^2}, \quad r \neq 0 \tag{3.5}$$

$$\hat{\pi}_{0t} = \frac{\sum_j \sum_r (\lambda_{jt}-1)(\phi_{jrt} - (1-\lambda_{jt}-\eta_{jrt})\hat{\pi}_{rt})}{R\sum_j (\lambda_{jt}-1)^2}, \quad r = 0. \tag{3.6}$$

[17]See Appendix B for a proof of this result. We have verified from our results that the values of σ_0^2 are 0.029, 0.026 and 0.027 for the rural, urban and combined samples respectively, while the corresponding values of $\sigma_1^2 + \sigma^2$ are 0.012, 0.010 and 0.010. Also, the values of ρ turn out to be greater than 0.6.

Under some simplifying assumptions[18], from (3.8) we have

$$Var(\hat{\pi}_{rt}-\hat{\pi}_{0t})=\frac{\sum_j\left(1-\lambda_{jt}-\eta_{jrt}\right)^2\eta_{jrt}^2 Var(\hat{\pi}_{0t})}{\left(\sum_j\left(1-\lambda_{jt}-\eta_{jrt}\right)^2\right)^2}. \quad (3.7)$$

So, introduction of AR(1) error structure in equation (2.6) will have its effect on the variances of the spatial price indices only through the efficiency gain in the estimated parameter π_{0t}.

On the other hand, for the temporal indices, we have

$$\begin{aligned}Var(\hat{\pi}_{rt_2}-\hat{\pi}_{rt_1})=&\frac{\sum_j\left(1-\lambda_{jt_2}-\eta_{jrt_2}\right)^2\left(\lambda_{jt_2}-1\right)^2 Var(\hat{\pi}_{0t_2})}{\left(\sum_j\left(1-\lambda_{jt_2}-\eta_{jrt_2}\right)^2\right)^2}\\&+\frac{\sum_j\left(1-\lambda_{jt_1}-\eta_{jrt_1}\right)^2\left(\lambda_{jt_1}-1\right)^2 Var(\hat{\pi}_{0t_1})}{\left(\sum_j\left(1-\lambda_{jt_1}-\eta_{jrt_1}\right)^2\right)^2}-2Cov(\hat{\pi}_{rt_2},\hat{\pi}_{rt_1}).\end{aligned} \quad (3.8)$$

Under "no-autocorrelation" the covariance term vanishes. Hence, for the temporal indices introduction of AR(1) error structure in equation (2.7) will have its effect not only through the efficiency gain in the estimated parameter $\pi'_{0t}s$, but also through the covariance term. Hence the efficiency gain under AR(1) structure is expected to be high for the temporal indices.

For the Urban-Rural indices, we have

$$\begin{aligned}Var\left(\hat{\pi}_{rt}^U-\hat{\pi}_{rt}^R\right)=&\frac{\sum_j\left(1-\lambda_{jt}^U-\eta_{jrt}^U\right)^2\left(\lambda_{jt}^U-1\right)^2 Var\left(\hat{\pi}_{rt}^U\right)}{\left(\sum_j\left(1-\lambda_{jt}^U-\eta_{jrt}^U\right)^2\right)^2}\\&+\frac{\sum_j\left(1-\lambda_{jt}^R-\eta_{jrt}^R\right)^2\left(\lambda_{jt}^R-1\right)^2 Var\left(\hat{\pi}_{rt}^R\right)}{\left(\sum_j\left(1-\lambda_{jt}^R-\eta_{jrt}^R\right)^2\right)^2}.\end{aligned} \quad (3.9)$$

Since both the variances on the r.h.s. will reduce under the AR(1) structure, the Urban-Rural indices are expected to be more efficient compared to the situation under 'no-autocorrelation'.

Spatial Autoregressive (SAR) Error structure: Introducing Regional Price Dependence in the Cross Sectional Specification

To determine the effect of introducing spatial weight matrices, we ignore the AR(1) structure in time dimension, for simplicity. As in the earlier case we assume that after correcting for the weights (population shares) the error terms are homoscedastic.

[18]Here we have ignored the variances of the parameters estimated from the first stage. Since we are dealing with the AR(1) error structure in the second stage, we treat these parameters as given.

The spatial weight matrix (link matrix) W is given as follows

$$w_{ij}=\begin{cases} 0 \ \ if \ \ i=j \\ 1 \ \ if \ \ i \ \ and \ \ j \ \ are \ \ spatially \ \ connected. \end{cases} \tag{3.10}$$

The matrix W is normalized to a row-stochastic matrix. Under SAR scheme in our set up we have

$$u_{jrt}=\lambda((I_N \otimes W) \otimes I_T)u_{jrt}+v_{jrt}, \tag{3.11}$$

where λ is the spatial correlation, I_N and I_T are identity matrices of order $N \times N$ and $T \times T$, respectively and v_{jrt} is the error term with a variance covariance matrix of the form

$$\sigma_2^2 I_T \otimes I_{NR.}$$

From (3.11) we have

$$(I_{NRT}-\lambda((I_N \otimes W) \otimes I_T))u_{jrt}=v_{jrt} \ \text{or,} \ \ u=I_T \otimes (I_N \otimes (I_R-\lambda W))^{-1} v. \tag{3.12}$$

Now, given that W is row-stochastic, the inverse term can be rewritten as[19]

$$u=I_T \otimes \left[I_N \otimes \left(\sum_{i=0}^{\infty} \lambda^i W^i \right) \right] v \tag{3.13}$$

The variance-covariance matrix of u is given by

$$\Omega=\sigma_2^2 \left\{ I_T \otimes \left[I_N \otimes \left(\sum_{i=0}^{\infty} \lambda^i W^i \right) \right] \right\} \left\{ I_T \otimes \left[I_N \otimes \left(\sum_{i=0}^{\infty} \lambda^i W^i \right) \right] \right\}'. \tag{3.14}$$

This can be written as

$$\Omega=\sigma_2^2 \left(ZZ' \right) \otimes I_T \otimes I_N,$$

where $Z=\sum_{i=0}^{\infty} \lambda^i W^i$.

Now, $\Sigma_0-\Omega=\left(\sigma_0^2 I_R-\sigma_2^2 (ZZ') \right) \otimes I_T \otimes I_N=\sigma_2^2 \left(\frac{\sigma_0^2}{\sigma_2^2} I_T-ZZ' \right) \otimes I_T \otimes I_N.$

The Maximum likelihood approach has the usual asymptotic properties. But nothing can be said about positive definiteness of ($\Sigma_0-\Omega$). Establishing efficiency gain introducing an AR(1) structure along with spatial autocorrelation with an additional dimension with respect to items may be analytically intractable. In finite samples, no exact results are available. OLS may perform acceptably and even be superior in terms of bias and mean squared error (Anselin, 1988, p. 111). It may, however, be noted that Elhorst (2008)[20] shows by Monte Carlo simulation

[19]See Lütkepohl (1996), p. 29.
[20]We are grateful to a referee for drawing this paper to our attention.

that there is an efficiency gain of maximum likelihood over OLS with serial and/ or spatial errors correlation.

4. Data Sets

This study uses the detailed information on household purchases of food and non-food items in both quantity and value terms, along with that on household size, composition and household type, contained in the unit records from the 55th (July, 1999–June, 2000), 61st (July, 2004–June, 2005), 66th (July, 2009–June, 2010) and 68th (July, 2011–June, 2012) rounds of India's National Sample Surveys.[21] The overall time period considered in this study, July, 1999–June, 2012 is long enough for a meaningful test of the time invariance of the spatial price indices and the introduction of a dynamic stochastic specification to be of interest. This was one of the most significant periods in independent India since it included the periods of economic reforms and the global financial crisis. India maintained a high growth rate throughout this period that witnessed several economic changes coinciding with high inflation and rising economic prosperity. It may be mentioned that only the items, for which unit values can be calculated, have been included in this study. This item list excludes items like housing, transportation and a number of durables, but the included items constitute approximately 63–65 percent of the per capita total expenditure for the two lower quartile groups and 50–60 percent for the two upper quartile groups for all rounds considered here. The 13 items used in the exercise along with the unit of their prices are listed in the Appendix Table A1. The 15 major states considered in this study, along with the number of districts in each state in each round, have been listed in Appendix Table A2. The temporal price indices, state and sector wise, that have been estimated in this study are compared with the official price indices used in policy applications in India such as the updating of poverty lines and the setting of minimum wages. Table A9 in the Appendix presents the comparison. The state wise consumer price index numbers for agricultural laborers have been used to generate rural price indices, while the corresponding state wise figures for urban industrial workers have been used to construct urban price indices. The official price figures have been sourced from the Labour Bureau, Ministry of Labour and Employment, Government of India. Both sets of price indices have been normalized with NSS round 55 as the base (1.0).

5. Results

The estimates of the principal parameters that determine the spatial price indices, π_{rt}, where r denotes the state, and t denotes the NSS round, have been presented in Appendix Tables A3–A4.[22] Note that the numeraire region ($r=0$) is All India which consists of the median values for 200 expenditure classes

[21]Since NSS goes way back in time, one can do this exercise over many years. In this study, we focus on the last four rounds to keep the calculations manageable and to ensure consistency in the definitions of variables between surveys.

[22]To focus attention on the spatial and temporal price estimates, and for space reasons, we have not presented the estimates of the parameters of the 1st stage equation. These are available on request.

TABLE 1

Wooldridge Test [F(1,194)] for Autocorrelation in Panel Data

	Estimate of (common) ρ	F-statistics
Rural	0.6449	38.862**
Urban	0.6505	25.810**
Combined	0.6777	15.705**

** Significant at 5% level.

calculated from all states combined for rural and urban sectors separately, and also for the combined sample. Tables A3 and A4 allow a comparison of the HRPD and DHRPD models and each table allows a further comparison between the rural and urban estimates.[23]All the π_{rt} estimates are well determined, with the urban estimates higher than the rural estimates in all cases. The π_{rt} estimates record an increase over time (t) in case of each state (r) and the reference region (0), with the increase somewhat larger between rounds 66 and 68. The introduction of dynamic specification, via the AR(1) parameter, ρ, has an appreciable impact on the π_{rt} estimates, though not a large one. There is no clear pattern on the nature of the impact. For example, in the initial NSS round 55, the π_{rt} estimates tend to increase everywhere with the introduction of AR(1) error structure, but the direction of change is reversed everywhere in the later rounds. However, as demonstrated formally in Section 3 (and also mentioned in footnote 13), introduction of AR(1) error structure clearly yields much lower standard errors of the estimates for all sectors and rounds and this is evident from the estimated t-statistics in the two tables. Table 1 presents the estimates of ρ (common for all periods). The Woolridge (2002) test[24] for autocorrelation in panel data, with state wise items constituting a panel over the four rounds, confirms the presence of first order autocorrelation.[25]

While π'_{rt}s may be interpreted as the natural logarithm of the value of a reference basket of items/commodities purchased at the prices of region r at time t, the estimates of the exponential of their differences with that of the numeraire region (π_{0t}) may be interpreted more readily as estimated spatial price indices, as explained earlier in Section 2. The estimates of the spatial prices in the four NSS rounds are presented in Tables 2a (rural), 2b (urban) and A5 (combined). The figures in parentheses are the t-statistics corresponding to the hypothesis that the spatial price in the state is one, i.e. no different from the numeraire region, making that state have "average prices".[26] There are some, but not many, rejections of the null hypothesis. There is not much change in the estimated spatial prices over the time period spanned by NSS rounds 55, 61, 66 and 68. The changes are mainly quantitative, not qualitative ones. There is hardly any case where the spatial price

[23]The estimates for rounds 55–66 are also available in Majumder and Ray (2015).

[24]The Wooldridge test was implemented using the new Stata command "xtgls", with the autocorrelation option.

[25]As Drukker (2003) has shown, "the new Wooldridge test has good size and power properties in reasonably sized samples".

[26]The standard errors have been calculated using delta method.

TABLE 2A
ESTIMATES OF SPATIAL PRICE INDICES: 55TH–68TH ROUNDS (RURAL)

	HRPD Model				DHRPD Model with AR(1) error terms			
State	55th Round	61st Round	66th Round	68th Round	55th Round	61st Round	66th Round	68th Round
AP	1.026	1.047	1.077	1.087	1.022	1.052	1.080	1.093*
	(0.385)	(0.756)	(0.926)	(1.015)	(0.477)	(1.112)	(1.566)	(1.828)
AS	1.156**	1.153**	1.126	1.057	1.148*	1.163**	1.138*	1.063
	(2.324)	(1.926)	(1.387)	(0.857)	(1.773)	(2.065)	(1.915)	(0.886)
BI	1.005	0.979	0.993	0.943**	0.963	0.931**	0.941*	0.909**
	(0.162)	(−0.464)	(−0.185)	(−2.010)	(−1.152)	(−2.246)	(−1.928)	(−3.166)
GU	1.099	1.085	1.048	1.067	1.085	1.073	1.012	1.056
	(1.533)	(1.125)	(0.705)	(0.890)	(1.301)	(1.157)	(0.144)	(0.640)
HA	1.057	0.988	1.031	1.007	1.059	1.003	1.048	1.024
	(0.689)	(−0.170)	(0.509)	(0.139)	(0.677)	(0.038)	(0.556)	(0.269)
KA	1.034	0.991	0.955	0.977	1.047	0.999	0.966	1.001
	(0.876)	(−0.177)	(−0.740)	(−0.400)	(0.740)	(−0.018)	(−0.600)	(0.015)
KE	1.104	1.067	1.026	1.037	1.093	1.080	1.035	1.052
	(1.109)	(0.821)	(0.325)	(0.419)	(1.276)	(1.163)	(0.432)	(0.622)
MA	1.056	1.009	1.034	1.063	1.053	1.007	1.032	1.065
	(1.157)	(0.210)	(0.663)	(1.464)	(1.087)	(0.159)	(0.695)	(1.346)
MP	0.949*	0.923**	0.984	0.962	0.941	0.918**	0.985	0.960
	(−1.942)	(−3.164)	(−0.502)	(−1.208)	(−1.433)	(−2.120)	(−0.367)	(−1.017)
OR	0.994	0.972	0.940	0.932	0.987	0.978	0.945	0.935
	(−0.126)	(−0.451)	(−0.837)	(−1.019)	(−0.219)	(−0.387)	(−1.003)	(−1.206)
PU	1.062	1.009	1.045	1.054	1.056	1.029	1.053	1.064
	(1.053)	(0.278)	(1.112)	(0.912)	(0.658)	(0.353)	(0.623)	(0.744)
RA	1.016	1.002	1.013	0.950	1.010	1.009	1.018	0.959
	(0.244)	(0.023)	(0.173)	(−0.615)	(0.207)	(0.184)	(0.388)	(−0.915)
TN	1.057	1.048	0.983	1.029	1.063	1.059	1.000	1.032
	(0.574)	(0.395)	(−0.130)	(0.187)	(1.067)	(1.009)	(−0.004)	(0.533)
UP	0.994	0.956	0.983	0.920**	0.991	0.967	0.988	0.927**
	(−0.185)	(−1.211)	(−0.355)	(−2.145)	(−0.336)	(−1.238)	(−0.458)	(−2.924)
WB	1.076	1.062	1.005	1.016	1.070	1.068	1.006	1.018
	(1.516)	(1.027)	(0.108)	(0.329)	(1.480)	(1.495)	(0.144)	(0.411)
All India	1	1	1	1	1	1	1	1
CV	0.050	0.057	0.047	0.055	0.052	0.062	0.051	0.058
Estimate of (common) ρ					0.6449			

Figures in parentheses are t-statistics for testing index=1.
*: Significant at 10% level; **: Significant at 5% level.

of a state moves from significantly below one to significantly above one, or vice versa. A comparison between Tables 2a and 2b shows that there are several cases of rural urban differences in a state's spatial prices. Each table also allows a comparison between the estimated spatial prices in the HRPD and dynamic models. The introduction of AR(1) errors does not show any general pattern in its effect on the estimated spatial price indices. However, it does not move any state from being a cheaper state (spatial price index significantly < 1) to being a more expensive state (spatial price index significantly > 1), or vice versa. The rural spread in spatial prices exceeded that in the urban areas in rounds 55 and 61, as evident in the fall in the coefficient of variation (CV) in each of these rounds as we move from the rural (Table 2a) to the urban (Table 2b) sector. It is interesting to note, however, that the direction of change in CV between the two sectors is sharply reversed in the later rounds 66 and 68.

TABLE 2B

Estimates of Spatial Price Indices: 55th–68th Rounds (Urban)

	HRPD Model				DHRPD Model with AR(1) error terms			
State	55th Round	61st Round	66th Round	68th Round	55th Round	61st Round	66th Round	68th Round
AP	0.998	1.008	1.071	1.033	0.980	1.000	1.076*	1.040
	(−0.043)	(0.169)	(1.086)	(0.543)	(−0.503)	(0.005)	(1.724)	(0.960)
AS	1.120**	1.109*	1.036	1.053	1.110	1.103	1.038	1.055
	(2.426)	(1.932)	(0.511)	(0.787)	(0.995)	(0.973)	(0.367)	(0.509)
BI	1.023	0.941	0.931**	0.915*	1.018	0.940	0.939	0.921*
	(0.859)	(−1.269)	(−2.111)	(−1.728)	(0.345)	(−1.301)	(−1.368)	(−1.757)
GU	1.091*	1.085	1.053	1.059	1.093*	1.072	1.036	1.051
	(1.757)	(1.398)	(1.102)	(1.366)	(1.829)	(1.536)	(0.810)	(1.118)
HA	1.049	1.005	1.009	0.990	1.051	1.008	1.010	1.001
	(0.711)	(0.084)	(0.184)	(−0.197)	(0.629)	(0.103)	(0.139)	(0.010)
KA	1.031	1.009	0.994	1.028	1.024	0.988	0.978	1.013
	(0.680)	(0.176)	(−0.119)	(0.471)	(0.516)	(−0.277)	(−0.483)	(0.267)
KE	1.038	0.980	0.917	0.898	0.999	0.983	0.926	0.926
	(0.469)	(−0.295)	(−1.343)	(−1.303)	(−0.017)	(−0.272)	(−1.521)	(−1.540)
MA	1.066	1.084**	1.120**	1.113**	1.066*	1.067**	1.105**	1.103**
	(1.600)	(2.258)	(2.650)	(2.417)	(1.932)	(1.987)	(2.975)	(3.018)
MP	0.975	0.969	0.988	0.966	0.973	0.967	0.990	0.960
	(−0.945)	(−1.016)	(−0.312)	(−0.825)	(−0.641)	(−0.809)	(−0.236)	(−0.958)
OR	1.012	0.940	0.930	0.854**	1.002	0.933	0.935	0.875*
	(0.173)	(−1.103)	(−0.969)	(−2.578)	(0.031)	(−0.945)	(−0.861)	(−1.815)
PU	1.003	0.994	0.976	0.973	1.002	0.999	0.980	0.990
	(0.075)	(−0.144)	(−0.582)	(−0.527)	(0.034)	(−0.011)	(−0.309)	(−0.159)
RA	1.008	0.978	1.007	0.959	1.011	0.975	0.999	0.965
	(0.161)	(−0.353)	(0.113)	(−0.885)	(0.199)	(−0.499)	(−0.013)	(−0.693)
TN	1.057	1.079	1.018	1.042	1.056	1.067*	1.020	1.041
	(0.736)	(0.913)	(0.157)	(0.331)	(1.452)	(1.721)	(0.511)	(1.044)
UP	1.012	0.971	1.001	0.996	1.003	0.967	0.993	0.978
	(0.395))	(−0.769)	(0.028)	(−0.101)	(0.101)	(−1.103)	(−0.236)	(−0.705)
WB	1.083**	1.072*	1.011	1.030	1.076*	1.067	1.014	1.029
	(2.492)	(1.861)	(0.315)	(0.713)	(1.728)	(1.578)	(0.346)	(0.703)
All India	1	1	1	1	1	1	1	1
CV	0.038	0.055	0.054	0.069	0.040	0.053	0.050	0.061
Estimate of (common) ρ					0.6505			

Figures in parentheses are t-statistics for testing index=1.
*: Significant at 10% level; **: Significant at 5% level.

Appendix Table A6 provides direct evidence of differences between the price indices in the 15 states by presenting the estimates of the pair wise differences between states in the estimated spatial price indices in NSS round 68 under AR(1) error structure. While the upper triangular estimates correspond to the rural areas, the lower triangular estimates refer to the urban areas. Though not everywhere, there are several statistically significant pair wise differences between the spatial prices providing evidence of regional price heterogeneity in both the sectors of the Indian economy. To test whether the pair wise differences are same between the two sectors, both qualitatively and quantitatively, we transformed the matrix in Table A6 by changing the signs of the elements in the lower triangular part (because for both the upper and lower triangular parts the differences are (Row state—Column state)) and then tested for symmetry of the transformed matrix. The test rejected the hypothesis of symmetry.[27] Hence, the pattern of pair wise differences between the estimated spatial price indices is different in the two sectors. This is another significant result since it shows that not only are there rural urban spatial price differences, but that the pair wise differences between the spatial price indices themselves vary between the two sectors of the Indian economy. To our knowledge, no previous study has provided evidence of such an extent of spatial price heterogeneity in the context of a large developing country.

Appendix Table A7 provides estimates of spatial prices in the HRPD framework under the assumption that they are time invariant over the four NSS rounds considered in this study. The *F*-statistics reported in the bottom row show that the hypothesis of time invariant spatial prices cannot be rejected for either the rural or the urban sector of the Indian economy. This result is consistent with our earlier observation, based on Tables 2a–2b, that there are no appreciable movements in the magnitudes of the estimated spatial prices for any state over the period covered by the four NSS rounds. This table helps to focus attention on the rural urban differences in the spatial price indices,[28] with the differences turning out to be more for some states, less for others. For example, while Karnataka's spatial price estimate moves from being less than one in the rural areas to greater than one in the urban areas, the reverse is the case in Kerala. One should not, however, exaggerate the significance of this reversal since in none of these four cases is the spatial price significantly different from one. A more significant result is that in Madhya Pradesh (MP) where the rural spatial price is significantly below one, but the high statistical significance weakens sharply to insignificance in the urban areas. The Eastern states of Bihar and West Bengal are examples of the opposite where the statistical insignificance of the spatial price's difference from unity in the rural sector strengthens sharply to high significance in the urban sector. It is worth pointing out that the rural urban differentials in spatial price indices are quite different from that in rural urban prices. Note that the numbers in Table A7 are estimates of rural urban differentials in spatial price indices, not the more commonly calculated rural urban differences in prices. For example, it is possible for the rural spatial price index $\left(S^{rural}\right)$ in a state to exceed its urban spatial price index $\left(S^{urban}\right)$, yet the urban prices could well be higher than rural prices in that state.

Following the estimation procedure outlined earlier in Section 2, the temporal price indices were calculated with NSS round 55 serving as the base round. The temporal price indices estimated using the HRPD and dynamic versions of the HRPD model have been presented in Appendix Tables A8a and A8b, respectively. The corresponding estimates for the combined sample, pooling the rural and urban data sets, have been presented in Table 3. Both the stochastic specifications agree that the second half of our chosen period witnessed a sharp increase in

[27]The test was carried out using the "isSymmetric" command in R. The output gave the result "FALSE" which means that the symmetry hypothesis is rejected.

[28]While some recent studies have provided evidence on rural urban differences in the price levels, for example, Dikhanov (2010), Majumder *et al.* (2012) and Hill and Syed (2015), there is hardly any evidence on rural urban differences in the spatial price indices that are comparable to the results presented in this study.

TABLE 3
ESTIMATES OF TEMPORAL PRICE INDICES (COMBINED SAMPLE): 55TH–68TH ROUNDS

	HRPD Model				DHRPD Model with AR(1) error terms			
State	55th Round	61st Round	66th Round	68th Round	55th Round	61st Round	66th Round	68th Round
AP	1	1.214	1.962**	2.537**	1	1.195	1.905**	2.461**
		(0.796)	(2.167)	(2.412)		(1.452)	(4.234)	(5.128)
AS	1	1.200	1.790**	2.252**	1	1.178	1.747**	2.177**
		(0.739)	(2.024)	(2.238)		(1.065)	(3.141)	(3.762)
BI	1	1.131	1.847**	2.215**	1	1.107	1.793**	2.156**
		(0.535)	(2.251)	(2.314)		(0.894)	(4.263)	(4.889)
GU	1	1.167	1.773**	2.375**	1	1.137	1.698**	2.292**
		(0.640)	(2.097)	(2.410)		(0.978)	(3.389)	(4.487)
HA	1	1.154	1.781**	2.308**	1	1.135	1.729**	2.225**
		(0.573)	(2.009)	(2.267)		(0.779)	(2.856)	(3.594)
KA	1	1.165	1.785**	2.334**	1	1.132	1.711**	2.274**
		(0.635)	(1.966)	(2.232)		(0.931)	(3.361)	(4.333)
KE	1	1.116	1.675*	2.172**	1	1.129	1.674**	2.187**
		(0.446)	(1.793)	(2.056)		(0.914)	(3.189)	(4.189)
MA	1	1.181	1.865**	2.500**	1	1.153	1.780**	2.395**
		(0.659)	(2.044)	(2.328)		(1.130)	(3.805)	(4.838)
MP	1	1.174	1.898**	2.403**	1	1.149	1.846**	2.323**
		(0.671)	(2.288)	(2.407)		(1.100)	(4.064)	(4.810)
OR	1	1.149	1.752*	2.251**	1	1.127	1.703**	2.171**
		(0.585)	(1.948)	(2.270)		(0.887)	(3.265)	(4.138)
PU	1	1.148	1.804**	2.385**	1	1.131	1.748**	2.302**
		(0.596)	(2.172)	(2.472)		(0.807)	(3.043)	(3.952)
RA	1	1.174	1.795**	2.273**	1	1.142	1.747**	2.198**
		(0.674)	(2.097)	(2.371)		(1.054)	(3.733)	(4.537)
TN	1	1.206	1.729*	2.360**	1	1.175	1.681**	2.261**
		(0.750)	(1.726)	(2.139)		(1.264)	(3.465)	(4.589)
UP	1	1.137	1.801**	2.259**	1	1.119	1.745**	2.179**
		(0.553)	(2.094)	(2.261)		(1.027)	(4.261)	(5.041)
WB	1	1.175	1.724*	2.305**	1	1.157	1.677**	2.229**
		(0.662)	(1.955)	(2.280)		(1.171)	(3.559)	(4.630)
All India	1	1.189	1.842**	2.401**	1	1.166	1.787**	2.317**
		(0.750)	(2.253)	(2.440)		(1.462)	(4.703)	(5.628)
Estimate of (common) ρ					0.6777			

Figures in parentheses are t-statistics for testing index=1
*: Significant at 10% level; **: Significant at 5% level.

inflation in both sectors, and that urban inflation outstripped rural inflation. Within this general picture, there are several cases of sharp differences in the temporal price indices between states, though no clear picture emerges on any relationship between a state's inflation and its economic affluence. A comparison between the estimates in Tables A8a and A8b shows that the stochastic specification has some impact on the magnitudes of the temporal price indices with a gain in efficiency. Though any generalization at the state level is hazardous in the context of India, we find that the introduction of AR(1) in the errors in the estimated equations leads to a reduction in the price indices. This is seen readily by comparing the temporal price indices between Tables A8a and A8b or, more clearly, by comparing the estimated temporal price indices on the rural-urban pooled samples between the HRPD and dynamic specifications, presented in the two halves in Table 3.

TABLE 4

State Wise Urban-Rural Indices (Rural=1 For Each State in Each Round): 55th–68th Rounds

	HRPD Model				DHRPD Model with AR(1) error terms			
State	55th Round	61st Round	66th Round	68th Round	55th Round	61st Round	66th Round	68th Round
AP	1.242	1.422	1.607	1.535	1.232*	1.389**	1.544**	1.435**
	(1.207)	(0.969)	(1.016)	(1.135)	(1.820)	(2.275)	(2.947)	(2.326)
AS	1.238	1.420	1.485	1.609	1.242	1.386*	1.414*	1.496**
	(1.213)	(0.967)	(0.930)	(1.271)	(1.322)	(1.766)	(1.928)	(2.003)
BI	1.300	1.420	1.515	1.568	1.358**	1.474**	1.547**	1.528**
	(1.586)	(0.937)	(0.990)	(1.238)	(2.519)	(2.637)	(3.153)	(2.702)
GU	1.267	1.477	1.623	1.604	1.294**	1.460**	1.587**	1.500**
	(1.278)	(1.032)	(1.079)	(1.261)	(1.956)	(2.391)	(2.696)	(2.258)
HA	1.268	1.503	1.582	1.588	1.276	1.467**	1.493**	1.474**
	(1.206)	(1.070)	(1.050)	(1.239)	(1.546)	(1.991)	(2.246)	(2.028)
KA	1.273	1.503	1.681	1.700	1.257*	1.444**	1.569**	1.526**
	(1.365)	(1.068)	(1.091)	(1.319)	(1.726)	(2.331)	(2.829)	(2.487)
KE	1.201	1.357	1.444	1.399	1.175	1.330*	1.387**	1.327*
	(0.981)	(0.872)	(0.884)	(0.990)	(1.202)	(1.832)	(2.067)	(1.705)
MA	1.290	1.588	1.750	1.693	1.301**	1.547**	1.659**	1.563**
	(1.421)	(1.175)	(1.142)	(1.312)	(2.207)	(2.802)	(3.391)	(2.788)
MP	1.313	1.551	1.622	1.624	1.328**	1.539**	1.558**	1.507**
	(1.613)	(1.163)	(1.092)	(1.284)	(2.322)	(2.781)	(3.069)	(2.566)
OR	1.300	1.428	1.599	1.481	1.305*	1.392**	1.532**	1.412**
	(1.435)	(1.002)	(1.040)	(1.136)	(1.790)	(2.000)	(2.479)	(2.006)
PU	1.207	1.456	1.509	1.491	1.219	1.418**	1.442**	1.403*
	(1.089)	(1.070)	(0.975)	(1.144)	(1.349)	(2.008)	(2.128)	(1.896)
RA	1.267	1.442	1.605	1.633	1.286**	1.412**	1.522**	1.517**
	(1.283)	(0.991)	(1.050)	(1.320)	(1.998)	(2.292)	(2.787)	(2.568)
TN	1.278	1.522	1.673	1.637	1.276**	1.471**	1.581**	1.520**
	(1.275)	(1.119)	(1.108)	(1.249)	(2.017)	(2.516)	(2.943)	(2.521)
UP	1.301	1.500	1.645	1.750	1.301**	1.460**	1.557**	1.589**
	(1.540)	(1.104)	(1.098)	(1.401)	(2.475)	(2.731)	(3.270)	(2.985)
WB	1.286	1.491	1.626	1.638	1.291**	1.459**	1.562**	1.524**
	(1.408)	(1.062)	(1.090)	(1.301)	(2.134)	(2.552)	(3.075)	(2.635)
All India	1.277	1.478	1.616	1.616	1.285**	1.461**	1.550**	1.508**
	(1.518)	(1.070)	(1.077)	(1.302)	(2.571)	(2.842)	(3.474)	(2.877)

Figures in parentheses are t-statistics for testing index=1.
*: Significant at 10% level; **: Significant at 5% level.

This discussion leads to the question: how do the temporal price indices based on unit values compare with the official price indices obtained from government sources? Appendix Table A9 provides evidence on this by comparing the temporal indices estimated in each state using the dynamic specification with that from the official figures used in cost of living calculations. In making this comparison, we need to remember that the official figures are based on a wider basket of items than those considered in this study which had to be restricted to items for which unit values can be calculated from the NSS data sets. Moreover, unlike the official figures which are aggregate figures on inflation, the magnitudes of inflation estimated in this study using the HRPD model take account of the heterogeneity in prices between households due to differences in their preferences, affluence and demographic characteristics. Notwithstanding such differences, Table A9 provides evidence of remarkable similarity between both sets of estimates at the All India level, especially in the rural sector, though there are several examples of differences at the level of states and between sectors. The official

TABLE 5
Tests of Spatial Autocorrelation

Test		Rural	Urban	Combined
Moran's Coefficient I	Observed Value	0.442	0.327	0.500
	Expected Value	−0.001	−0.001	−0.001
	z-score	16.673*	12.340	18.831
	(Test based on Normality)	(0.000)	(0.000)	(0.000)
Geary's Coefficient C	Observed Value	0.436	0.601	0.420
	Expected Value	1.000	1.000	1.000
	z-score	−17.033	−12.048	−17.518
	(Test based on Normality)	(0.000)	(0.000)	(0.000)

*Figures in parentheses are the p-values. All are highly significant.

figures tend to understate, quite noticeably, the inflation in the urban areas in rounds 66 and 68 in relation to those based on the estimated DHRPD model using unit values. It is significant that the match between the DHRPD estimates of inflation and the official figures in the latter rounds is much closer in the rural areas than in the urban. This suggests that items such as Housing that are excluded from our estimations due to lack of information on their unit values are more important in the urban areas than in the rural.

Table 4 provides evidence on rural urban differences in price indices by state, and at all India level, by presenting the estimated urban spatial price indices (rural=1) based on the alternative stochastic specifications of the HRPD model. Hill and Syed (2015) report a range of estimates of rural urban price differences from a selection of studies including that from Dikhanov's (2010) study on India. While there is no agreement in the literature on the rural urban price differential, the estimates of the price differential reported in Table 4 are higher than the 3.2 percent reported by Dikhanov (2010) that focused on food and clothing, and the estimates reported in Majumder *et al.* (2014, Table 3) based on food items only. Table 4 contains two other significant features that appear to hold for most states: (a) the rural urban differential in favor of higher urban values increased sharply in all states between rounds 55 and 66, but then the picture appears mixed to the extent that at the all India level the differential was unchanged between rounds 66 and 68 in the HRPD version, but recorded a decline in the dynamic specification that admits AR (1) errors; (b) a comparison between the two halves of the table shows that the introduction of AR(1) reduces the rural urban differential in most, though not all, cases while simultaneously increasing the efficiency of the estimates of this differential. Table 4 further underlines the importance and usefulness of a dynamic specification, especially the role that it can play in improving also the efficiency of the estimated price indices.

The stochastic specifications of the DHRPD equations used to estimate the spatial and temporal price indices that have been presented so far have assumed independence between the errors across different states and regions. There could be several reasons for doubting the validity of this assumption. For example, cultural and historical affinity between proximate states, such as, Gujarat and Maharashtra, Bengal and Bihar, Karnataka and Andhra Pradesh, could lead to correlation between the regional observations of the omitted variables that will destroy the assumed independence between the errors across the regions. We, therefore, relax this assumption and compute the indices incorporating spatial dependence between states. To preserve parsimony in the number of estimated parameters, we need to impose a structure that allows a limited interdependence without adding too many parameters. One such structure, which seems reasonable a priori, allows interdependence between neighboring or adjacent states, not otherwise. Let us recall that "neighboring states" have been defined in this study as contiguous states in India that share a common border.[29]

Table 5 provides the tests of significance of regional dependence using Moran's I (Moran, 1950) and Geary's C (Geary, 1954) test statistics for global spatial autocorrelation for continuous data. The former is based on cross-products of the deviations from the mean. Moran's I is similar but not equivalent to a correlation coefficient. It varies from -1 to $+1$. In the absence of autocorrelation and regardless of the specified weight matrix, the expectation of Moran's I statistic is $-1/(n-1)$, which tends to zero as the sample size n increases. A Moran's I coefficient larger than $-1/(n-1)$ indicates positive spatial autocorrelation, and a Moran's I less than $-1/(n-1)$ indicates negative spatial autocorrelation. Geary's C statistic is based on the deviations in responses of each observation with one another. Geary's C ranges from 0 (maximal positive autocorrelation) to a positive value for high negative autocorrelation. Its expectation is 1 in the absence of autocorrelation and regardless of the specified weight matrix (Sokal and Oden, 2002). If the value of Geary's C is less than 1, it indicates positive spatial autocorrelation. Table 5 clearly demonstrates the presence of significant positive spatial autocorrelation with both Moran's I and Geary's C agreeing on the sign of the spatial autocorrelation.

Appendix Table A11 presents the estimates of the second stage parameters (π's) and the spatial correlation under the AR(1) model with mutual dependence between neighboring states for the rural, urban and combined samples for all the four rounds. In other words, Table A11 corresponds to the stochastic specification that combines temporal correlation in the errors with spatial price dependence between the neighboring states. All the π parameter estimates and the estimated spatial correlations turn out to be highly significant. The parameter estimates are generally in line with those of the HRPD model (Table A3) and the model with AR(1) error specification (Table A4). The standard errors are generally much smaller (as indicated by the t-values) when compared with the HRPD model in Table A3.[30] But comparison with the AR(1) error specification in Table A4 shows that the t-values in Table A11 are smaller than the corresponding values in Table A4. This corroborates our claim in Section 3 regarding the uncertain effect of allowing a spatially correlated stochastic price structure on the efficiency of the estimated spatial prices.

[29]Appendix Table A10 presents the spatial weighting matrix used for the analysis.

[30]It may be noted that if the spatial autocorrelation pertains only to the errors, OLS will remain an unbiased estimator, thus validating comparison of indices. But OLS will no longer be efficient. Standard error estimates will be biased, producing Type I errors, thus distorting the t-values. However, at low levels of spatial error dependence, OLS standard errors remain unbiased (Darmofal, 2006).

Table 6 presents the spatial indices for the rural, urban and combined samples in the presence of correlation between the stochastic errors in the neighboring states. Table 7 presents the corresponding temporal indices. A comparison between the second half of Table A5 and the last four columns of Table 6 provides evidence on the impact of allowing regional dependence between the errors on the spatial price estimates. Both sets of estimates relate to the combined rural urban samples in each state and are conditional on the AR(1) error specification. The comparison shows several cases where the spatial price estimates need to be revised on admitting regional dependence. There are some cases, such as Bihar and Uttar Pradesh in round 68, where a strong statistical significance in the absence of regional dependence weakens to insignificance in the presence of regional dependence. Though the qualitative picture seems fairly robust between Tables A5 and 6, there are several cases of non-negligible changes to the magnitude of the spatial price estimates. A similar comparison between the second half of Table 3 and the last four columns of Table 7 shows that, due to the introduction of regional dependence, an upward revision to the temporal price indices is required in the period beyond the 61st round, and that by the 68th round the size of the upward revision in several cases, is quite large.

It is also instructive to compare the estimated spatial price indices in rural and urban areas for NSS rounds 61 and 66 presented in Table 6 with the corresponding estimates obtained by Almas *et al.* (2013) using their Engel curve based procedure and presented in Table 3 of their paper. The two tables are directly comparable since both studies report, for NSS rounds 61 and 66, the spatial price for each state with all India as the base at 1.0. There are several interesting similarities and differences between the two sets of estimates. Generally, but not always, states that record spatial price estimates at greater than one (i.e. above average cost of living) do so in both studies. The same is also generally true of states with below average cost of living. For example, rural Assam and rural West Bengal record above average cost of living in both studies. Rural Karnataka records below average cost of living in both studies. The spatial prices of the states generally deviate from one another and from the All India base of 1.0 much more in Almas *et al.* (2013, Table 3) than in the present study. This is reflected in the fact that the coefficient of variation between the states' spatial prices (around 1) is much higher, indeed three times or more, in Almas *et al.* (2013) than in our study. For example, the spatial prices reported in Almas *et al.* (2013, Table 3) for Assam and West Bengal are very high in both NSS rounds 61 and 66 with values ranging from 1.3 to 1.7, while that in Chhattisgarh and Madhya Pradesh are quite low at around 0.6. It is unlikely that prices fluctuate so wildly between the states in India.[31] In contrast, the spatial prices obtained in the present study are within the expected narrow range around 1.0. Both studies agree, however, that the coefficient of variation is much higher in rural areas than in the urban. It is interesting to note that, as reported in Almas *et al.* (2013, Table 3), the spread of spatial prices across states implied by the updated official poverty lines, measured by the coefficient of variation (CV), is more in line with the narrower spread and lower CV obtained in the present study than in Almas *et al.* (2013).

[31]We are grateful to Gaurav Datt for drawing these features of Almas *et al.*'s (2013) estimates to our attention.

TABLE 6

Estimates of Spatial Price Indices (DHRPD Model With AR(1) Errors and Dependence on Neighboring States): 55th–68th Rounds

	Rural				Urban				Combined			
State	55th Round	61st Round	66th Round	68th Round	55th Round	61st Round	66th Round	68th Round	55th Round	61st Round	66th Round	68th Round
AP	0.971	1.023	1.056	1.073	0.976	0.998	1.076	1.045	0.902	0.935	0.972	0.987
	(−0.189)	(0.121)	(0.290)	(0.432)	(−0.281)	(−0.019)	(0.686)	(0.485)	(−0.646)	(−0.445)	(−0.199)	(−0.096)
AS	1.219	1.252	1.231	1.155	1.065	1.057	0.990	1.014	1.126	1.165	1.129	1.082
	(1.149)	(1.114)	(1.057)	(0.876)	(0.609)	(0.473)	(−0.083)	(0.139)	(0.636)	(0.862)	(0.758)	(0.531)
BI	0.992	0.996	1.011	0.962	1.026	0.946	0.945	0.923	0.994	0.965	1.027	0.935
	(−0.053)	(−0.025)	(0.059)	(−0.259)	(0.267)	(−0.553)	(−0.559)	(−0.911)	(−0.037)	(−0.232)	(0.188)	(−0.514)
GU	1.027	1.032	0.993	1.033	1.143	1.128	1.095	1.097	1.092	1.093	1.073	1.106
	(0.164)	(0.167)	(−0.037)	(0.204)	(1.333)	(1.110)	(0.841)	(0.981)	(0.503)	(0.552)	(0.476)	(0.711)
HA	0.987	0.929	0.985	0.980	1.135	1.105	1.113	1.079	1.154	1.172	1.173	1.143
	(−0.084)	(−0.401)	(−0.084)	(−0.125)	(1.191)	(0.855)	(0.904)	(0.765)	(0.776)	(0.898)	(0.979)	(0.879)
KA	0.967	0.949	0.930	0.951	0.999	0.959	0.959	1.021	0.864	0.842	0.830	0.869
	(−0.200)	(−0.279)	(−0.393)	(−0.317)	(−0.011)	(−0.393)	(−0.386)	(0.210)	(−0.892)	(−1.142)	(−1.332)	(−1.043)
KE	1.046	1.046	0.995	1.021	1.000	0.969	0.924	0.919	0.896	0.861	0.827	0.839
	(0.267)	(0.228)	(−0.027)	(0.125)	(−0.001)	(−0.291)	(−0.739)	(−0.922)	(−0.661)	(−0.969)	(−1.334)	(−1.318)
MA	0.983	0.955	0.999	1.033	1.085	1.086	1.129	1.130	0.961	0.945	0.978	1.044
	(−0.106)	(−0.256)	(−0.003)	(0.201)	(0.828)	(0.760)	(1.112)	(1.285)	(−0.238)	(−0.366)	(−0.152)	(0.305)
MP	0.885	0.880	0.954	0.943	0.998	0.991	1.020	0.983	0.929	0.935	0.998	0.974
	(−0.841)	(−0.760)	(−0.273)	(−0.392)	(−0.018)	(−0.089)	(0.197)	(−0.197)	(−0.455)	(−0.456)	(−0.015)	(−0.201)
OR	0.982	1.000	0.958	0.951	0.989	0.924	0.923	0.868*	0.944	0.940	0.921	0.905
	(−0.123)	(−0.001)	(−0.252)	(−0.343)	(−0.126)	(−0.813)	(−0.805)	(−1.697)	(−0.358)	(−0.421)	(−0.608)	(−0.781)
PU	0.988	0.971	0.999	1.032	1.086	1.106	1.086	1.071	1.145	1.158	1.191	1.176
	(−0.077)	(−0.157)	(−0.007)	(0.190)	(0.786)	(0.847)	(0.703)	(0.692)	(0.735)	(0.838)	(1.065)	(1.065)
RA	0.937	0.954	0.956	0.919	1.081	1.057	1.079	1.019	1.081	1.128	1.103	1.055
	(−0.433)	(−0.258)	(−0.250)	(−0.565)	(0.766)	(0.502)	(0.668)	(0.203)	(0.440)	(0.727)	(0.644)	(0.378)
TN	1.002	1.002	0.946	1.003	1.004	1.011	0.998	1.068	0.875	0.858	0.803	0.898
	(0.012)	(0.010)	(−0.296)	(0.019)	(0.044)	(0.096)	(−0.014)	(0.649)	(−0.802)	(−0.992)	(−1.550)	(−0.771)
UP	0.939	0.927	0.949	0.900	1.053	1.027	1.056	1.033	1.050	1.034	1.061	1.016
	(−0.418)	(−0.431)	(−0.301)	(−0.717)	(0.547)	(0.256)	(0.497)	(0.340)	(0.283)	(0.212)	(0.401)	(0.113)
WB	1.117	1.139	1.075	1.077	1.046	1.025	0.967	0.985	1.060	1.063	1.020	1.043
	(0.689)	(0.689)	(0.397)	(0.469)	(0.447)	(0.217)	(−0.305)	(−0.152)	(0.328)	(0.374)	(0.132)	(0.294)
All India	1	1	1	1	1	1	1	1	1	1	1	1
CV	0.079	0.092	0.075	0.068	0.050	0.061	0.069	0.071	0.102	0.116	0.121	0.101

Figures in parentheses are t-statistics for testing index=1. *: Significant at 10% level;

TABLE 7

Estimates of Temporal Price Indices (DHRPD Model With AR(1) Errors and Dependence on Neighbouring States): 61st–68th Rounds (Index=1 for each state and All India for 55th Round)

State	Rural			Urban			Combined		
	61st Round	66th Round	68th Round	61st Round	66th Round	68th Round	61st Round	66th Round	68th Round
AP	1.132	1.948**	2.529**	1.189	2.106**	2.670**	1.174	1.961**	2.697**
	(0.703)	(3.049)	(3.788)	(0.934)	(3.020)	(3.798)	(0.881)	(2.884)	(3.792)
AS	1.105	1.809**	2.170**	1.153	1.776**	2.374**	1.170	1.824**	2.368**
	(0.551)	(2.876)	(3.388)	(0.728)	(2.350)	(3.250)	(0.779)	(2.522)	(3.230)
BI	1.079	1.826**	2.221**	1.071	1.759**	2.243**	1.099	1.882**	2.320**
	(0.469)	(3.046)	(3.632)	(0.375)	(2.451)	(3.240)	(0.514)	(2.726)	(3.374)
GU	1.080	1.734**	2.303**	1.146	1.828**	2.391**	1.132	1.788**	2.497**
	(0.451)	(2.743)	(3.588)	(0.715)	(2.527)	(3.366)	(0.654)	(2.499)	(3.467)
HA	1.012	1.788**	2.274**	1.132	1.872**	2.370**	1.150	1.850**	2.441**
	(0.068)	(2.773)	(3.386)	(0.632)	(2.509)	(3.273)	(0.657)	(2.414)	(3.162)
KA	1.055	1.724**	2.252**	1.115	1.833**	2.547**	1.104	1.749**	2.480**
	(0.282)	(2.315)	(3.165)	(0.566)	(2.438)	(3.395)	(0.510)	(2.320)	(3.245)
KE	1.075	1.704**	2.234**	1.126	1.764**	2.290**	1.088	1.681**	2.309**
	(0.391)	(2.384)	(3.245)	(0.638)	(2.415)	(3.300)	(0.470)	(2.342)	(3.337)
MA	1.044	1.821**	2.404**	1.163	1.987**	2.595**	1.113	1.853**	2.678**
	(0.248)	(2.800)	(3.571)	(0.769)	(2.737)	(3.555)	(0.553)	(2.515)	(3.480)
MP	1.069	1.930**	2.440**	1.153	1.951**	2.453**	1.138	1.955**	2.583**
	(0.400)	(3.179)	(3.794)	(0.767)	(2.821)	(3.521)	(0.672)	(2.793)	(3.544)
OR	1.095	1.748**	2.217**	1.086	1.782**	2.188**	1.127	1.776**	2.364**
	(0.556)	(2.929)	(3.646)	(0.472)	(2.531)	(3.364)	(0.676)	(2.636)	(3.542)
PU	1.057	1.812**	2.391**	1.183	1.910**	2.458**	1.145	1.893**	2.530**
	(0.319)	(2.754)	(3.530)	(0.836)	(2.557)	(3.370)	(0.642)	(2.489)	(3.334)
RA	1.096	1.830**	2.246**	1.136	1.906**	2.351**	1.181	1.858**	2.405**
	(0.552)	(3.031)	(3.560)	(0.662)	(2.558)	(3.280)	(0.822)	(2.531)	(3.275)
TN	1.075	1.692**	2.292**	1.169	1.898**	2.649**	1.109	1.670**	2.529**
	(0.387)	(2.323)	(3.228)	(0.795)	(2.517)	(3.535)	(0.535)	(2.167)	(3.316)
UP	1.061	1.810**	2.195**	1.134	1.914**	2.445**	1.115	1.840**	2.384**
	(0.364)	(2.986)	(3.508)	(0.674)	(2.680)	(3.436)	(0.561)	(2.543)	(3.270)
WB	1.097	1.725**	2.208**	1.138	1.764**	2.346**	1.136	1.752**	2.426**
	(0.550)	(2.827)	(3.584)	(0.655)	(2.305)	(3.216)	(0.660)	(2.387)	(3.342)
All India	1.075	1.792*	2.290**	1.162	1.909**	2.492**	1.132	1.820*	2.465**
	(0.285)	(1.920)	(2.708)	(0.839)	(2.687)	(3.837)	(0.455)	(1.715)	(2.362)

Figures in parentheses are t-statistics for testing index=1.
: Significant at 10 level; **: Significant at 5% level.

6. Conclusion

In many large, emerging economies, such as Brazil, China, India and Indonesia, price differences within the country can be as large, if not larger, than price differences between smaller economies. Since prices play a crucial role in comparisons of living standards within and between countries, the subject of spatial prices in large countries with heterogeneous population is of considerable importance. This calls for improved estimates of intra-country spatial prices and their changes over time. This paper proposes a framework that allows such an investigation, and a formal statistical test of time invariance of the estimated spatial prices. A methodological contribution of this paper is the introduction of the "Dynamic Household Regional Product Dummy Model" (DHRPD) that is used to estimate spatial and temporal price indices in India in a unified framework. An empirical result of some significance that is established in this study is that during the chosen period spanned by NSS 55th and 68th rounds, the spatial price indices in India have not changed significantly in either the rural or the urban sectors.

In its empirical application, the proposed model has two other features that add to its attractiveness: (a) it allows the movement in the spatial price indices to be correlated over time, and (b) it allows interdependence between price indices in neighboring states or regions in a country and proposes a formal test of such interdependence. The significance of these features is underlined by the evidence that the spatial price indices are correlated over time and between the neighboring states in India. This paper formally demonstrates that, under certain conditions, the introduction of an AR(1) error process improves the efficiency of the estimates of the urban rural price index differentials and of the temporal price indices, and provides empirical evidence in support of these statistical results.

It is important to stress that a significant limitation of this study stems from the use of unit values as proxy for prices. This results in (a) inadequate coverage of non-food items, (b) error in interpreting unit values for items such as clothing and fuel whose consumption is spread over multiple periods, and (c) the complete absence of prices for services. This sets a constraint on the interpretation of the spatial and temporal prices as true PPPs. A satisfactory resolution of this issue requires data on the expenditures and quantities of non-food items at a level of disaggregation that is not generally available and a separate treatment of services that is beyond the scope of this study. As more detailed data sets become available, such as exercise will be a useful extension of this study.

While the focus of this paper is on India, the proposed framework is also of interest in the context of cross country comparisons. With the results from the ICP(2011) now available to add to the 1993 and 2005 ICPs, the proposed methodology can also be applied to the common group of countries in the three ICPs to allow for and test for time varying and regionally interdependent PPPs over the past two decades. With the availability of improved and more disaggregated price information, there will also be scope for using more sophisticated stochastic specifications for modelling time dependence and regional interdependence in the price equations than has been done in this study. The empirical results for India point to the usefulness of the DHRPD model in future investigations.

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Supporting Information

APPENDIX A

Table A1: List of Items along with units of prices
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Table A3: Estimates of π's (HRPD Model): 55th -68th Rounds
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APPENDIX B
APPENDIX C