Price Index Convergence Among Indian Cities: A Cointegration Approach

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Abstract

We examine the price dynamics in Indian cities using cointegration analysis. We identify and then calculate a common trend for prices in these 25 cities. We obtain the impulse response functions to calculate the rates of convergence to the prices, and find that the half-life of any shock is very small for Indian cities. Although a close to three-month half-life seems too fast, there are some indications in the literature that half-life can be much smaller. We also analyzed how shock can be transmitted from one city to another and found no systematic behavior of price convergence.

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I. Introduction

Rigorous testing of the Law of One Price has received more attention recently (Engel and Rogers, 1996; Parsley and Wei, 2001). In the context of international trade the Law of One Price has received more attention, as it is intertwined with the real exchange rate and international competitiveness in the era of globalization. Using U.S.A. and Canadian city data, Engel and Rogers (1996) showed that the law of one price fails in the short run. These results received more support from studies conducted with data from other developed countries (Goldberg and Verboven, 2001, 2004; Haskel and Wolf, 2001) and developing countries (Morshed, 2003). What causes this failure of the law of one price in the short-run has remained an unresolved issue. Some argue that it is the transportation/transaction costs, represented by the distance from locations, while others argue that other forms of market segmentation play a significant role.

However, more recent efforts to understand price behavior of the same good at different locations have produced a body of literature that support the notion that the Purchasing Power Parity (PPP) holds in the long-run; however, over the short-term the real exchange rate can deviate from its PPP equilibrium. The consensus amongst economists is that deviation of the exchange rate from their PPP level damp out at a rate of roughly 15 per cent per year, implying that these deviations have a “half life” of three to five years (Rogoff, 1996; Obstfeld and Rogoff, 2000). The observed deviations may be due to many reasons, including the Balassa-Samuelson effect (Balassa, 1964; Samuelson, 1964) postulating that cross-country productivity differentials between traded and non-traded sectors will lead to changes in real costs and the price of traded goods relative to the non-traded goods, and subsequently affect the real exchange rate, in particular for the medium and long-term. Cheung and Lai (2000), however, found that cross-country variations in this half-life of a shock exhibit smaller half-life in developing countries.

Virtually all researchers argue that the presence of nominal exchange rate and trade barriers between locations are important factors in generating these results. This prompted researchers to conduct experiments with data from cities within a country with the benefit of less noise in the dataset with no trade barrier and no nominal exchange rate fluctuations. Parsley and Wei (1996) used a panel of 51 commodity prices from 48 cities in the U.S.A. to estimate the rate of convergence to purchasing power parity and found that the convergence rates were higher for relative prices calculated for cities nearby, but that the distance between locations can explain a smaller portion of the differential rates of convergence. They concluded that the half-life[1] of the price gap for traded goods is roughly four to five quarters, while it is fifteen quarters for services. However, Cecchetti et al. (2002) looked at the aggregate prices (consumer price indices) for 19 U.S. cities from 1918 to 1995 and found that the rate of convergence was slower. They found that the half-life of convergence to average CPI of these 19 U.S. cities was approximately nine years. Imbs et al. (2002), on the other hand, argue that the slow rate of convergence arises because of the aggregation in calculating CPI, which creates the bias that results in the sharp decline in the rate of convergence. Their empirical results with disaggregated data from the European Union (EU) countries indicate that the PPP holds even for the short-run. However, Chen and Engel (2004) showed that the aggregation bias suggested by Imbs et al. (2002) may not be responsible for the slow rate of convergence.

A clear understanding of this rate of convergence to the PPP is imperative, as this creates a possibility of persistent differentials in real interest rates at different locations within a country and thus might result in an undesirable allocation of resources. This might add complication for

[1] They calculated half-life as $\ln(0.5)/\ln(1+\beta+\gamma \ln(\text{distance}))$. This is a slightly different formula than the most common one, $\ln(0.5)/\ln(1+\beta)$, and β is the coefficient of the lagged price in the regression model for the augmented Dickey-Fuller test.

the monetary authorities designing an optimal monetary policy. Thus, monetary policy making becomes more difficult when a central bank is assigned to design a policy for a large number of countries that form an economic union.

The most developed economic union currently is the EU. European Central Bank (ECB) conducts monetary policy for all EU countries. ECB's stated inflation target is a year-on-year change in the Harmonized Index of Consumer Prices (HICP) of not more than 2%. ECB may be successful in achieving the target for the whole union, but the dispersion of inflation in countries may pose a serious concern regarding the allocation of resources. For example, Germany may prefer a contractionary monetary policy to combat inflation in Germany, while Spain may want to have an expansionary monetary policy to reduce unemployment in Spain. A compromise might be achieved but better knowledge about regional price movements would help the monetary policy makers to design an optimal mix. Moreover, ten more countries joined the EU in May 1, 2004.

Cecchetti et al. (2002) examined the city price movements in the United States with the assumption that the United States can be perceived as a collection of developed economies where monetary policy is conducted by one central bank, the Federal Reserve System. They found that the divergence of city prices was temporary but persistent. Since the EU is a collection of developed countries, and ECB conducts its monetary policy, the study of the city price convergence in the USA improved our understanding about regional variation of prices.

It is true that the EU and the U.S.A. are two similar common currency areas in terms of size and the level of industrial development, but regional diversity is much more pronounced in the EU countries. While almost everybody in the U.S.A. speaks a common language, English, there are 20 languages spoken in the EU countries[2]. While the economic and political history is essentially similar for the city economies of the U.S.A., it is very different in cities in the EU countries. This would probably make the mechanism of price formation in the EU cities different than that in the U.S. cities. In this context, we believe that the degree of relative price dispersion and the rate of convergence in the U.S.A. cities may not be observed in the EU cities.

Although the research on the relative price dispersion and the calculation of the rate of convergence in city prices in the U.S.A. is of great value, we believe that we also need to look at the city prices in a country where economic history and political situations are different in different regions. It would be optimal to look at a country with these properties along with similar industrial development to the EU countries to assess what might be important for the ECB in conducting monetary policy. However, a country with such a diversification does not exist in the world. The U.S.A. is comparable in terms of size and industrial development but not diverse enough in terms of economic, cultural, and political history. On the other hand, there is a large country, India, which is comparable to the EU in terms of size and diversity[3], but not in terms of industrial development. Information about price behavior in the cities in a diverse country like India would surely improve our understanding about the intricacies of the monetary policymaking in a diverse region. We believe that a solid understanding of the price movements in different cities in a country like India will improve our knowledge base and thus enable

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[2] The official languages are (in alphabetical order): Czech, Danish, Dutch, English, Estonian, Finnish, French, German, Greek, Hungarian, Italian, Latvian, Lithuanian, Maltese, Polish, Portuguese, Slovak, Slovenian, Spanish, and Swedish.

[3] For example, official language of India is Hindi; English also has official status. For use in certain official capacities, the constitution recognizes eighteen Scheduled Languages- Assamese, Bengali, Gujarati, Hindi, Kannada, Kashmiri, Konkani, Malayalam, Manipuri, Marathi, Nepali, Oriya, Punjabi, Sanskrit, Sindhi, Tamil, Telugu, and Urdu.

entities like the ECB to conduct a successful monetary policy. This will certainly be an essential input in monetary policy making when developing countries begin to form economic unions[4].

In this paper we empirically examine the consumer price behavior in 25 cities of India with monthly data for 156 months starting from October 1988. We attempted to calculate the rate of convergence to the PPP using cointegration technique. Generally, researchers use panel unit root tests to estimate autoregressive equations and then calculate half-life of the shocks to the city under consideration by employing an approximation technique. This approximation technique of calculation of half-life is correct only if there is a first order autoregressive process (Goldberg and Verboven, 2004, footnote 11). We used impulse response functions to calculate half-life and it is well known that impulse response analysis is applicable to any autoregressive structure.

We found that there was only one common trend for all cities in India. This unique common trend traced very closely to the overall CPI of the country. We decomposed the effects of a shock into a stochastic trend effect and a stationary effect. Examining impulse response functions for a shock in the price of the own city we found that the half-life, defined as the period when the marginal change of the stationary component becomes half of the initial jump, was much smaller. In fact, the average half-life was found to be around three months. This suggests a much faster rate of convergence than that reported in the literature. We believe that the impulse response function is the proper way to calculate half-life, and that the issue of temporal aggregation might hold the key to the observed differences in half-life calculations. Moreover, our use of cointegration technique allowed us to calculate shock transmission from a shock emanating in one city to another city. We observed no clear pattern in Indian cities. But there are

[4] For example, Korea Monetary and Finance Association (KMFA) held an International Forum on Monetary and Financial Cooperation for Asia in February 2004 at Seoul National University in Korea to discuss about the possibility and feasibility for East Asian monetary union and integration.

some indications that shock transmissions between two cities depend on the direction of transmission. For example, for a unit shock in Bombay, the half-life of its impact on the price in Nagpur was more than five months, while for a unit shock in Nagpur, the half-life of its impact on the price of Bombay was found to be two months. Consequently, the use of distance between locations in determining the differentials in half-life should be done with more caution.

This paper contributes to the literature in the following ways. First, we used cointegration technique to derive the common trend. Generally, researchers use an average for all locations as the common trend without any effort to ascertain the true common trend (Cecchetti et al., 2002). In order to compute the common trend for the U.S. cities we conducted cointegration analysis using Cecchetti et al.'s (2002) dataset and we found that the log of the price indices were cointegrated with cointegrating rank 18. Moreover, the underlying common trend was the mean of the log of the price indices. Thus, even though Cecchetti et al. (2002) did not explicitly identify the common trend, their choice of average of the log of the price indices turns out to be appropriate. This is certainly a coincidence. Not only is there a large possibility of having more than one common trend for any panel data, but also, even when there is only one common trend, the mean of the price indices may not be the true one. So, we would argue that for any exercise dealing with the convergence to the PPP, the common trend should be identified and calculated. In this paper one common trend for Indian city CPIs is identified and calculated. We then examine the rates of convergence of the city CPIs to this common trend.

It is necessary to define half-life more rigorously. For example, when one standard deviation shock in prices in a city is added, we decomposed this shock into two components: stochastic trend and stationary component. We calculated the immediate change in the stationary component. How long it takes to the marginal change in the stationary component to the half-way mark of the initial response is our half-life estimate. These measures are calculated with better precision by using impulse response functions. This method of calculating a common trend and the use of impulse response function to calculate the half-life of the stationary component is invariant with the order of autoregressive structure. The most common method of calculating half-life by using autoregressive coefficient in a formula is an approximation, and it is true when the underlying autoregressive structure is AR (1). This is an improvement over the most popular technique in terms of precision. We can get impulse response function not only for the shock to the city's own CPI, but also for shocks emanating from other cities[5]. This information about cross-city shock transmissions will allow monetary policy makers to identify the more important cities in relation to policy making. This will certainly increase efficiency of monetary policy making.

Section II describes the data and its collection in more detail. Section III discusses the appropriate methodology and why it is imperative to adopt the cointegration techniques. After a common trend is calculated, we use impulse response functions to calculate the half-life for own shock and also for shock originated in other cities. The results are reported in section IV. A final section summarizes our main conclusions.

II. Data

We collected monthly consumer price indices for industrial workers for 25 large cities of India for the period of 1988-2001. We tried to understand the behavior of recent price data. The Indian Labour Bureau changed its base year to 1982, starting from October 1988. In addition to this, India undertook conscious efforts to open up the economy and tried to make the economy more market friendly starting from 1991 (Rodrik and Subramanian, 2004). As a result, we

[5] Baskar and Hernandez-Murillo (2003) is an exception; they try to calculate effects of a shock in one city on the prices in a different city.

believe that it is imperative to examine more recent price data more carefully. These secondary data were collected from various issues of *Indian Labour Journal,* a monthly publication of the Indian Labour Bureau. The base year for CPI was 1982. These large cities are from 12 states of India and the federal territory of Delhi (shown in Table 1). The Indian Labour Bureau reports consumer price index data for about 70 large cities in India. Among them, we have selected 25 cities by the population size. Population data are from the 1991 census and were collected from the United Nations Statistics Division from the website http://unstats.un.org/unsd/citydata/.

Table 1
States and Cities in India Covered in the Present Study

State and Federal Territory	Cities
Andhra	Guntur and Hyderabad
Bihar	Jamshedpur
Gujrat	Ahmedabad and Bhavnagar
Jammu and Kashmir	Srinagar
Karnataka	Bangalore
Madhya Pradesh	Bhopal and Indore
Maharashtra	Bombay (Mumbai), Nagpur, and Sholapur
Punjab	Amritsar
Rajasthan	Ajmer and Jaipur
Tamil Nadu	Coimbatore, Madras (Chennai), and Madurai
Uttar Pradesh	Kanpur, Saharanpur, and Varanasi
West Bengal	Asansol, Calcutta (Kolkata), and Hawrah
Delhi	Delhi

We also collected CPI for India from the International Financial Statistics of the International Monetary Fund (IMF). Distance between cities in miles were calculated using latitude and longitude for each city in the website http://www.indo.com/distance/.

III. Methodology and Preliminary Data Analysis

Cecchetti et al. (2002) used the average of city price indices as the underlying stochastic trend, which can be viewed as a dynamic factor, and estimated the half-life of convergence of each of the 19 city price indices to this trend. They first employed the panel unit root test to check if the relative prices with respect to this trend were unit root processes, and then estimated the half-lives using the panel autoregressive model. However, their approach is not applicable if there is more than one stochastic trend, and it cannot capture long-run dynamics among the cities, as their model captures only the panel aspects for the trend component. Further, the formula to estimate the half-lives is similar to that based on the autoregressive model of order one, AR (1), for short-run dynamics, and thus is not an appropriate formula to use for the type of model considered in their analysis. (This point was addressed in Goldberg and Verboven, 2004).

Cecchetti et al. (2002) analyzed the time series properties of city real exchange rates in the United States. The city real exchange rates were computed by taking the natural logarithm of the consumer price index for each city and then dividing this by the natural log of the consumer price index in Chicago. Although Papell (1997) showed that the choice of numeraire currency is significant in the context of the international tests of the PPP, Cecchetti et al. (2002) argue that the panel unit root testing with common time trend effect make the choice of numeraire city irrelevant. The common time trend in panel unit root test takes into account the effects of any change in the numeraire price index.

Cecchetti et al. (2002) found that the real exchange rates between U.S. cities were stationary, i.e., they do not contain any unit root[6]. However, the deviation from the common trend was highly persistent, and the average half-life estimate was about nine years; the slower rate of convergence was weakly related to the higher distance between locations.

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[6] This implies that the log of the price index of one city and the log of the price index of the numeraire city, Chicago in this case, are cointegrated with a cointegrating vector $(1, -1)'$ and the cointegrating rank of the log of the price indices of 19 cities including Chicago is 18. Thus, there is one common trend, which is the mean of the log of the price indices.

In order to properly capture the long-run dynamics, we employed cointegration analysis by considering the log of the price indices of the 25 cities in India as a vector time series. This cointegration analysis enabled us to capture the short-run dynamics among the cities involved. As a by-product of cointegration analysis, we were able to obtain the impulse responses of each of the price indices, attributable not only to the shock to its own index, but also to the shocks to other cities' price indices. Based on these impulse responses, we determined the half-lives of price index convergences to their own shocks, as well as to the shocks in other cities[7].

Cointegration analysis is based of the following error correction representation of the vector autoregressive model:

$$\Delta \mathbf{y}_t = \boldsymbol{\delta} + \alpha\beta' \mathbf{y}_{t-1} + \sum_{j=1}^{p-1} \Phi_j^* \Delta \mathbf{y}_{t-j} + \boldsymbol{\varepsilon}_t , \tag{1}$$

where $\mathbf{y}_t$ is a 25-dimensional vector whose components are the logs of city price indices at time t and $\Delta \mathbf{y}_t = \mathbf{y}_t - \mathbf{y}_{t-1}$, α and β are $25 \times r$ matrices. (The cointegrating rank r is to be determined.) The matrix α is called the speed of adjustment matrix and the columns of β are linearly independent cointegrating vectors with $\beta' \mathbf{y}_{t-1}$ representing the long-run equilibrium errors. As there are structural breaks around July 1998 attributable to regional tensions due to nuclear tests in India and Pakistan and conscious efforts of the central bank of India to offset potential contagion of a financial crisis in East Asia by increasing money supply, the vector series $\mathbf{y}_t$ is adjusted for these structural breaks. Based on this representation we can obtain the common stochastic trends $\beta_\perp' \mathbf{y}_t$, where $\beta_\perp$ is a $25 \times (25 - r)$ matrix such that $\beta_\perp' \beta = 0$ and explain the short-run dynamics through the Φ_j^*. By inverting this model into

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[7]Cecchetti et al. (2002) were only able to investigate the half-lives to its own shock because of the shortcomings of their model.

$$\mathbf{y}_t = \mu + \sum_{j=0}^{\infty} \Psi_j \boldsymbol{\varepsilon}_{t-j}\,^{8},$$

we can obtain the impulse response, Ψ_j, through which the half-life is obtained.

Based on the Akaike Information Criterion, we identified the autoregressive order p as 2. In order to identify the cointegrating rank r, we examined the squared partial canonical correlations (SPCCs) between $\Delta\mathbf{y}_t$ and $\mathbf{y}_{t-1}$ adjusted for $\Delta\mathbf{y}_{t-1}$. The most commonly used test statistics for testing the null hypothesis of cointegrating rank of r are the trace statistic and the maximum eigenvalue statistic:

$$TR = -n\sum_{i=r+1}^{m} \ln(1-\hat{\lambda}_i) \text{ and } ME = -n\ln(1-\hat{\lambda}_{r+1}),$$

respectively, where $\hat{\lambda}_i$ is the i-th largest SPCC and n is the sample size. The asymptotic distributions of these statistics are well known and tabulated in, for example, Johansen and Jesulius (1990) for the case without structural break, and in Lütkepohl et al. (2003) for the case with structural shifts. Johansen et al. (2000) investigated the asymptotic distributions for the case with structural breaks in the deterministic trend and suggested using approximation based on simulation for the critical values. However, this approach is not directly applicable to our data, as the indices of some cities have different forms of structural breaks and different time points for structural breaks. Investigation of the asymptotic distribution of the above test statistics for the case of our data will be an interesting future econometric study and will not be

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[8] This is understood as $\mathbf{y}_t = \mu + \sum_{j=0}^{K} \Psi_j \boldsymbol{\varepsilon}_{t-j} + \mathbf{z}_{t-K}$ for some large K such that $\mathbf{z}_{t-K}$ embodies the "initializing" features of $\mathbf{y}_t$. The Ψ_j is obtained based on the recursion $\Psi_j = \sum_{k=1}^{p} \Phi_k \Psi_{j-k}$ with $\Psi_0 = I$ and $\Psi_j = 0$ for $j < 0$. See p. 103 of Box, Jenkins, and Reinsel (1994).

pursued here. As an exploratory measure, we examined the relative magnitude of the SPCCs that are tabulated in Table 2. The smallest SPCC was only about 14 percent of the second smallest SPCC, while the others were 70 to 90 percent of the next largest SPCC, except for the third smallest which was about 47 percent of the fourth smallest SPCC. Therefore, we tentatively identified the cointegrating rank of the logs of the price indices $\mathbf{y}_t$ as 24, and thus with one common trend[9].

Table 2

Squared partial canonical correlations, $\hat{\lambda}_i$ from Model (1)

0.790	0.715	0.694	0.641	0.610
0.547	0.531	0.471	0.430	0.407
0.386	0.325	0.312	0.276	0.267
0.236	0.224	0.192	0.170	0.158
0.117	0.104	0.049	0.035	0.005

Based on the estimates of the model in (1) with the cointegrating rank of 24, we obtained the common trend:

$$\hat{\beta}'_{\perp}\mathbf{y}_t = 0.0374y_{1t} + 0.0396y_{2y} + 0.0382y_{3t} + 0.0405y_{4t} + 0.0427y_{5t} + 0.0473y_{6t} + 0.0385y_{7t} + 0.0408y_{8t} + 0.0389y_{9t} + 0.0435y_{10t} + 0.0399y_{11t} + 0.0389y_{12t} + 0.0361y_{13t} + 0.0382y_{14t} + 0.0364y_{15t} + 0.0381y_{16t} + 0.0418y_{17t} + 0.0374y_{18t} + , 0.0383y_{19t} + 0.0362y_{20t} + 0.0415y_{21t} + 0.0393y_{22t} + 0.0413y_{23t} + 0.0446y_{24t} + 0.0447y_{25t}$$

where y_{it} is the log of the price index of the i-th city listed in Table 1. This estimated common trend displayed in Figure 1 is a weighted average of log of price indices of the 25 cities. These weights are closely tied to the sizes of the cities: Cities with a weight more than the average of

[9] With a cointegrating rank of 23, one may obtain numerically a second "common trend" that is orthogonal to the common trend obtained based on a cointegrating rank of 24. But this second one does not have a unit root, and thus we conclude that the $\mathbf{y}_t$ has one common trend and is of cointegrating rank 24.

0.04 are in general larger cities such as Ahmedabad (y_{4t}), Bombay (y_{10t}), Madras (y_{17t}), Calcutta (y_{23t}), and Delhi (y_{25t}) with population over three million. This common trend closely tracks the log of the Consumer Price Index (CPI) of India, as shown in Figure 2. The estimated generalized least squares regression model of the log of the CPI on the common trend is $LCPI_t = -1.051 + 0.987CT_t$ with R-square of almost one, where $LCPI_t$ is the log of the CPI and CT_t is the common trend. Therefore, the common trend is interpreted as the inflation factor. We note that the panel data approach used in, for example Cecchetti et al. (2002) and Goldberg and Verboben (2004) estimate a common trend by the simple cross sectional averages, while we have used weighted (cross sectional) averages.

Figure 1. Estimated Common Trend of the Log of the Price Indices of Twenty-five Cities

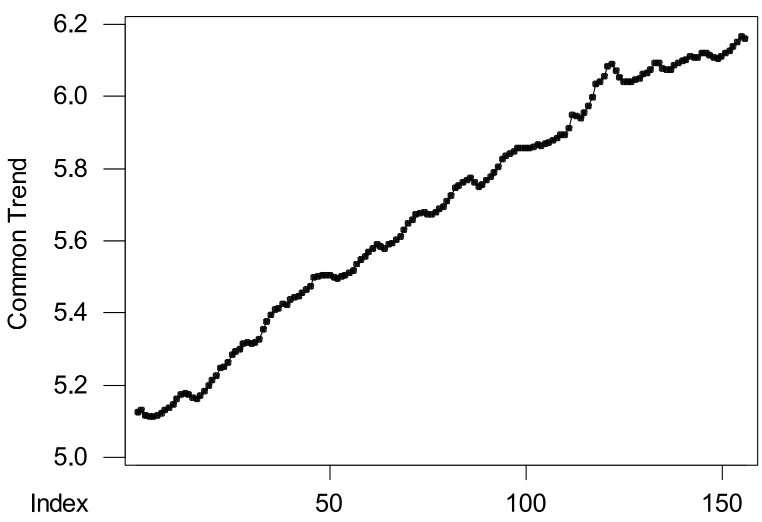
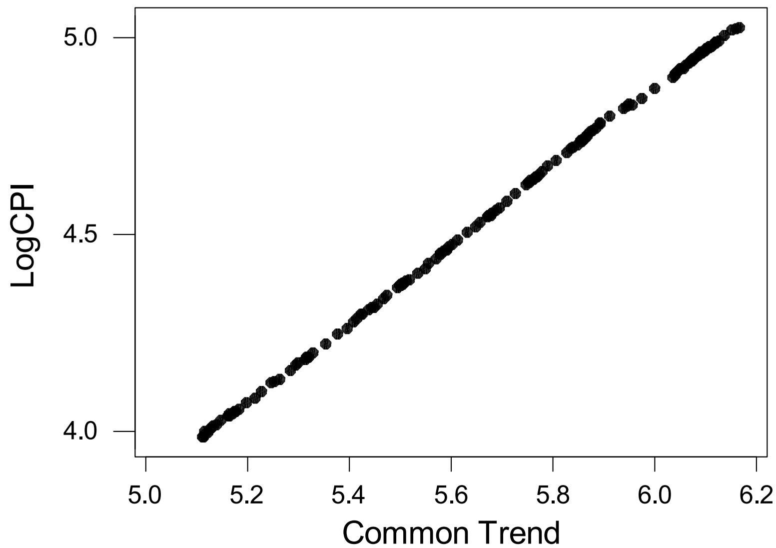


Figure 2. Scatter Plot Between the Log of the CPI and the Estimated Common Trend



Based on the orthogonal projection, we have the following decomposition

$$\mathbf{y}_t = \hat{\beta}(\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\mathbf{y}_t + \hat{\beta}_\perp(\hat{\beta}'_\perp\hat{\beta}_\perp)^{-1}\hat{\beta}'_\perp\mathbf{y}_t,$$

where the first term on the right side is the stationary (transitory) component and the second term is the nonstationary (permanent) component. The impulse response function of the stationary component can be obtained by $\hat{\beta}(\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\hat{\Psi}_j$, where $\hat{\Psi}_j$ is the estimated impulse response from the model in equation (1). From this we estimated the half-life of the convergence to the common trend in response to the shock of its own log of the price index of a city by examining the diagonal elements of $\hat{\beta}(\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\hat{\Psi}_j$ and to the shock of other cities by examining the off-diagonal elements. The latter type of half-life was not examined in the aforementioned panel data approach because the cross sectional dynamics were not considered in those analyses.

IV. Rates of Convergence and Half-life

Our metric to gauge the rate of convergence to the common trend is the half-life. The period in which the marginal change in the stationary component of the impulse response becomes half of the initial response is our definition of a half-life. The half-lives for own shocks are reported in Table 3.

Table 3
Half-life Estimates from Impulse Response Functions: Stationary Components (Own Shock)

One Month	Two Months	Three Months	Four Months
Ajmer	Hyderabad	Guntur	Delhi
	Jamshedpur	Bhavnagar	
	Ahmedabad	Srinagar	
	Bangalore	Sholapur	
	Bhopal	Varanasi	
	Indore	Calcutta	
	Bombay		
	Nagpur		
	Amritsar		
	Jaipur		
	Coimbatore		
	Madras		
	Madurai		
	Kanpur		
	Saharanpur		
	Asansol		
	Howrah		

The results shown in Table 3 indicate that the half-life for own price shocks in the Indian cities are much smaller compared to that observed in the literature. Indian capital Delhi yielded the highest half-life estimate (four months), while Ajmer yielded the lowest half-life estimate (one month). Out of 25 cities, 17 cities yielded a half-life of two months, while six cities yielded a half-life of three months. These are significantly high rates of convergence. The length of time it takes from the marginal change in the stationary component to the half-way mark of the initial response is our half-life estimate. However, if the half-life is defined by looking at how long it would take from the marginal change of both stationary and stochastic trend components together to be lower than the half-way mark of the initial response of both stationary and stochastic trend components together, we can observe a slightly higher average half-life. This is attributable to a slow adjustment of a non-stationary component to a shock. Although we believe that the proper definition for a half-life should be the marginal change related to the stationary component, we report the half-life calculation for total price change in Table 4.

Table 4
Half-life Estimates from Impulse Response Functions: Both Stationary and Trend Components (Own Shock)

One Month	Two Months	Three Months	Four Months	Five Months and Above
Ajmer	Bhopal	Srinagar	Guntur	Hyderabad
Amritsar	Nagpur	Sholapur	Ahmedabad	Jamshedpur
	Coimbatore	Calcutta	Jaipur	Indore
	Madras		Madurai	Bombay
	Kanpur		Delhi	Varanasi
	Saharanpur			
	Asansol			
	Howrah			

Although we found that the range of half-life is much larger for these estimates, 20 out of 25 cities yielded four months or lower half-life estimates. This implies that the Indian cities are substantially integrated. This, in essence, validates the Purchasing Power Parity doctrine We would like to mention here that generally half-life is calculated by calculating autoregressive coefficient, β, and using it in a simple formula, $\ln(0.5)/\ln(1+\beta)$. However, there is no direction in the literature as to how these β's with different frequencies are related. Basker and Hernandez-Murillo (2003) reported β for annual data to be –0.24, while it is –0.23 for semi-annual data for the USA (Table 4). Thus, the half-life from yearly data would be 2.53 years, while the half-life from semi-annual data would be 1.33 years (2.65 unit of six months). A more cautious approach should be taken to interpret the results if the low frequency data are a temporal aggregation of high frequency data. Since yearly data are calculated by averaging the twelve monthly data points (for instance, the Bureau of Labor Statistics in the United States follows this procedure in reporting consumer price index for different cities), we should take more care in choosing the data frequency and its interpretations.

Basker and Hernandez-Murillo (2003) have used time series data with various frequencies (monthly, quarterly, and annual) for cities in the USA and Canada, and they evaluated the role that distance between locations plays in determining the rate of convergence in price indices. They found, using the panel unit root test, that the transportation costs (distance) turns out to be very important, as city level prices converge towards neighboring cities faster than they converge to US average. They also observed that the choice of data frequency may yield different rates of convergence for the same cities.

We calculated half-life not only for a price shock originated in the city under consideration, but also for a price shock initially imposed on some other cities. For brevity, we report the results from only five cities in Table 5. These are the four largest cities in the “four corners” of India and Nagpur was chosen as a city at the geographic center (distance from Nagpur to other cities are reported in Table-5). Diagonal elements are half-life for own shock, while off-diagonal entries are half-life for shock emanating from the cities shown in the first row.

Table 5

Half-life Estimates (Months) from Impulse Response Functions for Five Main Cities

(Own Shock and Shocks in Other Cities)

	Bombay	Calcutta	Delhi	Madras	Nagpur	Distance From Nagpur (Miles)
Bombay	2	4	4	5	2	439
Calcutta	3	3	2	1	3	593
Delhi	>5	1	4	>5	>5	531
Madras	2	2	3	2	>5	561
Nagpur	>5	5	>5	2	2	

We found that effects of a shock in one city have differential impact on the other cities. For example, a unit shock in the price of Bombay would have a half-life of two months, while it would have a half-life of more than five months for Nagpur and Delhi, while the half-lives would be two and three months for Madras and Calcutta, respectively. We observed similar variations in cross-city transmission of price shocks. It is also interesting to note that the origin of the shock affects same city pairs. The half-life for a shock originated in Bombay on prices in Madras was two months while the half-life for a shock originated in Madras on prices in Bombay was found to be five months. Although we did not calculate the confidence intervals for half-lives presented here, we may argue from our results that the role of distance in convergence to prices should be analyzed with much care.

V. Conclusions

The main focus of this paper has been to examine how prices in different cities are formed and how they fluctuate around a common trend. A clear understanding of this regional variation of prices would make monetary policy-making in a diverse region like the European Union more efficient. Ceccehetti et al. (2002) analyzed price convergence among U.S. cities, which, however, is not very diverse compared to the EU cities. The diversity between Indian cities is to a great extent comparable to that in the EU, although India is not industrialized like the EU. Still, knowledge about price formation in a diverse region would enable policy makers to fine-tune their policy stance. For this reason, the rate of CPI convergence in 25 large cities of India was calculated. We followed cointegration technique to identify a common trend. Interestingly, the common trend turns out to be closely related to the overall CPI of India. The rate of convergence for a unit shock imposed on a city was calculated by using impulse response functions, which we believe to be a precise way of calculating the half-life. Moreover, our approach is flexible enough that we can calculate the half-life of a shock in one city on the shock imposed on another city. We found that the rate of convergence to the stochastic trend is much faster, with an average half-life of around three months. Although Murray and Papell (2002) and Goldberg and Verboven (2004) reported the half-life of convergence to be in the international context less than one year for a few real exchange rates, and Cheung and Lai (2000) showed that the rate of convergence is much lower for developing countries, we believe that this study looked at the half-life issue more rigorously and these results provide support to the PPP theory.

In terms of cross-city shock transmissions, we found that the shock in a particular city would have differential effects on different cities. Moreover, shock transmissions to other cities are not invariant to the shock on particular city. For example, the nature of shock transmission from Bombay to Nagpur would be different from the nature of shock transmission from Nagpur to Bombay. This suggests that the use of city distance to calculate the transport costs in the case of price formation in different cities warrants caution. Monetary authorities should use this information to identify the more important impact cities to design an optimal monetary policy.

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