Department of Social Systems and Management

Discussion Paper Series

No. 1158

Purchasing Power Parity: Further Evidence from Japanese Municipal Data

by

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September 2006

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JAPAN

Purchasing Power Parity: Further Evidence from Japanese Municipal Data

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1st version: September 2004
This version: September 2006

Abstract

This paper empirically analyzes Purchasing Power Parity (PPP) among Japanese municipalities from 1990 to 2003. Using panel unit root tests including one that considers cross-sectional dependency in the data (Moon and Perron 2004), we find evidence in favor of PPP, confirming the stationarity of relative prices in Japan and thus the long-run comovement of municipal prices. Furthermore, the half-life of a shock is found to be about two years, which is faster than that of the international PPP. As in the European and US studies, short-term deviations from PPP can be explained by income differentials and distance between cities.

JEL classification: E300, F300

Keywords: Purchasing power parity, panel unit root tests, convergence speed, Japanese municipal data, GMM

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1. Introduction

In the area of international finance, much research has been carried out in order to test the purchasing power parity (PPP) concept. In logarithmic form, it can be expressed as $s_t = p_t - p_t^*$ where s_t is nominal exchange rates, and p_t and p_t^* are domestic and foreign prices. The stationarity of $s_t - p_t + p_t^*$ provides evidence in favor of the long-run PPP. While many theories on open market economies hinge on PPP, its validity is highly questionable on empirical grounds. Violation of PPP seems to be attributable to, among many other factors, the existence of tariff and non-tariff barriers, taxes, transportation costs, as well as the heterogeneous composition and weight of commodities included in the basket to produce the aggregated price indices (e.g., Rogoff 1995).

In recognition of these problems, some studies have been conducted using municipal data. Analysis of PPP within a single country allows us to ignore exchange rates, i.e., s_t=0, and furthermore will reduce the likelihood of any barriers across borders (such as heterogeneous tariffs, and data compilation methods). For this reason, empirical research, often under the name of "price convergence," has been carried out using municipal data. Notably, Engle and Rogers (1996) and Parsley and Wei (1996) raise evidence for price convergence among US cities. Furthermore, Parsley and Wei report that the half-life of a shock is from about one to four years using the consumer price index (CPI) for 48 cities in the US. This convergence speed is slightly faster than that of the international PPP of three to five years (Rogoff 1995).[1] Similarly, Rogers (2001) argues that convergence is especially evident for traded goods. In this connection, Goldberg and Verboven (2005) offer evidence in favor of PPP using a detailed product-level data set (car prices), and point out that the half-life of shocks is about 1.3 years. This convergence speed is within the range reported in Parsley and Wei (1996). In the Japanese context, using the data of 7 prefectural cities, Esaka (2003) shows the validity of the long-run PPP, but convergence speed is not calculated.

Against this background, this paper empirically analyzes PPP using data from all prefectures across Japan, and extends Esaka (2003) in several ways which have far-reaching policy implications. First, this paper employs a more comprehensive set of CPI data, including the overall price data of all (47) prefectural capitals. Secondly, we implement a more advanced panel unit root test (Moon and Perron 2004) which takes cross-sectional

[1] Unlike other studies referred to in this paper, Cecchetti, Mark, and Sonora (2002) study the stationarity of *price levels* rather than relative prices.

dependency in the data into consideration. This point has drawn considerable attention from researchers since O'Connell (1998) argued that cross-sectional dependency severely affects the finite sample properties of standard panel tests. Thirdly, convergence speed is calculated in the presence of price convergence using Japanese data. Finally, this paper looks into explanations for heterogeneous prices across cities using income differentials and transportation costs.[2]

2. Data

Our analysis is based on the annual data of the 47 prefectural capital cities. The relative price indices are readily available and were obtained from the Annual Report on the Consumer Price Index published by the Statistics Bureau, Ministry of Public Management, Home Affairs, Posts, and Telecommunications. This index measures city-to-city differences in the level of consumer prices, using Tokyo prices as a benchmark. With respect to prefectural income data, compensation per employee is obtained from the Annual Report on Prefectural Accounts published by the Department of National Accounts, Economic and Social Research Institute, Cabinet Office, Government of Japan. These data based on the 1993 Systems of National Accounts are available for the period from 1990 to 2003, and thus our analysis is based on this time period (644 observations in total). To be consistent with relative prices, income differentials for each prefecture are calculated using Tokyo as the benchmark.[3]

Tables 1 and 2 report the average values of these relative indicators during our sample period. Since Tokyo is our benchmark city, therefore relative prices for city i at time t can be written as $Q_{i,t} = P_{Tokyo,t}/P_{i,t}$ and relative incomes as $Inc_{i,t} = Y_{Tokyo,t}/Y_{i,t}$. Notably, these values are all greater than one, reflecting the fact that price and income levels in Tokyo are higher than those in other cities.

3. The Stationarity of Relative Prices and Incomes

This section examines the time series properties of our data (both relative prices and incomes) since our statistical model is based mainly on these two factors and therefore

[2]We did not consider differences in taxation (e.g., municipal taxes) since differences are less significant than is the case in Europe and the US.

[3]We follow Esaka (2003) in choosing Tokyo as a benchmark. Our choice is also based on the fact that Tokyo is the nation's capital and the largest prefecture in terms of population in Japan. Furthermore, Tokyo is the center of economic activities, and goods and services are constantly being transferred from/to Tokyo. However, we acknowledge that the results are sensitive to the choice of the benchmark city.

requires them to be integrated of the same order so that the model will be statistically balanced. In order to improve the deficiencies of cross-section (individual) unit root tests in a near-unit root case, most previous research has employed panel unit root tests. Parsley and Wei (1996) use the panel unit root developed by Levin and Lin [LL] (1993), while Cecchetti, Mark, and Sonora (2002) use tests developed by LL, and Im, Pesaran, and Shin [IPS] (2003). Esaka (2003) uses the IPS and Fisher (1932) tests.[4]

In order to achieve continuity with previous studies, this paper uses the following panel unit root tests; namely, the Im, Pesaran, and Shin [IPS] (2003) and Fisher (1932) tests as well as the Levin-Lin-Chu [LLC] (2002) test. This last one is a modified version of the LL test (see Appendix for details of these tests). However, one drawback of these tests is their assumption of no cross- sectional dependency in the data. This assumption, however, does not seem to hold in most economic and financial data sets, including ours, because of the existence of common exogenous shocks such as changes in monetary policy by the central bank (Bank of Japan). Therefore, previous research often used the common time dummy in attempt to extract the common movements in the data.

Recently, Moon and Perron [MP] (2004) have proposed an alternative approach for dealing with cross-sectional dependency. They suggest estimating cross-sectional components using the principal component method. Therefore, in addition to the above-mentioned methods, we analyze the PPP using this method as well.[5] This test can be summarized using the following three equations.

$$q_{i,t} = \alpha_i + q^0_{i,t} \tag{1}$$

$$q^0_{i,t} = \rho_i q^0_{i,t-1} + u_{i,t} \tag{2}$$

$$u_{i,t} = \lambda_i^{'} f_t + e_{i,t} \tag{3}$$

where $i = 1, ..., N$ and $t = 1, ..., T$. When analyzing the stationarity of relative prices, $q_{i,t} = ln(Q_{i,t})$, and $q_{i,t}$ will be replaced with $y_{i,t} = ln(Inc_{i,t})$ for the analysis of relative incomes. Like the IPS and Fisher tests, this test examines the null hypothesis of the unit root (i.e.,

[4]For details of these tests, see Maddala and Kim (1998). Among these tests, the Fisher, followed by the IPS, seems to be most reliable in terms of its ability to distinguish statistical hypotheses.

[5]The MP method adopts probably one of the most general approaches for testing the unit root in the panel context. For example, Pesaran (2003) considers cross-sectional dependency with only one common factor. The test developed by Bai and Ng [BN] (2004) is another general test like MP. However, it is difficult to draw a general conclusion from this test since the stationarity of the common and idiosyncratic components is examined separately. Furthermore, to our knowledge, the theory is not yet fully developed as regards the case where the common components are non-stationary but co-integrated.

$\rho_i = 1 \ \forall_i$) against the alternative of stationarity (i.e., $\rho_i < 1$ for some i.) The unique feature of this test can be summarized in equation (3) where $\lambda_i^{'} f_t$ represents the common components of $u_{i,t}$ and $e_{i,t}$ idiosyncratic factors. The latter are factors specific to individual i and $e_{i,t} = \sum_{j=0}^{\infty} d_{i,j} v_{i,t-j}$ where $v_{i,t-j}$ are $IID(0,1)$ across i and t, whereas $\lambda_i^{'} f_t$ can be decomposed into a vector of common factors (f_t) and factor loadings (λ_i). Thus, when $\lambda_i^{'} f_t = 0$, $u_{i,t}$ contains only idiosyncratic factors, and $u_{i,t}$, on the other hand, only contains common factors if $e_{i,t} = 0$. MP proposes to decompose $u_{i,t}$ into two such components using the standard principle component method. The estimation of the common factors involves optimizing the following problem.

$$V(k, F^k) = \min_{\Lambda} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(u_{i,t} - \lambda_i^k F_t^k \right)^2 \tag{4}$$

where $\Lambda = (\lambda_1, \lambda_2, ..., \lambda_N)'$ and superscript, k, refers to an arbitrary number of common factors ($k <$min(N,T)). Thus, λ_i^k and F_t^k are factor loadings and common factors corresponding to those with k common factors.

When using the principle component method, it is necessary to decide the true number of common factors in the data which essentially reduce the size of dimensionality. In this connection, we follow the recommendation of MP (2004) and implemented the modified information criterion (BIC) developed by Bai and Perron (2002) which can be obtained as:

$$BIC_3 = V(k, \hat{F}^k) + k\sigma_e^2 \frac{N+T-k}{NT} \ln(NT) \tag{5}$$

where $\sigma_e^2 = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} E(e_{i,t})^2$. Among several criteria considered, BIC_3 is found to perform best for selecting the number of factors when $\min(N,T) \leq 20$ (Bai and Perron 2004). Like the standard information criteria, the smallest value of BIC_3 indicates the best fit of the model to the data. Here, the maximum number of common factors is set at three.

Table 3 summarizes the results from the panel unit root tests, and provides strong evidence of stationary relative prices (i.e., PPP) and incomes when cross sectional dependency is properly taken into account. The MP test suggests one common factor and rejection of the null hypothesis at the one percent significance level, confirming stationary relative prices and thus that prices in provincial areas do not diverge from price levels in Tokyo in the long-run. This finding is consistent with existing research (see Section 1) using European, Japanese and US data. Furthermore, we have analyzed convergence in relative incomes ($y_{i,t} = ln(Inc_{i,t})$) using the same methods, and show evidence of their stationarity in Table 3. Stationary relative incomes are consistent with Barro and Sala-i-Martin (1992) who concluded that there was convergence of regional growth in Japan. These results are confirmed using another method (Pesaran 2006) known as the individual cross-sectionally augmented ADF (CADF) which, in order to eliminate the cross-dependence, augments that standard ADF with the cross sectional averages of lagged levels and the first differences of the data (see the summary of this test in the Appendix).

We note that the results are sensitive to the treatment of cross- sectional dependency. While the tests (LLC, IPS and Fisher) without using the common time dummy, are implemented, no evidence is obtained of stationarity, which is consistent with those from the individual ADF tests (Tables 4 and 5). Therefore, as O'Connell (1998) discussed, economic data are highly cross-sectionally dependent, and without appropriate consideration, results seem highly misleading.[6]

Finally, we have computed the convergence speeds for Japan, the half-life of a shock to $q_{i,t}$ based on the MP test. Using the formula, $ln(0.5)/ln(\rho)$ which has been frequently employed in this type of research, we have computed ρ which is common to all cities under the null and thus it enables us to draw a general conclusion on convergence speed. The estimates of ρ for relative prices and incomes are also reported in Table 3. This shows that a shock to both relative prices and incomes decreases by 50 percent within about two years. The convergence speed for relative prices and incomes is similar but this is not very surprising since the nominal income is often adjusted based upon inflation. Our estimated speed is within the expected range from European and US data (Parsley and Wei 1996) using a similar methodology and data definition to ours, and is clearly faster than that reported from the international PPP.

Since we find that both sets of our data are $I(0)$, relative incomes shall be used in the next section to explain why discrepancies in prices exist between Tokyo and the provinces.

4. Explanations of Price Differentials

Now, given the stationary relative prices and incomes, the next question is what factors can explain the deviation from PPP. While we find that local prices seem to move in tandem

[6]While not reported here, we have also computed the LLS and IPS tests by a rather crude method, i.e., subtracting the common time effect which is equivalent to the average of relatives at a particular time. The results are consistent with those from the MP test.

with price levels in Tokyo in the long-run, this finding obviously allows some divergence from the PPP level in the short-run.

Engle and Rogers (1996) and Parsley and Wei (1996) argue that price differentials across cities are closely linked with transportation costs, which can be approximated by geographical distance. In addition, we consider income differentials as an important candidate in explaining relative prices between cities.[7]

The price-income relationship can be theoretically explained by the Phillips curve. It suggests that at least in the short-term there is a trade-off between price and output. Following Mankiw(2003), we derive the relationship between the relative prices and incomes.[8] Firstly, the Philips curve in its modern form is expressed as:

$$\pi_{i,t} = \pi^e_{i,t} - \beta(u_{i,t} - u^n) + v_{i,t} \tag{6}$$

where $\pi_{i,t}$ is the inflation rate, $\pi^e_{i,t}$ is the expected inflation rate, and $(u_{i,t} - u^n)$ is cyclical unemployment for city i at time t. The u^n is a natural rate of unemployment.

Next, Okun's law gives the relationship between output and unemployment as:

$$\frac{1}{\alpha}(z_{i,t} - \bar{z}) = -\beta(u_{i,t} - u^n) \tag{7}$$

where z is output, and $\bar{z}$ is the natural level of output assumed to be an average of relative incomes among cities and over time. We can substitute $\frac{1}{\alpha}(z_{i,t} - \bar{z})$ for $-\beta(u_{i,t} - u^n)$ in the Phillips curve equation to obtain

$$\pi_{i,t} = \pi^e_{i,t} + \frac{1}{\alpha}(z_{i,t} - \bar{z}) + v_{i,t} \tag{8}$$

for city i and

$$\pi_{j,t} = \pi^e_{j,t} + \frac{1}{\alpha}(z_{j,t} - \bar{z}) + v_{j,t} \tag{9}$$

for city j $(i \neq j)$, where $\pi_{i,t} = p_{i,t} - p_{i,t-1}, \pi^e_{i,t} = p^e_{i,t} - p_{i,t-1}$. Finally, we obtain the relationship between relative prices and incomes as:

$$p_{i,t} - p_{j,t} = p^e_{i,t} - p^e_{j,t} + \frac{1}{\alpha}(z_{i,t} - z_{j,t}) + (v_{i,t} - v_{j,t}) \tag{10}$$

This relationship can be extended to include distance between cities as one explanation of price differentials. When $p^e_{i,t} - p^e_{j,t}$ is assumed constant and equals β_0, equation (10)

[7] We did not consider the discrepancy in taxes (e.g., sales tax and consumption tax) here since it is negligible among Japanese cities.

[8] The relationship between the relative prices and incomes can also be theoretically obtained using the Balassa-Samuelson theorem (see Nagayasu and Ying 2006).

becomes:

$$q_{i,t} = \beta_0 + \beta_1 Log(D_i) + \beta_2 y_{i,t} + \theta_t + u_{i,t} \tag{11}$$

where D_i represents the distance (in kilometers) between city i and the benchmark city, Tokyo, reported in Table 6. The term $y_{i,t}$ is a natural logarithmic form of relative incomes for city i at time t. Furthermore, we include the time dummy to capture the year-specific shocks, θ_t. The term, $u_{i,t}$, is a residual and corresponds to $v_{i,t} - v_{j,t}$ in equation (10).

The expected signs for key parameters are $\beta_1 > 0$ and $\beta_2 > 0$. When $\beta_1 > 0$, the greater the distance between cities, the wider discrepancies in their prices. Parameter β_2 can be interpreted as the elasticity of relative incomes to relative prices, and $\beta_2 > 0$ indicates that higher relative prices can be explained by its higher relative incomes. Here, we estimate equation (11) using several estimation methods, the OLS, OLS with AR(1) correction, and GMM.

In order to reach final conclusion, we need to detect whether there is any violation of the following assumptions when using the OLS. One is that the regression disturbances are homoskedastic with the same variance across time and prefectures. The other is that the regression disturbances are serially independent. Ignoring heteroskedasticity and serial correlation when they are present results in consistent but inefficient estimates of the regression coefficients. Also, the standard errors of these estimates will be biased and so one should compute robust standard errors correcting the possible presence of heteroskedasticity and serial correlation.

At first, we test the heteroskedasticity. The Breusch-Pagan statistic is the standard test of heteroskedasticity in an OLS regression. We report that in column (I) of Table 7. The null of no heteroskedasticity is rejected at the 10 percent level. As this test relies heavily on the normality assumption (Koenker 1981), we also report Koenker's test statistics distributed as χ^2 with m, degree of freedom under the null of no heteroskedasticity.[9] The null hypothesis of no heteroskedasticity is strongly rejected here.

Next, we test the presence of serial correlation of error terms. Following Wooldridge (2002), we use a simple way to detect serial correlation by writing the AR(1) model as:

$$u_t = \rho_1 u_{t-1} + e_t \tag{12}$$

under the null hypothesis of no serial correlation, $\rho_1 = 0$. One way to proceed is to write

[9]The m indicates the number of variables, named indicator variables, that are hypothesized to be related to the heteroskedasticity.

the dynamic model under AR(1) serial correlation as:

$$q_t = \mathbf{x}_t\beta + \rho_1 u_{t-1} + e_t, t = 2, \ldots, T. \tag{13}$$

To operationalize this procedure, the u_{t-1} is replaced with the pooled OLS residuals.[10] Therefore, we run the regression $q_{i,t}$ on $\mathbf{x}_{i,t}, \hat{u}_{i,t-1}, t = 2, \ldots, T, i = 1, \ldots, N$ and do a standard t test on the coefficient of $\hat{u}_{i,t-1}$. We report the estimated coefficient and standard error of ρ_1 in column (II) of Table 7. It suggests that we reject the null hypothesis of $\rho_1 = 0$, and serial correlation is indeed detected here.[11] We also test the serial correlation of the error term by using another test statistic. Bhargava, Franzini and Nerendranathan (1982) generalized the Durbin-Watson type statistics to test the residuals from the fixed effects model for serial independence. They suggested testing for $H_0 : \rho_1 = 0$ against the alternative that $|\rho_1| < 1$, using the statistics defined as:

$$d_p = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}(\hat{w}_{wit} - \hat{w}_{wit-1})^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{w}_{wit}^2} \tag{14}$$

where $\hat{w}_{wit}$ are Within residuals rather than OLS residuals. Regarding the upper and lower bounds of d_p, they argue that it is not necessary to compute these bounds, but simply test if d_p is less than two when testing against serial correlation. The Bhargava et al (1982) Durbin-Watson statistic is 0.066 and rejects the null hypothesis of no first-order serial correlation.

Given the presence of heteroscedasticity and autocorrelation, we are motivated to use the Generalized Method of Moments (GMM). The GMM generates efficient estimates in the presence of autocorrelation and heteroscedasticity in the residual term. Results are summarized in column (III) of Table 7 where the instruments we use for GMM estimation are one and two-period lagged relative incomes.[12]

When implementing the GMM, we consider two requirements which an instrumental variable must satisfy. One is that it must be orthogonal to the error process and the other is that it must be correlated with the instrumented variable. The consequence of excluded instruments with little explanatory power is increased bias in the instrumental variable coefficients (Staiger and Stock, 1997). To check these requirements we report the following

[10]The right hand side of equation(11) except the error term is described here as $\mathbf{x}_t\beta$ expediently.

[11]t statistics here are obtained by the usual heteroskedasticity-robust t statistic in the pooled regression.

[12]We have also estimated equation (11) using prefectural income data (not per capita). While the results are not reported here, the overall conclusion from the different data set is consistent with those presented in this paper.

test statistics in column (III) of Table 7. The Anderson canonical correlations likelihood-ratio test statistic and the Cragg-Donald chi-squared test statistic provide a measure of instrument relevance, and both statistics reject the null and indicate that the model is identified. We also report the Anderson-Rubin test, which is robust to the presence of weak instruments, under the null hypothesis that the coefficients of the endogenous regressor in the structural equation is equal to zero, numerically equivalent to testing that the coefficients of the excluded instruments are jointly equal to zero. Furthermore, instrument orthogonality to the error term is reflected by Hansen's J-statistic and this does not reject the null hypothesis. Overall, our chosen instruments pass all of these tests.

The GMM results are reported in Table 7 (III), and are consistent with the results from other estimation methods which we discussed. The coefficient for distance, β_1, is significantly positive, and this means the greater the distance between cities, the higher the deviation in relative prices. In addition, we confirm that coefficient for relative incomes, β_2, is also significantly positive. The β_2 below unity suggests that a change in relative incomes does not have a one-to-one effect on relative prices. In short, our findings suggest that distance, an approximation of transportation costs, and relative incomes go some way in explaining the deviation in price differentials.

5. Summary and Discussion

We do find evidence of convergence in Japanese relative prices (i.e., PPP) and note that the half-life of a shock is about two years. Furthermore, as in Europe and the US, we discover that relative incomes and transportation costs can explain the deviation in price differentials in Japan.

Thus, our research provides additional evidence regarding concerns about 'one-size-fits-all' monetary policies implemented in heterogeneous economic regions like Europe. Particularly, the significance of transportation costs in our study suggests that the larger the economy, the greater the price differential among cities, and thus the European Central Bank will likely face increased difficulty in setting appropriate monetary policies in an enlarged euro zone.

Appendix

The general statistical specification of these tests can be expressed as:

$$\Delta q_{i,t} = \alpha_i + \theta_t + \beta_i q_{i,t} + + \sum_{j=1}^{k_i} \psi_{i,j} \Delta q_{i,t-j} + \varepsilon_{i,t}, \tag{15}$$

where $i = 1, ..., N$ and $t = 1, ..., T$. The term, $q_{i,t}$, is a natural logarithmic form of relative prices for city i at time t (i.e., $q_{i,t} = ln(Q_{i,t})$). City specific events are captured by α_i. Finally, the term, $\varepsilon_{i,t}$, is a white noise residual.

As in the univariate ADF test, $q_{i,t}$ is covariance stationary (i.e., $I(0)$) when $|\rho_i| < 1$, where $\beta_i = \rho_i - 1$. The stationary relative prices indicate the validity of PPP. If $\rho_i = 1$, then $q_{i,t}$ is said to follow the unit root process (i.e., $I(1)$). Statistical hypotheses differ slightly depending on the test employed. The LLC assumes a common unit root process across cross-sections (i.e., $\rho_1 = \rho_2 = \cdots = \rho_N = \rho$) and thus β_i becomes β in equation (1). Therefore, it tests the null hypothesis of $H_0 : \beta = 0$ against the alternative of $H_1 : \beta < 0$. In contrast, the IPS and Fisher tests relax the assumption of the common unit root process and analyze the null of $H_0 : \beta_i = 0$ for all i against the alternative of $H_1 : \beta_i < 0$ for $i = 1, 2, \cdots, N_1$ and $\beta_i = 0$ for $i = N_1 + 1, N_1 + 2, \cdots, N$.[13] One difference between these two tests is that while the IPS computes a panel unit statistic based on a modified t statistic,[14] the Fisher test relies on p-values for each ADF test (Maddala and Wu 1999). The critical values for IPS are reported in IPS and the Fisher test has χ^2 distribution with N degrees of freedom.

Pearan (2006) proposes the individual cross sectionally augmented ADF (CADF). This method assumes one common factor and eliminates the cross sectional dependence by including the cross section averages of lagged levels and first differences of the data. The specification is based on:

$$\Delta q_{i,t} = \alpha_i + \rho_i q_{i,t-1} + c_i \bar{q}_{t-1} + \sum_{j=0}^{k} d_{i,j} \Delta \bar{q}_t + \sum_{j=0}^{k} \beta_{i,j} \Delta q_{i,t-j} + \mu_{i,t} \tag{16}$$

where $\bar{q}_{i,t-1} = \frac{1}{N} \sum_{i=1}^{N} q_{i,t-1}$ and $\Delta \bar{q}_{i,t-1} = \frac{1}{N} \sum_{i=1}^{N} \Delta q_{i,t-1}$, and $k = 1$. The results reported in Table 3 is the $Z(N, T)$ version in Pesaran (2006) which are based on the

[13] Both the IPS and Fisher tests are based on N cross section ADF unit root tests, and thus their testable specification is identical to equation (1).

[14] The IPS test is based on the average of t statistics of cross section ADF tests. Based on the Monte Carlo experiments, IPS provides an appropriate size of mean and variance in order to adjust this average t statistic to the context of the panel data.

inverse normal test statistic defined as:

$$Z(N,T) = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}(p_{i,T}) \tag{17}$$

The $Z(N,T)$ is normally distributed under the null hypothesis of the unit root.

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Table 1: **Average Relative Prices by Prefecture, 1990-2003**

City		City		City		City	
Hokkaido	1.080	Tokyo	–	Shiga	1.100	Kagawa	1.120
Aomori	1.102	Kanagawa	1.025	Kyoto	1.060	Ehime	1.146
Iwate	1.119	Niigata	1.092	Osaka	1.043	Kochi	1.110
Miyagi	1.088	Toyama	1.104	Hyogo	1.070	Fukuoka	1.083
Akita	1.125	Ishiwaka	1.105	Nara	1.092	Saga	1.122
Yamagata	1.106	Fukui	1.097	Wakayama	1.094	Nagasaki	1.088
Fukushima	1.120	Yamanashi	1.099	Tottori	1.133	Kumamoto	1.117
Ibaraki	1.107	Nagano	1.114	Shimane	1.096	Oita	1.128
Tochigi	1.097	Gifu	1.102	Okayama	1.095	Miyazaki	1.155
Gunma	1.118	Shizuoka	1.063	Hiroshima	1.113	Kagoshima	1.110
Saitama	1.067	Aichi	1.076	Yamaguchi	1.125	Okinawa	1.145
Chiba	1.086	Mie	1.107	Tokushima	1.128		

Note: Data from the Annual Report on the Consumer Price Index. (Statistics Bureau, Ministry of Public Management, Home Affairs, Posts, and Telecommunications). Tokyo serves as the benchmark city.

Table 2: **Average Relative Incomes by Prefecture, 1990-2002**

City		City		City		City	
Hokkaido	1.420	Tokyo	–	Shiga	1.436	Kagawa	1.257
Aomori	1.581	Kanagawa	1.268	Kyoto	1.263	Ehime	1.602
Iwate	1.623	Niigata	1.446	Osaka	1.085	Kochi	1.369
Miyagi	1.407	Toyama	1.316	Hyogo	1.198	Fukuoka	1.425
Akita	1.702	Ishikawa	1.404	Nara	1.233	Saga	1.489
Yamagata	1.578	Fukui	1.526	Wakayama	1.357	Nagasaki	1.602
Fukushima	1.555	Yamanashi	1.402	Tottori	1.516	Kumamoto	1.463
Ibaraki	1.349	Nagano	1.424	Shimane	1.460	Oita	1.502
Tochigi	1.377	Gifu	1.438	Okayama	1.340	Miyazaki	1.352
Gunma	1.312	Shizuoka	1.368	Hiroshima	1.315	Kagoshima	1.514
Saitama	1.281	Aichi	1.295	Yamaguchi	1.453	Okinawa	1.616
Chiba	1.166	Mie	1.394	Tokushima	1.402		

Note: Data from the Annual Report on Prefectural Accounts (Department of National Accounts, Economic and Social Research Institute, Cabinet Office, Government of Japan). Tokyo serves as the benchmark.

Table 3: **The Panel Unit Root Tests**

Type of test	Relative prices Statistics (p-value)	Relative incomes Statistics (p-value)
Assuming no cross-sectional dependency		
LLC	8.288 (0.999)	-0.647 (0.259)
IPS	4.676 (0.999)	-2.141 (0.984)
Fisher-ADF	33.757 (0.999)	73.475 (0.922)
Considering cross-sectional dependency		
MP	-10.448 (0.000)	-10.734 (0.000)
CADF	-1.722 (0.042)	-2.152 (0.016)
ρ from MP	0.728	0.696
Half-life	2.183	1.913
BIC_3		
$k = 0$	0.648	0.755
$k = 1$	0.340	0.353
$k = 2$	0.387	0.412

Note: LLC stands for the Levin-Lin-Chu panel unit root test, IPS for the Im-Pesaran-Shin test, Fisher-ADF for Maddala-Wu test, and MP for the Moon-Phillips test. The CADF test has been developed by Pesaran (2006) and is the $Z(N,T)$ version (eq. (4.32) in Pesaran (2006)) which has the normal distribution under the null hypothesis. The BIC_3 is the information criterion proposed by Bai and Perron (2002) and k is the number of common factors.

Table 4: **The Augmented Dickey-Fuller Test for Relative Prices**

Prefecture	ADF	Lag	p	Prefecture	ADF	Lag	p
Hokkaido	-0.784	0	0.790	Shiga	-1.810	0	0.360
Aomori	-0.424	0	0.880	Kyoto	-0.830	0	0.780
Iwate	-0.528	0	0.855	Osaka	-1.064	0	0.700
Miyagi	-1.301	0	0.600	Hyogo	-1.599	0	0.455
Akita	-0.604	0	0.840	Nara	-1.570	0	0.470
Yamagata	0.191	0	0.960	Wakayama	-1.606	0	0.455
Fukushima	-0.290	0	0.905	Tottori	-0.381	0	0.885
Ibaraki	-1.209	0	0.640	Shimane	-0.714	0	0.810
Tochigi	-0.900	0	0.755	Okayama	-1.125	0	0.675
Gunma	-1.949	0	0.300	Hiroshima	-0.497	0	0.865
Saitama	-1.700	0	0.410	Yamaguchi	-0.016	0	0.940
Chiba	-1.804	0	0.360	Tokushima	-1.047	0	0.705
Kanagawa	0.090	0	0.950	Kagawa	0.031	0	0.945
Niigata	-0.677	0	0.820	Ehime	-0.628	0	0.835
Toyama	-0.873	0	0.765	Kochi	-0.810	0	0.785
Ishikawa	-0.150	0	0.925	Fukuoka	-1.477	0	0.515
Fukui	-1.857	0	0.340	Saga	-0.164	0	0.920
Yamanashi	-0.557	0	0.850	Nagasaki	-0.117	0	0.930
Nagano	-0.647	0	0.830	Kumamoto	-0.364	0	0.890
Gifu	-1.706	0	0.405	Oita	-0.486	0	0.865
Shizuoka	-1.061	0	0.700	Miyazaki	-0.408	0	0.880
Aichi	-0.328	0	0.895	Kagoshima	-0.679	0	0.820
Mie	-1.221	0	0.635	Okinawa	-1.527	0	0.490

Note: The lag order is determined by the Schwarz Information Criterion.

Table 5: **The Augmented Dickey-Fuller Test for Relative Incomes**

Prefecture	ADF	Lag	p	Prefecture	ADF	Lag	p
Hokkaido	-0.996	1	0.720	Shiga	-3.177	0	0.045
Aomori	0.506	0	0.980	Kyoto	-0.033	0	0.940
Iwate	-1.479	0	0.510	Osaka	0.439	0	0.975
Miyagi	-1.890	0	0.325	Hyogo	-0.102	0	0.930
Akita	-0.195	0	0.915	Nara	0.322	0	0.970
Yamagata	0.229	0	0.960	Wakayama	-1.679	0	0.420
Fukushima	-1.764	0	0.380	Tottori	0.505	0	0.980
Ibaraki	-0.716	0	0.810	Shimane	-1.007	0	0.715
Tochigi	-2.162	0	0.225	Okayama	-0.110	0	0.930
Gunma	-0.489	1	0.865	Hiroshima	-0.484	1	0.865
Saitama	-0.228	0	0.910	Yamaguchi	-1.443	0	0.530
Chiba	-1.728	0	0.395	Tokushima	-2.666	0	0.105
Kanagawa	-1.292	0	0.600	Kagawa	-1.049	0	0.700
Niigata	-1.961	0	0.300	Ehime	-0.497	0	0.860
Toyama	-0.142	0	0.925	Kochi	-0.606	0	0.840
Ishikawa	-1.307	0	0.590	Fukuoka	-1.629	0	0.440
Fukui	-2.466	0	0.145	Saga	-1.979	1	0.295
Yamanashi	-0.247	0	0.910	Nagasaki	-0.962	1	0.730
Nagano	-0.762	0	0.795	Kumamoto	-2.139	0	0.235
Gifu	-0.769	0	0.795	Oita	-1.865	0	0.335
Shizuoka	-2.646	0	0.110	Miyazaki	-2.506	0	0.135
Aichi	-2.024	0	0.275	Kagoshima	-1.566	0	0.470
Mie	-2.603	0	0.115	Okinawa	-3.934	0	0.015

Note: The lag order is determined by the Schwarz Information Criterion.

Table 6: **Geographical Distance of Each City from Tokyo**

City	Km	City	Km	City	Km	City	Km
Hokkaido	1135.4	Tokyo	–	Shiga	493.6	Kagawa	777.2
Aomori	720.4	Kanagawa	33.6	Kyoto	503.2	Ehime	887.8
Iwate	546.9	Niigata	341.9	Osaka	551.5	Kochi	860.2
Miyagi	372.0	Toyama	440.7	Hyogo	580.9	Fukuoka	1136.1
Akita	612.7	Ishikawa	495.6	Nara	528.4	Saga	1184.3
Yamagata	387.8	Fukui	524.1	Wakayama	624.7	Nagasaki	1273.4
Fukushima	294.4	Yamanashi	136.5	Tottori	718.5	Kumamoto	1234.3
Ibaraki	119.2	Nagano	248.0	Shimane	807.4	Oita	1036.8
Tochigi	133.3	Gifu	396.7	Okayama	706.5	Miyazaki	1415.4
Gunma	130.9	Shizuoka	181.2	Hiroshima	853.5	Kagoshima	1401.8
Saitama	32.5	Aichi	354.0	Yamaguchi	979.0	Okinawa	2108.8
Chiba	47.6	Mie	435.1	Tokushima	677.1		

Note: Information shows distance between Tokyo and prefectural capitals and is obtained from the MapFan website (http://www.mapfan.com). Okinawa is the only prefecture not linked by bridge or tunnel with the mainland.

Table 7: **The Determinants of the Relative Prices**

	OLS	OLS with $AR(1)$	GMM
Independent variables	(I)	(II)	(III)
Constant (β_0)	0.030 [0.006]**	0.005 [0.001]**	0.030 [0.012]*
Distance (β_1)	0.015 [0.002]**	0.015 [0.000]**	0.015 [0.004]**
Relative Income (β_2)	0.099 [0.010]**	0.093 [0.002]**	0.098 [0.019]**
$\hat{u}_{t-1}$ (ρ_1)	-	0.968 [0.011]**	-
Test Statistics			
Breusch-Pagan statistic $\chi^2(12)$	18.835(0.092)	-	-
Koenker's statistic $\chi^2(12)$	26.475(0.009)	-	-
Bhargava et al. statistic	0.066	-	-
Anderson canonical correlations statistic $\chi^2(2)$	-	-	1739.30(0.000)
Cragg-Donald chi-squared test statistic $\chi^2(2)$	-	-	15232.78(0.000)
Anderson-Rubin test $\chi^2(2)$	-	-	25.28(0.000)
Hansen's J-statistic $\chi^2(1)$	-	-	0.178(0.672)

Note: Based on equations (11). The standard errors are reported in brackets. ** indicates significance at the 1 percent level, and * indicates significance at the 5 percent level. In estimation (III), heteroskedastic and autocorrelation consistent (HAC) standard errors and covariance estimation are carried out using the ivreg2 stata module by Baum et.al (2003). For test statistics, figures in parenthesis are p-values.