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Heterogeneity in the persistence of relative prices: What do the Japanese cities tell us?

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This paper employs diverse measures of persistence to analyze the convergence speed of intercity relative prices in Japan using consumer price subindices during 1970–2002. Regardless of the persistence measures, the median estimated half-lives are found to be less than two years in the vast majority of CPI items considered, which is compatible with economic models based on price rigidities. However, there exists a large heterogeneity in the persistence not just between tradable and nontradable items as is widely known, but within the categories of tradables or nontradables. The heterogeneity is substantive across cities in each CPI item as well. Our findings are robust to a subsample analysis though it points toward a presence of structural change around 1985. We conjecture that the extent of heterogeneity across CPI items is linked to the degree of tradability and market structure, while physical distance and relative city size may play some roles in the heterogeneity across cities. *J. Japanese Int. Economies* **21** (2) (2007) 260–286. Department of Economics, University of New Hampshire, USA; Faculty of Economics, Nagoya City University, Japan.

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1. Introduction

Ever since first noted by Rogoff (1996), the so-called PPP puzzle has drawn enormous attention from researchers in international economics chiefly because the seemingly consensus

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estimates of 3 to 5 year half-life of deviations from PPP are too long to be explained by usual economic models based on price rigidity. Among numerous explanations for the sluggish adjustment, inclusion of nontradable goods in aggregate CPI has been considered as one of the factors responsible for the slow convergence speed of relative prices as exemplified by the famous Harrod-Balassa-Samuelson effect. Provided that shocks affecting nontradable good prices die out more slowly than those hitting traded goods prices, highly persistent deviations of non-traded goods from PPP may lead to the slow convergence of the general price indices that involve a mix of both traded and non-traded goods. Indeed evidence collected by numerous studies (e.g. Burstein et al., 2005; Kakkar and Ogaki, 1999; Kim, 2005; and Stockman and Tesar, 1995, to cite a few) suggests that prices for nontradable goods are much more dispersed than their traded counterparts and exclusion of nontradables accelerate the convergence speed well within the permissible range predicted by the sticky price models.[1]

This dichotomous approach, however, is susceptible to a couple of critical issues. First, a clear distinction between tradable and nontradable is not an easy task especially for consumer price data in which nontradable component is incorporated in the measure of tradable prices and vice versa. In fact, virtually all goods have both tradable and nontradable components and even typical traded goods contain substantial nontradable components in the form of wholesale and retail services, marketing, advertising, and local transportation services.[2] Second, even if every good is seamlessly classified into the two categories, it is not reasonable to expect that relative prices within each category exhibit identical persistence of deviations from PPP possibly due to different extents of tradability across products. In fact, the literature now abounds with studies that present convincing arguments for heterogeneous dynamics of individual commodity prices. For example, in a recent study examining price adjustment in the US at the individual good-level, Bils and Klenow (2004) find that the frequency of price changes differs dramatically across goods: prices of some goods seldom changes, such as newspaper and taxi service, while prices of gasoline, tomatoes, and airfares change very frequently. Moreover, using a broad set of actual prices of European cities, Crucini et al. (2005) report that deviations from the Law of One Price (LOP) vary substantially across products. Interestingly they find a systematic link between the degrees of deviations and measures of the tradability of the good, larger deviations for non-traded goods and for branded products within traded goods. As such, it seems more appropriate to focus on the type of goods rather than the tradability per se in search of potential explanations for the slow convergence speed of the overall price level.

The main objective of this paper is to analyze the heterogeneity in the persistence of relative prices across differing types of good. To this end we apply a variety of time series techniques to the consumer price subindices of Japan during 1970–2002. A primary merit of utilizing intranational data must be the harmonization of price data.[3] Collected for identical sets of goods and services based on the same methods to introduce new goods and to adjust for quality changes, intranational data bear certain advantages over international data particularly when one com-

[1] On the other side, however, some studies (e.g. Rogers and Jenkins, 1995; Engel, 1999; and Chari et al., 2002) based on variance decompositions of US real exchange rates document that fluctuations in the relative price of nontradable goods account for only a small fraction of real exchange rate changes, implying that deviations from PPP for traded goods are comparable to the corresponding deviations for nontradable goods.

[2] According to Betts and Kehoe (2005), outputs of different sectors have differing degrees of tradability that are largely determined by real transactions costs of trade of the type and by the magnitude of imperfect substitutability in consumption of the same type of good produced in different places.

[3] Wolf (2004) summarizes three advantages from using intranational data: (i) more homogeneous institutional market arrangements; (ii) lower trade barriers; and (iii) the fixed exchange rate.

pares the dynamic behavior of relative prices across differing types of goods. Another benefit of studying intranational price adjustment is to allow us to focus on the factors influencing within a national border while minimizing the impact of factors that obstruct price convergence across borders such as the nominal exchange-rate and trade barriers. Moreover the discussion of intranational price convergence has relevance to the topics beyond PPP such as output convergence and macro-policy implications. For example, a better understanding on regional price movements is essential for monetary authorities to design an optimal monetary policy. If price levels are initially homogeneous at different locations within a country, convergence to a common price level across regions would imply similarity in inflation rates. Given that nominal interest rates are identically and uniquely set by the monetary authority, similar regional inflation rates lead to homogeneous real interest rates and thus little distortion in resource allocations. In this sense the behavior of disaggregated price indices rather than prices of individual commodities is of more interest to monetary authorities as they contain a broader coverage of goods and services sold in various locations.

Of course the present study is certainly not the first to make this kind of attempt. Indeed there is substantial amount of research that examine the dynamics of relative prices at the individual good level, including a handful of studies devoted to intranational analysis (e.g. Esaka, 2003; Jenkins, 1997; O'Connell and Wei, 2002; and Parsley and Wei, 1996). This paper is closely related to Parsley and Wei (1996) and O'Connell and Wei (2002) who investigate the time series behavior of disaggregated relative prices using a panel of micro level data. Our study, however, is distinctive from theirs on several dimensions. First we employ direct measures of persistence in lieu of testing procedures. From an economic viewpoint, the degree of mean reversion in relative prices is of more interest than mean reversion per se. But results from standard tests for nonstationarity offer little information about the speed at which deviations from PPP die out. Moreover it is particularly challenging for existing testing tools to capture mean-reversion when relative prices exhibit very slow convergence (e.g. Choi, 2004). This failure of standard testing techniques to provide informative guidance has inspired researchers to measure directly the speed of mean reversion. Given that our primary focus rests on exploring heterogeneity in underlying persistence of relative intercity prices, direct measure of persistence would serve our purpose better. Second we concentrate on Japan instead of the US by which much of the empirical work has proceeded.[4] Due to geographical concentration and less marked regional diversity, Japan is believed to have relatively higher factor mobility than the US or Europe. In this vein, the speed of price convergence estimated from Japanese cities may be arguably viewed as a lower bound of the rate of convergence toward PPP for the respective CPI items. In addition, compared to the US, Japan has rich observations of consumer prices in terms of the subindices as well as cities. The Japanese consumer price indices are available for 75 subcategories among 167 cities. Third and more important, we use subindices of consumer prices rather than actual prices of individual goods.[5] Although both data collections are believed to avoid potential problems

[4] Esaka (2003) documents possible heterogeneity in the persistence of disaggregated Japanese CPI. By applying popular panel unit-root tests to the panel of 13 disaggregated CPI items from seven Japanese cities over the period 1960–1998, Esaka (2003) rejects the null hypothesis of unit-root for eight tradable goods and for two out of five nontradable goods. The current study provides an advance over Esaka's study in terms of data coverage and methodology. More importantly, Esaka focused just on the mean reversion per se while the current study focuses on the degree of mean reversion.

[5] Parsley and Wei (1996) and O'Connell and Wei (2002) use a data set consisting of 51 prices for final goods and services from 48 US cities originally collected from ACCRA (the American Chamber of Commerce Research Association).

posed by nontradable goods included in the aggregate price index, consumer price subindices may have certain appeals over individual good level price data in several senses: a wider coverage of goods and services, more relevance to macro-policy issues, and availability of data with longer time series which is a crucial feature in the analysis of dynamic properties of relative prices.[6]

However, for being index, the subindice price data are open to a couple of criticisms shared by aggregate CPI data. The first criticism concerns the lack of information on the absolute size of price discrepancies between locations. Since it is impossible to pin down the exact location of the mean of real exchange rates using price index data, relative prices based on price index are not informative as to which levels PPP deviations converge toward. However, price index data still can be used to investigate dynamics of relative prices by studying the speed at which relative prices adjust per se, without knowing how close to parity does any such adjustment bring the relative prices. With relative price based on subindices data, therefore, one can learn about the relative speeds of adjustment of prices of different goods. The second criticism involves the use of time series techniques in the analysis of dynamic behavior of relative prices. Like aggregate CPI, subindices of consumer price are constructed from various constituting prices. Provided that different commodities are subject to different speed of convergence, the behavior of a broad price index may mask the heterogeneity in the underlying dynamics of individual commodity prices. One notable consequence, as documented by Imbs et al. (2005), may be that use of aggregated price index data overstates the persistence of deviations from PPP by ignoring sectoral heterogeneity in the convergence rate to the law of one price across commodity categories embedded in the index. This argument has been supported by some recent studies (e.g. Crucini and Shintani, 2004) that find evidence of much faster convergence rate using individual good level prices. They attribute the slow convergence found in macro level data to the failure to account for heterogeneity in price adjustment dynamics at the individual good level. However we claim that this issue is far less relevant to our case, not only because consumer price subindices contain far fewer and much more homogeneous constituents than the overall aggregate CPI, but also because Reidel and Szilagyi (2005) recently illustrate that the heterogeneity bias is not significant for relatively short samples of 40 years (monthly data) to 50 years (annual data) which are comparable to our data set.

This paper is structured as follows. The next section describes data. Section 3 contains our econometric analysis. We adopt diverse measures of persistence based on linear and nonlinear models to compare the results. This section also carries out a subsample analysis to explore possible presence of structural changes in the dynamics of intercity relative prices. Section 4 investigates the roles of physical distance and relative city-size in explaining the heterogeneity across CPI items and across cities in the persistence of relative prices. Section 5 concludes.

2. The data

Our data set comprises monthly price indices for 36 disaggregated CPI items in 46 prefectural capital cities of Japan over the period of 1970:1 to 2002:12. The original data set contains monthly consumer price indices (CPI) of 167 Japanese cities over 75 disaggregated CPI items collected from the Statistical Library of the Statistics Bureau, Ministry of Internal Affairs and

[6] Since consumer price indices cover a wide category of goods and services purchased by consumers in various locations, they are of interest to policymakers who are more concerned with measures of aggregate inflation than the change of the price of individual commodities.

Communications. Among 167 cities we consider 46 prefectural capital cities based on the consistence of constituents of CPI items and they are presented in Table A.1 in Appendix A.[7]

In each city, price indices are available for 75 CPI items from *cereal* to *rent*. Among them we drop some items whose prices are heavily controlled by governments, such as communication, transportation, education, and medical care, as well as items like food, housing, furniture and household utensils, etc., that have further subcategories. Table A.2 in Appendix A lists the resulting 36 items that embrace 27 tradables, 8 nontradables, and the all-item CPI.[8] Beware that the average weight relative to the overall CPI changes over CPI items and that each CPI item has different numbers of constituents. It should be also noted that cities place slightly different weights on the same CPI item and each city accounts for different share for the overall CPI. This observation provides the motivation to use every city as numeraire to construct relative prices instead of setting a specific city as benchmark.

3. Econometric analysis

In this section we compare the persistence of relative intercity prices across CPI items in Japan by employing several measures of persistence. Before proceeding it is worthwhile to note that relative intercity prices at time t between cities i and j are computed as $p_{it} - p_{jt}$ where p_{it} denotes the logarithm of the consumer price indices in city i at time t. Since we set every city as numeraire rather than fixing a specific city as benchmark, there are 1035 relative prices ($= \frac{46\times 45}{2}$) for each CPI item.

3.1. Measures of persistence and bias issues

Persistence is often defined as the long-run effect of a shock, or the time it takes for a variable to return to its previous level after a unit shock. There are several popular approaches to measuring the persistence of relative prices in linear model. The first one is the sum of autoregressive coefficients (SARC) employed in Andrews and Chen (1994), Cecchetti et al. (2002), Clark (2003), and Rapach and Wohar (2004), to name a few. Consider the following AR(p) process,

$$y_t = \beta_0 + \sum_{j=1}^{p} \beta_j y_{t-j} + \varepsilon_t, \tag{1}$$

where $\sum_{j=1}^{p} \beta_j$ denotes the SARC. This AR(p) process can be rearranged to the usual ADF regression such that

$$y_t = \alpha + \rho y_{t-1} + \sum_{k=1}^{p-1} \zeta_k \Delta y_{t-k} + \varepsilon_t, \tag{2}$$

[7] The monthly prices used for constructing CPI are mid-month prices, i.e., prices on one day of either Wednesday, Thursday, or Friday in a week including 12th of a month, except for the prices of fresh food that are simple averages of every-ten-day survey due to a large fluctuations of prices even in a month. There are 47 prefectures in Japan, but Naha in Okinawa is excluded here because it has slightly different constituents for CPI items from the other prefectural capital cities.

[8] Though we are well aware that the issue surrounding the distinction between tradables and nontradables is not settled, we follow a common practice in the literature here by designating the service-type items as "nontradable" and consider the rest to be "tradable" (e.g. Engel, 1999 and Engel and Rogers, 1996) mainly for the purpose of comparison with earlier studies.

where $\beta_1 = \rho + \zeta_1$, $\beta_h = \zeta_h - \zeta_{h-1}$, and $\beta_p = -\zeta_{p-1}$.[9] Since ρ in Eq. (2) is equivalent to $\sum_{j=1}^{p} \beta_j$ in Eq. (1), the cumulative long-run impact of y_t to a shock captured by $1/(1-\sum_{j=1}^{p} \beta_j)$ is directly related to ρ. Hence, a larger value of ρ corresponds to a higher persistence of shock on y_t and a slower speed of convergence. SARC is a attractive scalar measure of persistence, not merely because it can be directly obtained from estimating the ADF equation in Eq. (2), but also because it is a more informative measure of persistence than the largest root of the AR(p) process which ignores the effects of other roots (Andrews and Chen, 1994).

Another popular measure of persistence must be the half-life of deviations that has become a standard tool to quantify persistence by measuring the magnitude of mean reversion. In the AR(1) case of $y_t = \alpha + \rho y_{t-1} + \varepsilon_t$, a half-life is commonly computed using $\ln(0.5)/\ln(\rho)$ with ρ as AR(1) coefficient. In more general AR(p) case as in Eq. (1), however, this is no longer valid because higher order AR processes are not necessarily characterized by a constant rate of decay in general (see Mark, 2001, p. 32).[10] When half-life is a non-monotonic function of higher AR parameters, either impulse response function (IRF) approach advocated by Cheung and Lai (2000) and Kilian and Zha (2002) or an analytical measure suggested by Rossi (2005) is more appropriate.[11] In the present study we follow Cheung and Lai (2000) to calculate the IRF-based half-life (hereafter HL_{IRF}) for higher order autoregressive models. Specifically it is obtained from $Sup_{l \in L} |\frac{\partial y_{t+l}}{\partial \varepsilon_t}| \geqslant 0.5$ where $L = [0, 120]$ in our analysis positing 10 year (= 120 months) as maximum period.

Both SARC and HL_{IRF} for the intercity relative prices can be estimated by applying usual OLS estimator to the ADF regression in Eq. (2). However, there exists a critical issue in association with the estimation of persistence using these measures. As highlighted by Choi et al. (2005), simple point estimates for ρ in Eq. (2) suffers from three biases in finite sample which considerably deteriorate the precision of estimation of half-lives. Given the nonlinear nature of the half-life formula, a small bias in the estimated value of dynamic lag coefficients is translated into a large change in half-life predictions. The three potential sources of bias are

(i) cross-sectional aggregation bias;
(ii) time aggregation bias; and
(iii) small sample estimation bias.

The cross-sectional aggregation bias arises when price indexes constructed from aggregating a number of individual good-level prices are used. Use of aggregate price indexes is known to result in overestimation of the persistence of real exchange rates by masking the potential heterogeneity in persistence of individual good prices. According to Imbs et al. (2005), sectoral heterogeneity in convergence rates to the law of one price can lead to upward bias in the estimated half-life of deviations from PPP. The time aggregation bias was first discussed by Working (1960) and then extended by Taylor (2001). It is an upward bias induced in estimation of ρ in Eq. (2) as source statistical agencies report price indices that are formed as averages of goods prices

[9] Throughout the paper we use the Hall's (1994) sequential t-test method to determine optimal lag length (k) from data. As discussed in what follows, this ADF regression equation is useful in calculating the half-lives based on impulse response function.

[10] As noted by Pivetta and Reis (2004), ρ tends to be larger for a process with an impulse response function which rises quickly to large levels and fall steeply back than for a process with a slowly decaying impulse response but increases by little in the beginning, although the latter is intuitively more persistent.

[11] Rossi's analytical approach is given by $\ln(0.5 \times (1 - \sum_{k=1}^{p-1} \hat{\zeta}_k))/\ln(\hat{\rho})$.

over a particular interval rather than point-in-time sampled prices. The downward small sample estimation bias emerges when dynamic regression is run with a constant. As originally discussed in Marriott and Pope (1954) and Kendall (1954), usual least squares estimators for convergence speed in autoregressive model are downward biased in finite sample as inclusion of an intercept in the regression engenders correlation between lagged dependent variables and residuals. The downward small sample estimation bias works in opposite directions with the other two biases.

In our analysis there is good reason to believe that the downward small sample bias dominates the other two upward biases on a couple of grounds. First, we use disaggregated CPI items which substantively attenuate the impact from cross-sectional aggregation bias. Moreover, Reidel and Szilagyi (2005) recently demonstrate that the cross-sectional aggregation bias is not consequential to relatively short samples pertaining to our data set. Second, by comparing small sample bias with time aggregation bias in the context of dynamic panel data, Choi et al. (2004) show that the two pieces largely offset each other in the vicinity of AR(1) coefficient of $\rho = 0.9$ while the downward small sample bias dominates the upward time aggregation bias when the true value of ρ lies above 0.9, and vice versa. In view of the mean values of SARC estimates which are a way above 0.9 in the great majority of cases considered here, it is reasonable to expect a net downward bias in our data set.

In this vein, it is important to correct for the small sample bias in estimating persistence of relative prices. Several bias correction strategies have been suggested in the literature. These include mean unbiased estimation, median unbiased estimation, and recursive mean adjustment strategies.[12] Among them, recursive mean adjustment proposed by So and Shin (1999) has been found to be a useful bias reduction technique in the regression context. Our third persistence measure is a pooled recursive mean adjusted generalized least squares estimator (hereafter the RGLS estimator) due to Choi et al. (2005) who extend recursive mean adjustment strategy into panel data framework. As a bias reduction strategy in dynamic panel regressions, RGLS estimator is known to be efficient and effective in reducing the small sample bias particularly when the underlying persistence of individual series in the panel are relatively homogeneous.[13] Considering that the net bias is perhaps downward but probably less than the small sample bias per se, the RGLS estimator may provide an upper bound of persistence estimates while the other two measures are more likely to produce a lower bound estimate as they are not corrected for small sample bias. We reckon that the true underlying persistence may lie somewhere between them.

3.2. Half-life estimation from three persistence measures

For the convenience of comparison, we represent all the persistence estimates in terms of half-lives in years. To calculate the half-lives based on SARC, we use the so-called approximation technique of $\ln(0.5)/\ln(\hat{\rho})$ where $\hat{\rho}$ denotes the SARC estimate from usual LS estimators hence small sample bias is not corrected. The half-lives based on the RGLS estimator are computed in a similar fashion but small sample bias is now handled. A clear drawback of this approximation approach must be that it provides only an approximation to the true half-life for more general dynamic models. In this sense the half-life computed by impulse response analysis may be more pertinent, but it is also associated with a thorny issue that the half-life may not be unique on account of nonmonotonic impulse responses. This justifies the use of three persistence measures.

[12] See Choi et al. (2005) for further discussion on this issue.

[13] Appendix B contains a brief description of this panel data estimator.

Table 1
Half-life estimates (full sample)

Item	SARC			IRF			RGLS			Nonlinear		
	mean	median	[5%, 95%]	mean	median	[5%, 95%]	mean	median	[5%, 95%]	mean	median	[5%, 95%]
1	1.9	1.6	[0.6, ∞]	1.6	1.1	[0.2, 5.2]	1.2	1.3	[0.8, 2.9]	1.5	1.0	[0.4, 3.9]
3	1.1	1.0	[0.4, 4.1]	0.8	0.6	[0.2, 2.0]	0.9	0.9	[0.5, 1.6]	3.7	1.1	[0.4, 4.1]
4	0.9	0.8	[0.3, 3.8]	0.3	0.1	[0.1, 1.1]	0.4	0.4	[0.3, 0.9]	0.6	0.5	[0.2, 1.4]
5	2.1	1.8	[0.8, 8.2]	2.1	1.5	[0.4, 6.0]	2.7	2.8	[1.6, 5.8]	2.1	1.8	[0.6, 4.6]
6	0.7	0.6	[0.2, 11.5]	0.3	0.1	[0.1, 0.2]	0.3	0.3	[0.2, 0.5]	0.7	0.6	[0.3, 1.4]
7	0.4	0.4	[0.2, 1.2]	0.2	0.1	[0.1, 1.0]	0.2	0.2	[0.2, 0.3]	0.3	0.3	[0.1, 0.6]
8	0.2	0.2	[0.1, 0.8]	0.1	0.1	[0.1, 0.1]	0.1	0.1	[0.1, 0.1]	0.2	0.2	[0.1, 0.4]
9	1.1	0.9	[0.4, 3.0]	0.4	0.2	[0.1, 1.3]	0.6	0.6	[0.4, 1.1]	1.3	1.1	[0.5, 3.0]
10	1.6	1.4	[0.7, 4.8]	1.5	1.2	[0.3, 3.6]	2.0	1.9	[1.3, 4.9]	2.1	1.5	[0.5, 4.7]
11	1.3	1.0	[0.4, 4.4]	0.9	0.6	[0.1, 3.0]	0.9	1.0	[0.5, 2.5]	1.9	1.1	[0.4, 3.7]
12	1.2	1.0	[0.5, 3.6]	1.0	0.7	[0.1, 2.8]	1.2	1.2	[0.7, 3.4]	1.3	1.1	[0.5, 2.9]
14	1.4	1.2	[0.6, 4.4]	1.3	1.1	[0.3, 3.2]	2.1	2.2	[1.1, 5.0]	1.9	1.4	[0.5, 4.5]
17	2.9	2.4	[1.0, 11.5]	3.4	2.8	[1.0, 9.8]	8.6	8.5	[3.9,∞]	3.6	2.4	[0.7, 9.0]
25	5.2	3.6	[0.8, ∞]	4.9	2.4	[0.3, ∞]	5.8	6.1	[2.4, 244.3]	5.6	1.7	[0.4, 12.0]
26	2.6	2.2	[0.9, 9.6]	2.9	2.1	[0.7, 8.6]	4.5	4.6	[2.0, 18.3]	2.9	2.0	[0.7, 7.2]
27	2.5	2.0	[0.7, 57.7]	2.6	1.4	[0.2, ∞]	2.6	2.6	[1.3, 8.3]	2.4	1.6	[0.5, 7.3]
28	2.2	1.8	[0.8, 6.4]	2.4	1.9	[0.7, 5.6]	3.8	3.6	[2.4, 8.8]	2.6	2.1	[0.7, 5.7]
29	1.1	1.0	[0.4, 5.2]	0.7	0.4	[0.1, 2.0]	0.8	0.8	[0.5, 1.8]	1.4	1.1	[0.4, 3.4]
30	2.0	1.7	[0.8, 6.4]	2.1	1.5	[0.6, 5.4]	3.6	3.7	[2.1, 9.7]	3.7	1.4	[0.3, 5.7]
33	3.0	2.5	[1.1, 11.5]	3.1	2.4	[0.6, 9.2]	4.6	4.7	[2.4, 21.1]	4.0	1.8	[0.3, 8.2]
34	0.7	0.6	[0.2, 2.5]	0.4	0.2	[0.1, 1.1]	0.3	0.3	[0.2, 0.6]	0.5	0.4	[0.2, 1.2]
36	0.7	0.6	[0.2, 2.7]	0.4	0.2	[0.1, 1.1]	0.3	0.3	[0.2, 0.5]	0.4	0.4	[0.2, 0.9]
37	2.3	2.0	[0.8, 28.9]	2.2	1.4	[0.3, 7.0]	2.6	2.8	[1.5, 6.2]	1.8	1.4	[0.4, 4.1]
38	1.5	1.3	[0.5, 7.2]	1.8	1.1	[0.2, 5.7]	1.1	1.2	[0.6, 2.8]	1.7	1.2	[0.3, 4.2]
40	1.7	1.4	[0.5, 14.4]	1.6	1.1	[0.2, 4.9]	1.4	1.4	[0.8, 3.9]	1.6	1.1	[0.4, 4.8]
41	1.6	1.4	[0.6, 11.5]	1.6	1.1	[0.1, 4.5]	1.1	1.2	[0.5, 1.9]	1.2	0.9	[0.3, 3.3]
42	3.6	2.9	[1.1, 28.9]	4.0	3.0	[0.7, ∞]	8.9	9.7	[4.3, 34.6]	2.7	2.0	[0.6, 6.5]
56	4.1	3.2	[1.0, ∞]	5.2	3.6	[0.6, ∞]	8.2	8.3	[3.4, ∞]	4.4	2.0	[0.5, 12.2]
57	0.8	0.7	[0.3, 3.4]	0.1	0.1	[0.1, 0.2]	0.3	0.3	[0.2, 0.5]	0.8	0.6	[0.2, 2.1]
58	0.8	0.4	[0.1, 2.5]	0.5	0.3	[0.1, 1.6]	0.5	0.6	[0.1, 0.9]	1.3	0.8	[0.2, 3.3]
59	2.3	1.8	[0.6, 19.2]	2.4	1.5	[0.4, 9.0]	2.6	2.7	[1.3, 7.0]	1.3	0.9	[0.3, 3.4]
61	1.6	1.2	[0.4, 7.2]	1.3	0.9	[0.2, 3.9]	1.8	2.0	[1.0, 4.3]	1.9	1.3	[0.4, 4.8]
62	1.7	1.3	[0.6, 4.4]	1.4	1.1	[0.1, 3.5]	2.0	2.0	[1.2, 4.8]	1.7	1.2	[0.5, 3.8]
63	2.7	2.2	[0.9, 8.2]	2.7	2.1	[0.6, 6.6]	3.7	3.7	[2.1, 13.4]	2.7	2.1	[0.7, 6.5]
73	3.4	3.0	[1.3, 14.4]	4.1	3.4	[1.2, ∞]	6.7	6.4	[3.5, ∞]	4.5	2.8	[0.8, 9.6]
74	4.1	3.4	[1.5, 14.4]	4.9	4.1	[1.3, ∞]	7.9	7.6	[5.2, ∞]	4.9	2.9	[0.8, 8.2]
TA	1.1	0.9		1.4	0.9		2.0	1.6		1.9	1.2	
NTA	2.3	1.9		2.9	2.3		4.1	4.3		3.1	1.9	

Note: Bold-faced items represent the nontradable goods. Mean, median, 5%, and 95% denote the corresponding values of the half-life estimates from 1035 intercity relative prices (46 for RGLS).

Table 1 presents the half-life estimates for the full sample period of 1970–2002. In each CPI item, mean, median, 5%, and 95% are computed from 1035 intercity relative prices for SARC and HL_{IRF} estimates and from 46 panels of relative prices for RGLS estimates with each city as numeraire. Interestingly the estimated half-lives from three persistence measures take similar general profiles in the majority of cases considered. It is worth noting that the half-lives based on the RGLS are slightly larger than those from the other two measures probably due to the consideration of small sample bias. Several features of the results from Table 1 deserve further notice.

First, we could confirm the stylized fact that prices converge much faster within border. Irrespective of persistence measures, the half-life of deviations from PPP among cities in Japan is shorter than what is found internationally. The mean and median half-life estimates for item #1 (ALL-ITEM CPI) are consistently below two years which is known to be an upper limit of persistence allowable by the sticky price models. In other words the overall relative intercity prices in Japan converge fast enough to be viewed as consistent with usual economic models based on price rigidities. A similar pattern can be observed in the majority of subindices. The mean values of the IRF-based half-life, for example, are below two years in 20 out of 35 subindices while the number increases to 25 out of 35 items in terms of median value. Most of them are tradable items as one would expect. In 12 CPI items, moreover, which amounts to roughly one third of the total subindices under study, even the upper 5% half-lives lie within the two year range.

Second, there exists a substantial variation of half-lives across CPI items. The median value of the IRF-based half-life estimate is merely 0.1 years for items #6 (DAIRY PRODUCTS), #7 (VEGETABLES), and #8 (FRUITS), but longer than 4 years for item #74 (RENT). In line with the general intuition, the half-lives of tradable items are on average shorter than those of nontradable items. A simple arithmetic average of half-life estimates for nontradable items is more than twice as long as that of tradable items. For some nontradable items, the variations are wide enough to contain infinite half-lives which indicate lack of convergence of relative prices. It should be noted that the heterogeneity of persistence is obvious not only between tradable and nontradables but within the category of tradables or nontradables. Some tradable items such as items #25 (HOUSEHOLD DURABLES) and #56 (RECREATIONAL DURABLES) exhibit far slower rates of convergence than most nontradable items, whereas some nontradable items (e.g. item #14 (EATING OUT)) display faster convergence speed than many tradables. This finding corroborates our initial belief that dichotomous approach may mask the heterogeneity in the underlying dynamics of relative prices across CPI items.

Third, among tradable items, the convergence speed of perishable products is pronounced. Perishables like fruit and dairy products have much shorter half-lives and hence less persistent than nonperishables and manufacturing goods. This finding is rather puzzling to whom believe arbitrage cost as a major impediment of price convergence because perishable products have limited possibility of arbitrage as they are more likely to spoil within short period of time and hence should provide more pricing power to producers (Wolf, 2004). Instead we conjecture market structure may play certain role in this case as perishables are more likely to be produced by large number of firms under perfect competition, while many nonperishable products under study are either produced or distributed by small number of firms under more oligopolistic environment.[14] Indeed we could witness some evidence of inverse relationship between convergence speed and the 'concentration ratio' of industry measured by Herfindahl–Hirschman Index (HHI).

[14] Similar findings have been reported in other studies. Using the quarterly US city prices of 51 products during the period of 1975–1992, Parsley and Wei (1996) find that the estimated median half-life for nonperishable goods is 5.28 quarters, for perishable goods 4.05 quarters, and for services 15.4 quarters. Also Dhyne et al. (2004) report that in the EU area prices change very often in unprocessed food and in (oil-related) energy sector, while price changes are less frequent in non-energy industrial goods sector and even less in the services sector. They conclude that the frequency of price changes is influenced by factors like seasonality, outlet type, VAT changes, the use of attractive prices as well as aggregate or product-specific inflation. Bils and Klenow (2004, p. 958) also note that products closely linked with primary inputs (raw products) display more frequent price changes.

Fourth, the differentials in half-lives between the fastest 5% city pairs and the slowest 5% city pairs, represented in the column of [5%, 95%], are greater for the CPI items with longer mean half-lives. That is, the degree of heterogeneity in the persistence of relative prices gets larger (smaller) for the CPI items with longer (shorter) average half-lives. As visualized in Fig. 1 which plots empirical density functions of IRF-based half-life estimates, the density is more dispersed for the items with longer half-lives. Item #42 (CLOTHING RELATED SERVICES), for example, has the average half-lives of around 3.5 years with the fastest 5% city pairs of less than a year while the slowest 5% city pairs of infinite half-lives. By contrast, for item #8 (FRUITS) the differential is rather trivial as its density function looks highly condensed. Given the observed close linkage between average persistence and degree of heterogeneity across city pairs, it does not come as a surprise that nontradable items entertain higher heterogeneity across cities in the persistence of relative prices. This finding certainly begs a relevant question as to what factors account for the heterogeneity across city pairs. We attempt to address this question in the upcoming section with regression analysis focusing on two potential candidates, physical distance and relative city size.

3.3. Half-life estimation based on nonlinear model

Some theoretical models of real exchange rate determination postulate nonlinear adjustment process toward PPP in the presence of goods market frictions such as transportation costs and trade barriers (e.g. Dumas, 1992; Sercu et al., 1995; Obstfeld and Taylor, 1997; O'Connell, 1998). The basic idea is that small deviations of real exchange rates from long-run equilibrium will not be corrected until they are large enough to cover the cost of tradings so far as transportation costs in goods market arbitrage are not zero. As a result, deviations from PPP will behave in nonlinear fashion: non-mean-reverting in the vicinity of long-run equilibrium while more mean-reverting the further they stray away from equilibrium. Following these theoretical justifications, a stream of empirical studies have employed various nonlinear dynamic models to characterize the behavior of real exchange rates. Using threshold autoregressive (TAR) model to capture this type of nonlinear adjustment process, some studies (e.g. Obstfeld and Taylor, 1997, and O'Connell and Wei, 2002, to cite just a few) find appealing evidence of nonlinear mean reversion with faster convergence speeds, but primarily for selected commodities focusing on deviations from LOP. If the adjustment of relative prices is characterized by TAR model in individual commodity level, it can be better described by STAR (Smooth Transition Autoregressive) type model for consumer price subindices as their aggregation.[15]

Unfortunately, estimating half-lives for nonlinear models involves practical difficulty in the interpretation and computation. Since the shape of impulse response function hinges on the history of time series as well as on the size of shocks, exact half-life based on IRF is neither uniquely determined nor computationally simple. To sidestep this issue, Taylor et al. (2001) rely on simulation approach to estimating the IRF-based half-lives using ESTAR models under various scenarios with regard to the size of shocks. This approach, however, is of reduced interest to our case given the large number of intercity relative prices under consideration. Recently a

[15] The difference between the two models is that the model adjustment between regimes occurs abruptly for the TAR model while smoothly for the STAR model. Among various specifications in the class of STAR model, exponential smooth transition autoregressive (ESTAR) model has been popularly adopted to fit a variety of different PPP data sets at different levels of aggregation (e.g., Kilian and Taylor, 2003; Michael et al., 1997; Taylor et al., 2001).

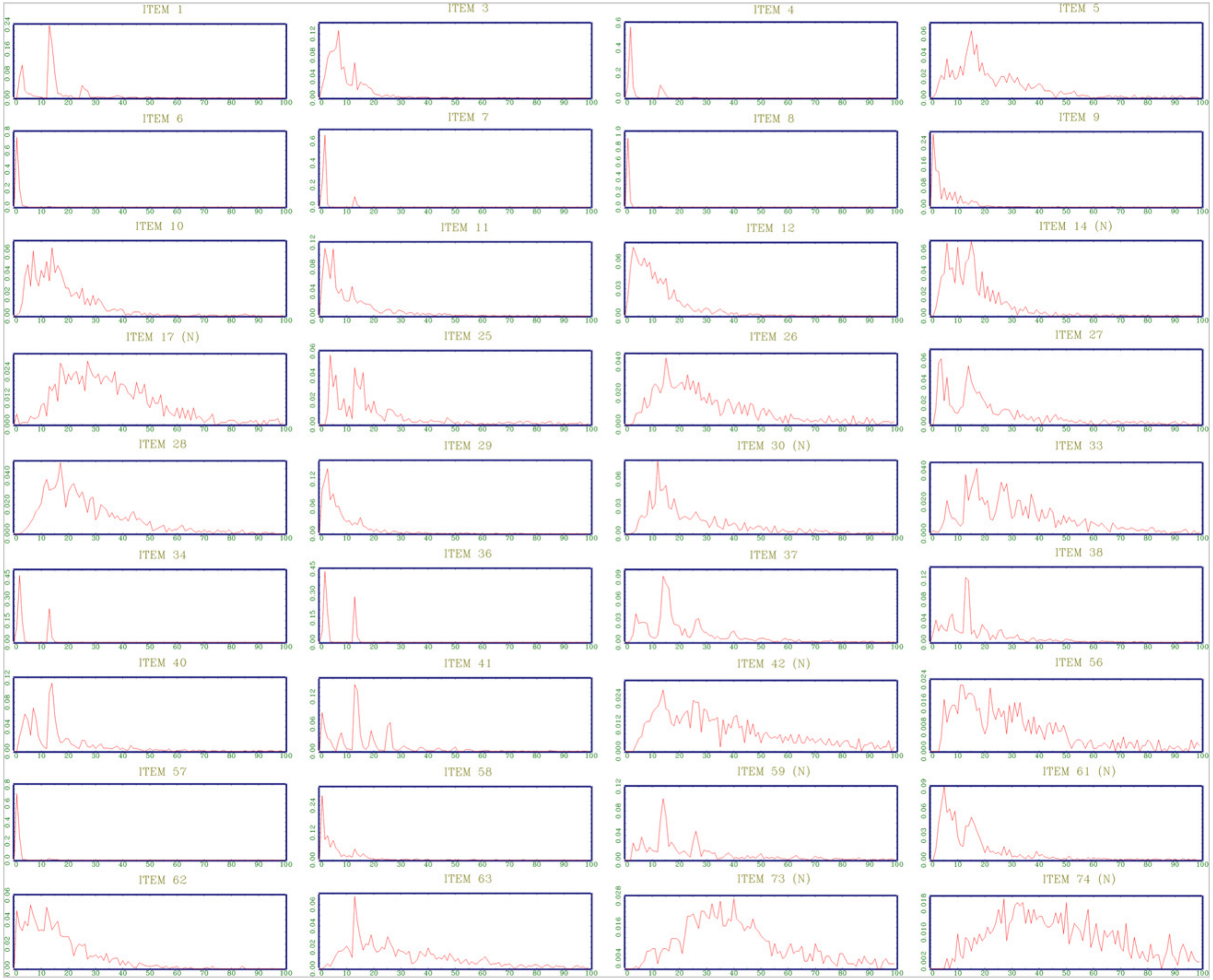

Fig. 1. Empirical density functions of IRF-based half-life estimates (in months) by CPI item.

computationally simple alternative half-life measure is proposed by Shintani (2005) based on the largest Lyapunov exponent that can be readily applicable to nonlinear AR models, including ESTAR-type model. In addition to the computational convenience, another relative merit of Shintani's method is to facilitate us to evaluate the effect of nonlinearity in comparison with results based on linear models because it can be interpreted as the half-lives of the locally linearized nonlinear processes.[16]

Table 1 presents the mean, median, 5%, and 95% values of the half-life estimates obtained from applying Shintani's method to 1035 intercity relative prices for each CPI item. It is reassuring to note that the purpose of this section is not to assess the validity of nonlinear mean reverting models in characterizing intercity relative prices but to compare nonlinear model based half-life estimates with those obtained from linear model based counterparts. As can be seen from Table 1, the results from Shintani's method qualitatively reinforce the conclusions from the linear model based persistence measures in the previous section as the nonlinear model based half-life estimates also vary widely across CPI items as well as across cities. But we witness a bit mixed signal with regard to the gain in the convergence speed. Unlike our prior intuition as well as popular thinking, we cannot find any compelling evidence that nonlinear characterization brings about a reduction in half-life estimates for tradable items. Instead, for some typical tradable items such as items #6 (DAIRY PRODUCTS), #7 (VEGETABLES), and #8 (FRUITS), the half-life estimates appear to be slightly greater under nonlinear model. By contrast, we observe some gain in convergence speed for a couple of nontradable items such as items #42 (CLOTHING RELATED SERVICE) and #59 (RECREATIONAL SERVICE). Given that the rationale of nonlinear characterization of relative prices is much rooted in transaction costs that play more important role in the behavior of tradable items than nontradable equivalents, this evidence on the speed gain for some nontradable items but not for tradable items is rather unexpected. We conjecture that this unanticipated outcome may stem from smaller role of transport costs within national border. Though we feel that this is a possibility, we leave further analysis of this issue to future research as it is apparently beyond the scope of the current study.

3.4. Subsample analysis

Multiple studies in the literature offer concrete evidence of close connection between the dispersion of relative price and the rate of inflation not only in goods market (e.g. Lach and Tsiddon, 1992; Parsley, 1996; Head and Kumar, 2005) but in financial market (e.g. Parsley and Popper, 2004). For example, using a panel data set of actual prices in the United States, Parsley (1996) find a significant positive relationship between inflation rates and cross-sectional dispersion of relative prices and of relative rates of inflation, both at the product level and at the city level. As exhibited in Fig. 2 the annualized inflation rates of national CPI in Japan has experienced a consistent decline from the outbreak of the first oil shock in 1974 until the mid-1980s when it got stabilized afterward. Similar picture can be found in the cases of many subindices. In view of the empirical evidence on the positive link between inflation rates and dispersion of relative prices, it is instructive to examine whether these changes in the Japanese inflation rates have resulted in any dramatic change in the dynamic behavior of intercity relative prices. To gain some insights on this issue we implement the testing methodology for structural changes proposed by Bai and Perron (1998, 2003). An especially useful feature of the technique is that it helps us to locate

[16] As echoed in El-Gamal and Ryu (2006), however, half-life estimates based on the Shintani's method could be biased downward. See Appendix C for a brief description of the Shintani's method.

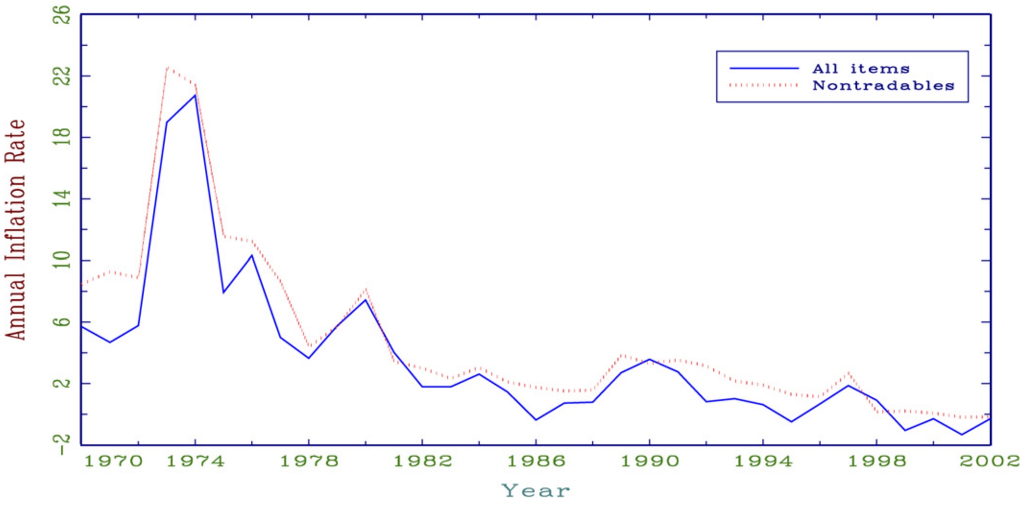

Fig. 2. Annual inflation rates of overall CPI and nontradables.

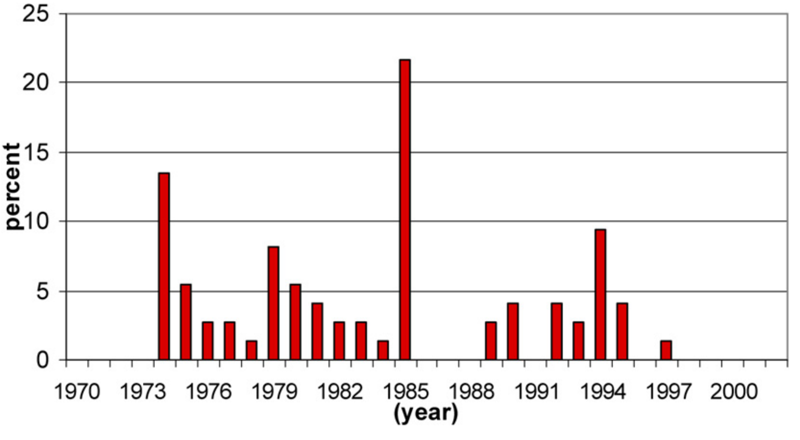

Fig. 3. Frequency of structural break points in the price dispersion.

multiple structural breaks.[17] Figure 3 displays the frequency of structural changes in the overall inflation in each year. The frequency is noticeable in 1974, 1985, and 1994, but 1985 stands out. Though the result seems in accord with our visual inspection from Fig. 3, it is rather astounding because the economic events occurred in 1985 are not as well-known as those took place in 1974 (the first oil shock) and 1994 (the impact of bubble burst).[18] The events took place around 1985 include:

[17] A brief description of the Bai–Perron method is contained in Appendix D.

[18] The Japanese economy has not experienced deflation until mid-1990s because the impact of bubble burst in 1992 has been delayed partly due to an overstatement of CPI in inflation rate (Shiratsuka, 1999).

(1) a big swing of the US dollar around the Plaza Agreement;
(2) deregulation in financial and other industries;
(3) concentration to Tokyo and other metropolitan areas;
(4) start of bubble economy;
(5) a change in the distribution system in Japan.[19]

To probe further whether these events had certain impact on the dynamic behavior of intercity price possibly via market segmentations, we conduct a subsample analysis for the periods of 1970–1985 and 1986–2002, positing 1985 as a possible break point. A marked difference in the results between the two subsamples may point toward the presence of structural change around 1985 in the price convergence process. Table 2 reports the results from subsample analysis which illustrate several points. First, there is a non-negligible difference in the estimated half-lives between the two subsamples. In almost all cases considered relative intercity prices display higher persistence during the second sample period of 1986–2002 regardless of the measures of persistence. At first this seems at odds with previous empirical studies that put forward strong evidence on positive relationship between inflation rates and dispersion of consumer prices. However, since previous studies concentrated on the connection between overall inflation rates and the dispersion of consumer prices rather than between inflation rates of disaggregated CPI items and the persistence of relative intercity prices, our results do not necessarily refute their conclusions. Second, the rise in persistence during the second sample period is driven by an upsurge in the persistence of nontradable items. To be specific, the simple average of median half-lives for nontradable items increases from $1.0 \sim 2.8$ years in the first sample to $1.4 \sim 7.8$ years in the second sample while that for tradable items changes mildly from $0.7 \sim 1.2$ years to $0.7 \sim 1.7$ years. Third, the estimated half-lives for the full sample period seem qualitatively similar to those of the second subsample period of 1986–2002, insinuating that the persistence of relative intercity prices during the second subsample period exerts an important influence on the persistence of the entire sample period. In sum our results from subsample analysis basically support the visual evidence shown in Fig. 3 as they point to a presence of structural change around 1985 in the persistence of intercity relative prices.

4. Explanations for the heterogeneity in the PPP deviations across cities

A main empirical finding from our study must be substantial heterogeneity of persistence of relative prices across consumer price subindices. Our analysis thus far hints that the heterogeneity is more or less linked to the magnitude of tradability and market structure. We also find that there exists a wide variation of the PPP deviations across city pairs for given CPI item. As visualized in Fig. 1, the variation appears to be positively associated with the degree of persistence such that CPI items with longer half-lives exhibit wider variation. It is then natural to ask what factors are accountable for the variation of the PPP deviation across cities and to what extent they matter for the persistence.

[19] According to Maruyama (1993), the Japanese economy has experienced several drastic changes in the distribution system around 1985. For instance, the number of small-size retail stores has decreased substantially since 1985 while the numbers of mid- and large-size retail stores have increased. Also, concentration ratios of retailing have increased since 1985 and diffusion of information technology in retailing has accelerated since the mid 1980s. Sales per outlet of chain stores jumped in 1985 as well.

Table 2
Half-life estimates (sub-samples)

Item	1970–1985								1986–2002							
	SARC		IRF		RGLS		Nonlinear		SARC		IRF		RGLS		Nonlinear	
	mean	median	mean	median	mean	median	mean	median	mean	median	mean	median	mean	median	mean	median
1	0.5	0.6	0.6	0.4	0.5	0.5	0.6	0.5	2.1	1.3	1.9	1.1	1.4	1.4	1.2	0.8
3	0.6	0.8	0.8	0.5	0.8	0.8	0.9	0.8	1.2	0.8	0.9	0.5	0.7	0.7	2.0	0.8
4	0.3	0.4	0.3	0.1	0.3	0.3	0.4	0.4	0.7	0.5	0.3	0.1	0.3	0.3	0.5	0.4
5	1.0	1.2	1.7	1.2	2.5	2.4	1.5	1.1	1.9	1.2	1.6	0.9	1.1	1.3	3.2	1.1
6	0.2	0.2	0.1	0.1	0.1	0.1	0.3	0.3	0.6	0.5	0.6	0.1	0.3	0.3	0.7	0.5
7	0.1	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.3	0.3	0.2	0.1	0.2	0.2	0.3	0.2
8	0.1	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.2
9	0.7	0.8	0.7	0.5	0.9	0.9	0.9	0.7	0.8	0.6	0.3	0.1	0.3	0.3	1.0	0.7
10	0.9	1.0	1.1	0.9	1.5	1.6	1.2	0.9	2.1	1.6	2.5	1.2	1.9	2.0	3.3	1.1
11	0.6	0.7	0.9	0.4	0.7	0.8	1.0	0.6	1.3	1.1	0.9	0.6	0.9	0.9	1.3	1.1
12	0.8	1.0	1.1	0.9	1.4	1.4	1.2	0.8	1.0	0.5	0.5	0.1	0.3	0.3	0.8	0.6
14	0.7	0.8	0.9	0.7	1.3	1.5	1.0	0.8	1.5	1.8	2.6	1.7	3.8	3.7	2.8	1.4
17	1.2	1.5	1.7	1.5	4.1	4.2	1.5	1.2	3.6	4.1	5.0	3.9	15.2	21.7	4.6	1.8
25	0.7	0.8	0.8	0.5	0.9	0.9	0.8	0.6	3.4	3.4	4.8	2.6	9.1	10.0	3.7	1.2
26	1.3	1.7	2.6	1.6	2.7	2.8	2.1	1.3	3.6	1.4	2.2	1.4	2.2	2.3	3.4	1.2
27	0.8	1.0	1.1	0.8	1.0	1.0	1.1	0.8	2.3	1.5	2.5	1.2	2.0	2.0	2.2	1.0
28	1.1	1.4	1.7	1.3	2.7	2.6	1.8	1.2	2.4	1.5	2.1	1.3	2.5	2.5	2.1	1.2
29	0.4	0.5	0.4	0.3	0.4	0.5	0.8	0.6	0.8	1.1	0.9	0.6	0.8	0.8	1.4	0.9
30	0.9	1.0	1.4	0.9	1.9	1.8	1.2	0.8	3.4	2.2	2.8	2.0	5.7	6.0	2.2	1.0
33	1.4	1.9	2.3	1.6	3.0	3.2	2.4	1.1	2.6	2.1	2.9	1.8	2.9	3.6	4.1	1.2
34	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.9	0.8	1.2	1.0	0.5	0.4	0.6	0.4
36	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.9	0.7	0.9	1.0	0.4	0.4	0.6	0.4
37	0.8	1.0	1.1	1.0	1.4	1.4	0.9	0.7	1.7	1.8	2.5	1.6	2.9	3.3	2.2	1.0
38	0.8	0.9	1.1	0.9	1.1	1.1	1.3	0.8	1.0	1.1	2.0	1.0	0.7	0.7	2.0	0.7
40	0.6	0.7	0.9	0.6	0.9	0.9	0.9	0.7	1.3	1.0	1.4	0.7	0.8	0.9	1.6	0.7
41	0.8	1.0	1.2	1.0	0.8	0.9	1.0	0.7	1.2	1.0	1.4	1.0	0.6	0.6	0.9	0.5
42	1.1	1.4	2.1	1.3	2.9	2.9	1.5	1.0	3.4	2.9	3.9	2.8	9.9	10.3	6.1	1.7
56	1.1	1.2	2.0	1.1	2.7	2.7	1.5	1.1	3.6	2.5	4.1	2.1	5.7	5.8	2.9	1.1
57	0.3	0.3	0.1	0.1	0.2	0.2	0.4	0.3	0.5	0.6	0.5	0.1	0.3	0.3	0.7	0.5
58	0.3	0.5	0.6	0.3	0.4	0.5	1.1	0.6	0.6	0.6	0.6	0.1	0.5	0.5	1.2	0.6
59	0.8	1.0	1.1	0.8	1.8	1.9	0.9	0.7	2.1	1.3	2.1	1.5	1.1	1.3	1.0	0.5
61	0.6	0.8	0.9	0.6	0.9	1.0	0.9	0.6	2.5	1.6	2.0	1.5	3.2	3.2	2.3	1.1
62	1.0	1.5	1.5	1.2	2.4	2.5	1.4	0.8	1.8	0.8	1.4	0.5	0.5	0.5	2.8	0.7
63	1.1	1.5	1.9	1.2	1.9	2.0	1.4	1.0	2.7	1.7	2.3	1.6	2.6	2.7	2.6	1.3
73	1.6	2.0	2.4	2.1	3.9	4.1	1.8	1.4	4.1	3.2	4.2	3.4	8.6	7.7	4.3	1.8
74	1.8	2.2	3.1	2.4	5.3	5.4	2.1	1.5	3.8	2.9	3.8	2.8	7.6	8.4	4.8	1.8
TA	0.7	0.8	1.0	0.7	1.2	1.2	1.0	0.7	0.9	0.7	1.4	0.9	1.6	1.7	1.8	0.8
NTA	1.1	1.3	1.7	1.3	2.8	2.8	1.4	1.0	2.7	2.2	3.3	2.4	6.9	7.8	3.5	1.4

Note: Bold-faced items represent the nontradable goods. Mean, median, 5%, and 95% denote the corresponding values of the half-life estimates from 1035 intercity relative prices (46 for RGLS).

The PPP literature provides a rich menu of potential explanations for the slow adjustment of relative price. A partial list includes:

(i) volatility of the nominal exchange rate;
(ii) trade barriers such as tariffs and quotas;
(iii) transportation costs;
(iv) imperfect competition in product markets; and
(v) the presence of non-traded goods in the price basket.

The first two factors can be readily dropped from our consideration as they are more relevant to the price dispersion across national borders. Among the remaining three factors, the last two are thought to be more related to the heterogeneous deviations from PPP across CPI items than across cities provided that goods in the same subindex category may take similar general profiles in terms of tradability and market structures. Here we concentrate on two possible candidates which fall into the category of (iii), physical distance and relative city size, in order to uncover their systematic connections to the heterogeneity across city pairs for each CPI item.

4.1. Physical distance

Whether physical distance plays a role in the adjustment of relative price has been a frequently asked question in the literature. Since it costs time and money to transport goods and the costs to transport tend to increase in distance, physical distance between locations are often used as surrogate for transportation cost (Engel and Rogers, 1996; Parsley and Wei, 1996). Relative prices between two cities that share geographic proximity are likely to adjust more quickly to certain disturbances than cities that are remotely apart. Moreover, cities located spatially close to each other are more prone to common random shocks. Consequently two cities far apart are liable to display more volatile relative price and less likely to converge over time. Taken these together it is reasonable to posit that volatility of relative intercity prices is positively related to the physical distance between two cities. We turn to regression analysis to explore this issue further following Parsley and Wei (1996, 2001).

Table 3 reports the results of cross-sectional regressions in which the dependent variable of the volatility of the relative prices between cities i and j is regressed onto two explanatory variables, physical distance between the two cities and 'region dummies.'

$$V_{ij} = \alpha + \beta \ln(\text{distance}) + \text{region dummies} + \text{error term}. \tag{3}$$

The volatility of the relative prices (V_{ij}) is measured by the time series sample standard deviation of the log price differentials between city pair.[20] We use the distance between railway stations of the two cities as measure of physical distance.[21] To explore whether the administrative regional

[20] On the measure of relative price variability, the standard deviation of the rates of change of price is often used (e.g. Lach and Tsiddon, 1992, p. 355) where $s.d.(\Delta p) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\Delta p_{it} - \overline{\Delta p_t})^2}$.

[21] Raw data are downloaded from the homepage of Japan Railway East (http://www.jreast.co.jp/e/index.html). Parsley and Wei (2001) used latitude-longitude data from the United Nation. Though latitude-longitude information provides an accurate minimum distance between two locations, it is economically less meaningful in the case of Japan in which the great portion of land is covered by mountains except for some plains where metropolitan areas such as Tokyo and Osaka are located. Given that 'economic' distance, i.e. how much it takes from one city to the other, is more relevant to our analysis than 'physical' distance, distance measured by length of railway between two cities is more appropriate.

Table 3
Results of regression analysis

Item	Regression 1				Regression 2			
	ln(distance)		Region dummy		Pop-diff		ln(distance)	
1	0.0011*	(0.0003)	0.0009	(0.0006)	7.39*	(2.67)	1.09	(0.94)
3	0.0017*	(0.0005)	−0.0020	(0.0013)	5.38*	(1.39)	−0.64	(0.49)
4	0.0064*	(0.0012)	0.0006	(0.0027)	−0.41	(0.60)	0.76*	(0.21)
5	0.0045*	(0.0013)	0.0108*	(0.0026)	0.19	(2.58)	1.78**	(0.90)
6	0.0033*	(0.0005)	−0.0018***	(0.0010)	0.20	(1.89)	0.00	(0.66)
7	0.0153*	(0.0010)	−0.0049*	(0.0019)	1.15*	(0.38)	1.19*	(0.13)
8	0.0035*	(0.0012)	0.0019	(0.0026)	−0.24	(0.15)	0.05	(0.05)
9	−0.0002	(0.0005)	0.0017	(0.0011)	−2.61*	(0.64)	−0.27	(0.23)
10	0.0030*	(0.0008)	−0.0043**	(0.0021)	−4.02**	(1.76)	−0.65	(0.62)
11	−0.0009	(0.0013)	0.0040	(0.0030)	−1.49	(1.37)	−0.42	(0.48)
12	0.0047*	(0.0007)	−0.0042*	(0.0018)	−6.16*	(1.13)	1.29*	(0.40)
14	0.0014**	(0.0006)	0.0014	(0.0013)	−4.66*	(1.59)	−0.97***	(0.56)
17	0.0100*	(0.0014)	−0.0135*	(0.0033)	7.18**	(3.09)	4.42*	(1.09)
25	−0.0017	(0.0020)	0.0081***	(0.0047)	−2.23	(5.70)	0.39	(2.00)
26	−0.0062**	(0.0031)	0.0111	(0.0072)	−5.04***	(3.05)	−6.22*	(1.07)
27	0.0012	(0.0027)	−0.0002	(0.0067)	−12.58*	(3.90)	−1.23	(1.37)
28	0.0043*	(0.0012)	−0.0042	(0.0030)	6.13*	(2.30)	3.61*	(0.81)
29	0.0016	(0.0010)	0.0026	(0.0025)	−2.41**	(1.20)	0.79***	(0.42)
30	−0.0099*	(0.0035)	0.0200*	(0.0080)	15.67*	(2.16)	−2.00*	(0.76)
33	0.0154*	(0.0028)	−0.0182*	(0.0072)	−2.89	(3.11)	2.84*	(1.09)
34	0.0018	(0.0015)	−0.0015	(0.0030)	−1.18**	(0.56)	−0.41**	(0.20)
36	0.0095*	(0.0015)	−0.0061***	(0.0036)	0.19	(0.57)	0.47**	(0.20)
37	0.0091*	(0.0016)	−0.0109*	(0.0037)	−6.79*	(2.81)	2.28**	(0.99)
38	0.0006	(0.0010)	0.0012	(0.0023)	−14.15*	(2.70)	−3.15*	(0.95)
40	0.0084*	(0.0019)	−0.0087***	(0.0048)	−8.48*	(2.46)	1.11	(0.86)
41	0.0010	(0.0014)	−0.0020	(0.0037)	−7.55*	(2.35)	0.58	(0.82)
42	0.0099*	(0.0014)	−0.0094*	(0.0033)	−0.20	(4.00)	6.08*	(1.40)
56	−0.0026	(0.0020)	0.0010	(0.0048)	2.60	(5.16)	−3.60**	(1.81)
57	0.0048*	(0.0009)	−0.0025	(0.0019)	0.18	(0.23)	−0.04	(0.08)
58	−0.0003	(0.0008)	0.0028	(0.0021)	0.35	(0.92)	−0.38	(0.32)
59	0.0011	(0.0007)	0.0011	(0.0019)	2.53	(3.23)	0.86	(1.13)
61	0.0046*	(0.0011)	−0.0007	(0.0023)	2.87	(1.89)	2.85*	(0.66)
62	0.0009	(0.0007)	0.0003	(0.0014)	−1.21	(1.63)	0.12	(0.57)
63	0.0142*	(0.0018)	−0.0187*	(0.0048)	−4.21	(2.61)	2.91*	(0.92)
73	0.0093*	(0.0015)	−0.0116*	(0.0036)	10.74*	(3.36)	6.81*	(1.18)
74	0.0060*	(0.0019)	−0.0015	(0.0046)	7.62**	(3.75)	6.31*	(1.32)

Notes. Bold-faced items represent the nontradable goods. Equation for regression 1 is $s.d.(p_{ij}) = \alpha + \beta \ln(\text{distance}) +$ region dummies + error term, where p_{ij} represents the log price differentials between city pair i and j. *Region dummy* takes the value of 1 for relative prices involving city pairs in different regions. Equation for regression 2 is $HL_{ij} = \alpha + \beta \text{pop-diff} + \ln(\text{distance}) + \text{error term}$. 'Pop-diff' is computed by $\frac{max(pop_i, pop_j) - min(pop_i, pop_j)}{max(pop_i, pop_j)}$ where pop_k denotes the population of city k. Distance is measured by the railroad length between cities. The numbers in parentheses report the standard errors after correcting for heteroskedasticity.

* Statistical significance at the 1% error level.
** Idem, 5%.
*** Idem, 10%.

classification exercises any impact on the dynamics of relative prices, we add a dummy variable in the regression which takes the value of 1 when the two cities are from different regions and 0 otherwise.[22]

As can be seen from Table 3, in the vast majority of CPI items the coefficient for 'physical distance' has the anticipated sign and statistically different from zero at the usual significance level, indicating that geographic distance plays a role in the adjustment of relative prices. Its impact on the persistence, however, is small judging by the point estimates of $0.001 \sim 0.015$ which implies that the relative prices will become approximately $0.001 \sim 0.015$ percentage points more volatile if the distance increases by 2.718 times ($\ln(2.718) = 1$). In addition we fail to find any solid link between the coefficient estimates and the observable characteristics of each CPI item such as tradability. The results for 'regional dummies' are rather discouraging because the coefficient is either statistically insignificant or has an unanticipated sign when it is statistically significant in many CPI items.

4.2. *Relative city size*

Given that densely populated cities are more likely to exhibit higher prices with higher wages and higher rents, two cities with different sizes are likely to experience slower convergence of price. In this context, the magnitude of persistence of relative price may also depend on the relative size of cities which is usually proxied by population. In fact, it has been often suggested in urban economics that variations in population sizes may have effects on the relevant pricing mechanisms (Henderson, 1988). Moreover, in relation to the potential role of market structure, population could be a relevant factor provided that competitive pressures increase with population size (Wolf, 2004). To gain further insights on this matter, we regress the following equation under a *prior* that cities of similar sizes are more likely to experience faster price convergence.

$$HL_{ij} = \alpha + \beta \text{pop-diff} + \ln(\text{distance}) + \text{error term}, \tag{4}$$

where HL_{ij} denotes the estimated IRF-based half-life (in months) between cities i and j and ln(distance) represents the log railway length between cities; pop-diff is the population difference which is computed by $\frac{max(pop_i, pop_j) - min(pop_i, pop_j)}{max(pop_i, pop_j)}$ where pop_k denotes the population of city k.

As presented in Table 3, the results on the significance of population difference are rather mixed in the explanation of the heterogeneity. In many tradable items the coefficient estimates for pop-diff have unanticipated negative signs when they are statistically significant, which runs counter to the standard predictions of theory. However, the theoretically correct sign can be found in nontradable items particularly for items #17 (REPAIRS & MAINTENANCE), #30 (DOMESTIC SERVICES), #73 (HOUSING), and #74 (RENT), whose prices are more influenced by the immobile factor like land.

[22] Table A.1 in Appendix A displays the 46 prefectures are classified into eight major regions based on geographic proximity.

5. Concluding remarks

This paper uses consumer price subindices of Japan to analyze the persistence of relative intercity price adjustment during 1970–2002. Our analysis reveals several interesting findings. First, we could confirm the stylized fact that prices converge much faster within national border and/or for tradable goods than across borders and/or for nontradables. In the majority of CPI items, the median values of estimated half-lives are less than two years which is knowingly the upper limit of persistence allowable by the sticky price models. In this respect our results are comparable to those from micro-data analysis which tend to provide significantly faster rates of price convergence than in related studies based on aggregated CPI data. Second, we find a large heterogeneity across CPI items in the deviations from PPP. Interestingly the heterogeneity is manifest not only between tradables and nontradables, but also within the categories of tradables or nontradables. As summarized in Table 4, though relative prices in general exhibit much higher persistence for nontradable items than their tradable counterparts, some tradables display slower convergence speed than most nontradables while some nontradable items achieve faster convergence than many tradable items. Among all the CPI items considered, perishable products like fruit or vegetables exhibit the fastest convergence speed with the shortest half-lives of far below one year. We relate the heterogeneity of persistence to some characteristics of CPI items such as the degree of tradability and market structure. Third, in each CPI item there exists a wide variation across city pairs in the dynamics of relative intercity prices. More persistent CPI items show greater heterogeneity in the persistence across cities. In the quest of factors accountable for the heterogeneity across cities, our regression analysis suggests that physical distance as a proxy for transportation cost has some explanatory power for the heterogeneity in both tradables and nontradables albeit its impact is not sizable. However relative city size proxied by population difference matters primarily for nontradable items that are closely related to land, an immobile production factor. Fourth, nonlinear model specification brings about reduction in half-lives of relative price, but mainly for nontradable items and not much for tradable items which is rather a bit hard to compromise with general perception. Finally, our main findings on the heterogeneity of persistence across CPI items are still valid to our subsample analysis for the subsample periods of 1970–1985 and 1986–2002. Interestingly there seems a structural change in the persistence of relative price around 1985 in most CPI items under study.

The central message of this paper is straightforward. Although the average convergence rates of relative intercity price fall well within the permissible range envisaged by the price rigidity models, the heterogeneity is noticeable not only across differing types of good as echoed in more recent empirical literature on the LOP deviations, but across locations even within national border to which less attention has been paid thus far. Despite relatively fast factor mobility, the half-life of the overall CPI varies substantially across city pairs even though the mean and median values remain well below two years. Fortunately this wide variation is not observed in the inflation among cities. The inflation differentials across cities are found to be relatively small in Japan partly by virtue of the central government's efforts through regional transfers (e.g. tax allocation grant), or partly due to the price control set by the government on major nontradable items such as communication, transportation, education, and medical care. A related policy implication of our study must be that the heterogeneity in the dynamics of relative intercity prices may exert a bigger impact on the convergence of overall price if the influence of government control on some CPI items diminishes.

Table 4
Relative order of persistence by CPI items

SARC		IRF		RGLS		Nonlinear	
8	Fruits	8	Fruits	8	Fruits	8	Fruits
7	Vegetables, seaweed	57	Recreational goods	7	Vegetables, seaweeds	7	Vegetables, seaweeds
58	Books & reading	7	Vegetables, seaweed	6	Dairy products	36	Shirts & sweaters
6	Dairy products	6	Dairy products	34	Clothing	34	Clothing
34	Clothing	4	Fish & shellfish	36	Shirts & sweaters	4	Fish & shellfish
36	Shirts & sweaters	34	Clothing	57	Recreational goods	6	Dairy products
57	Recreational goods	9	Oils,fats,seasonings	4	Fish & shellfish	57	Recreational goods
4	Fish & shellfish	36	Shirts & sweaters	9	Oils, fats, seasonings	41	Other clothing
9	Oils,fats,seasonings	58	Books & reading	29	Domestic non-durab.	9	Oils, fats, seasonings
29	Domestic non-durab.	29	Domestic non-durab.	11	Cooked food	12	Beverages
3	Cereals	3	Cereals	3	Cereals	58	Books & reading
11	Cooked food	11	Cooked food	38	Footwear	**59**	**Recreational serv.**
12	Beverages	12	Beverages	58	Books & reading	29	Domestic non-durab.
14	**Eating out**	**61**	**Personal care serv.**	12	Beverages	1	All-items
61	**Personal care serv.**	**14**	**Eating out**	41	Other clothing	40	Cloth & thread
38	Footwear	62	Toilet articles	1	All-items	38	Footwear
62	Toilet articles	10	Cakes & candies	40	Cloth & thread	62	Toilet articles
40	Cloth & thread	1	All-items	**14**	**Eating out**	37	Underwear
41	Other clothing	41	Other clothing	**61**	**Personal care serv.**	11	Cooked food
10	Cakes & candies	40	Cloth & thread	62	Toilet articles	**14**	**Eating out**
1	All-items	38	Footwear	10	Cakes & candies	**61**	**Personal care serv.**
30	**Domestic serv.**	**30**	**Domestic serv.**	**59**	**Recreational serv.**	5	Meat
59	**Recreational serv.**	5	Meat	5	Meat	10	Cakes & candies
5	Meat	37	Underwear	**30**	**Domestic services**	27	Bedding
28	Domestic utensils	28	Domestic utensils	37	Underwear	28	Domestic utensils
37	Underwear	**59**	**Recreational serv.**	27	Bedding	**42**	**Serv. to clothing**
27	Bedding	27	Bedding	28	Domestic utensils	63	Personal effects
26	Interior furnishings	63	Personal effects	63	Personal effects	26	Interior furnishings
63	Personal effects	26	Interior furnishings	26	Interior furnishings	**17**	**Repairs & maint.**
17	**Repairs & maint.**	33	Japanese clothing	33	Japanese clothing	3	Cereals
33	Japanese clothing	**17**	**Repairs & maint.**	**17**	**Repairs & maint.**	**30**	**Domestic services**
42	**serv. to clothing**	**42**	**serv. to clothing**	**42**	**Serv. to clothing**	33	Japanese clothing
73	**Housing w/o rent**	**73**	**Housing w/o rent**	**73**	**Housing w/o rent**	56	Recreational durables
56	Recreational durables	25	Household durables	25	Household durables	**73**	**Housing w/o rent**
74	**Rent**	**74**	**Rent rent**	**74**	**Rent**	**74**	**Rent**
25	Household durables	56	Recreational durables	56	Recreational durables	25	Household durables

Note: Bold-faced items represent the nontradable goods.

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Appendix A. Data description

Table A.1
Japanese prefectures and capital cities

Region name	City code	Prefecture	Capital city	Weight (%)
I. Hokkaido-Tohoku [8]	1	Hokkaido	Sapporo	1.38
	2	Aomori	Aomori	0.23
	3	Iwate	Morioka	0.22
	4	Miyagi	Sendai	0.75
	5	Akita	Akita	0.26
	6	Yamagata	Yamagata	0.22
	7	Fukushima	Fukushima	0.27
	8	Niigata	Niigata	0.42
II. Kanto-Koshin [9]	9	Ibaraki	Mito	0.20
	10	Tochigi	Utsunomiya	0.36
	11	Gunma	Maebashi	0.22
	12	Saitama	Saitama	0.46
	13	Chiba	Chiba	0.74
	14	Tokyo	Tokyo	7.38
	15	Kanagawa	Yokohama	3.29
	16	Yamanashi	Kofu	0.16
	17	Nagano	Nagano	0.28
III. Chubu [7]	18	Toyama	Toyama	0.31
	19	Ishikawa	Kanazawa	0.38
	20	Fukui	Fukui	0.20
	21	Gifu	Gifu	0.33
	22	Shizuoka	Shizuoka	0.38
	23	Aichi	Nagoya	1.64
	24	Mie	Tsu	0.13
IV. Kinki [6]	25	Shiga	Otsu	0.24
	26	Kyoto	Kyoto	1.20
	27	Osaka	Osaka	2.05
	28	Hyogo	Kobe	1.26
	29	Nara	Nara	0.30
	30	Wakayama	Wakayama	0.29
V. Chugoku [5]	31	Tottori	Tottori	0.10
	32	Shimane	Matsue	0.11
	33	Okayama	Okayama	0.50
	34	Hiroshima	Hiroshima	0.92
	35	Yamaguchi	Yamaguchi	0.10
VI. Shikoku [4]	36	Tokushima	Tokushima	0.21
	37	Kagawa	Takamatsu	0.25
	38	Ehime	Matsuyama	0.33
	39	Kochi	Kochi	0.25
VII. Kyushu [8]	40	Fukuoka	Fukuoka	0.89
	41	Saga	Saga	0.12
	42	Nagasaki	Nagasaki	0.30
	43	Kumamoto	Kumamoto	0.48
	44	Oita	Oita	0.31
	45	Miyazaki	Miyazaki	0.21
	46	Kagoshima	Kagoshima	0.40

Note: Numbers in the bracket represent the number of prefectures in regions.

Table A.2
CPI items

No.	Item	Tradability	Weight (%) [min,Max]	Constituents
1	All-Items	both	100 [100,100]	596
3	Cereals	tradable	2.38 [1.95, 2.83]	14
4	Fish & shellfish	tradable	2.76 [2.17, 3.82]	31
5	Meat	tradable	2.03 [1.47, 2.98]	10
6	Dairy products & eggs	tradable	1.13 [0.98, 1.31]	8
7	Vegetables & seaweeds	tradable	2.87 [2.27, 3.29]	43
8	Fruits	tradable	1.11 [0.93, 1.55]	20
9	Oils, fats & seasonings	tradable	1.01 [0.83, 1.28]	16
10	Cakes & candies	tradable	2.20 [1.93, 2.63]	17
11	Cooked food	tradable	2.61 [2.09, 3.33]	14
12	Beverages	tradable	1.44 [1.24, 1.73]	15
14	Eating out	non-tradable	6.26 [4.71, 8.33]	21
17	Repairs & maintenance	non-tradable	2.85 [1.60, 4.48]	15
25	Household durables	tradable	1.15 [0.84, 1.46]	19
26	Interior furnishings	tradable	0.37 [0.23, 0.85]	5
27	Bedding	tradable	0.31 [0.15, 0.48]	5
28	Domestic utensils	tradable	0.79 [0.62, 1.02]	15
29	Domestic non-durables	tradable	0.70 [0.61, 0.83]	9
30	Domestic services	non-tradable	0.29 [0.12, 0.62]	4
33	Japanese clothing	tradable	0.23 [0.23, 0.23]	2
34	Clothing	tradable	2.28 [1.83, 2.92]	27
36	Shirts & sweaters	tradable	1.16 [0.98, 1.49]	14
37	Underwear	tradable	0.48 [0.37, 0.63]	9
38	Footwear	tradable	0.62 [0.55, 0.76]	7
40	Cloth & thread	tradable	0.09 [0.06, 0.15]	3
41	Other clothing	tradable	0.45 [0.37, 0.58]	10
42	Services related to clothing	non-tradable	0.39 [0.32, 0.61]	5
56	Recreational durables	tradable	1.19 [0.86, 1.61]	13
57	Recreational goods	tradable	2.48 [2.19, 3.06]	32
58	Books & other reading materials	tradable	1.60 [1.32, 2.01]	11
59	Recreational services	non-tradable	6.11 [4.40, 7.43]	27
61	Personal care services	non-tradable	1.19 [1.03, 1.73]	6
62	Toilet articles	tradable	1.23 [1.03, 1.53]	19
63	Personal effects	tradable	0.88 [0.65, 1.52]	10
73	Housing, excluding imputed rent	non-tradable	6.76 [13.80, 0.15]	1
74	Rent, excluding imputed rent	non-tradable	3.91 [1.22, 7.60]	1

Notes. The original description in Japanese is posted at http://www.stat.go.jp/data/cpi/7.htm. 'Weight' denotes the weight of each item to the overall CPI in percent (%). 'Max' represents the largest weight among 46 cities and 'min' represents the smallest weight among 46 cities.

Appendix B. The RGLS estimator

As a bias reduction strategy to estimating the dominant root in dynamic panel data regressions, Choi et al. (2005) propose several dynamic panel estimators based on the recursive mean adjustment. So long as homogeneity restrictions can be imposed, a recursive mean adjusted pooled least squares estimator (RPLS) is an effective bias reduction strategy when the observations are cross-sectionally independent, whereas a pooled recursive mean adjusted generalized least squares (RGLS) estimator is preferred when the observations exhibit cross-sectional dependence and the error terms are represented by a factor structure. This approach is shown to be an efficient and effective bias reduction strategy and is easy to implement. While conventional bias correction approaches such as mean and median unbiased estimators are generally unavailable for higher ordered panel autoregressive models, the recursive mean adjusted estimators can be directly applied in the general AR(p) case.

To illustrate the panel estimators, consider the following panel AR(p) environment

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_j y_{it-j} + u_{it} = \alpha_i + \rho y_{it-1} + \sum_{j=1}^{p-1} \gamma_{j+1} \Delta y_{it-j} + u_{it}$$

where $\rho = \sum_{j=1}^{p} \beta_j$, $u_{it} = \delta_i \theta_t + \epsilon_{it}$, $\theta_t \overset{\text{iid}}{\sim} (0, 1)$, $\{\epsilon_{it}\}$ has mean zero, finite $2 + 2\nu$ moments for some $\nu > 0$, and has covariance matrix $\Sigma = E(\epsilon_{1t}, \ldots, \epsilon_{Nt})'(\epsilon_{1t}, \ldots, \epsilon_{Nt}) = \mathrm{diag}[\sigma_1^2, \ldots, \sigma_N^2]$.

RGLS estimator is obtained from the following procedure. First, rewrite the regression in recursive mean-adjusted form as

$$(y_{it} - \mu_{it-1}) = \rho(y_{it-1} - \mu_{it-1}) + \underline{z}_{it}\underline{\phi}' + e_{it}, \tag{B.1}$$

where $\underline{z}_{it} = (\Delta y'_{it-1}, \ldots, \Delta y'_{it-p+1})'$ and $\underline{\phi}' = (\phi_2, \ldots, \phi_p)$ where $\phi_j = \sum_{i=j+1}^{p} \gamma_i$, $j = 1, \ldots, p-1$, $\mu_{it-1} = (t-1)^{-1} \sum_{j=1}^{t-1} y_{jt}$, $e_{it} = \alpha_i + (u_{it} - (1-\rho)\mu_{it-1})$ and $E(e_{it}) = 0$. Running OLS on (B.1) without a constant gives the RPLS estimators for ρ and $\underline{\phi}$. A second stage regression is run by treating the RPLS estimate as the true value of ρ with a view to effectively controlling for bias in the ϕ_j coefficients.

Second, run the following regression by OLS to obtain the bias corrected estimates for higher order terms, $\hat{\underline{\phi}}^{\dagger}$,

$$y_{it}^{\dagger} = \underline{z}_{it}\underline{\phi}' + u_{it}^{\dagger} \tag{B.2}$$

where $y_{it}^{\dagger} \equiv y_{it} - \rho_{\mathrm{RPLS}} y_{it-1}$.

Third, use ρ_{RPLS} and $\hat{\underline{\phi}}^{\dagger}$ to construct the residuals $\hat{\tilde{u}}_{it}^{\dagger} = \hat{u}_{it}^{\dagger} - (1/T)\sum_{t=1}^{T} \hat{u}_{it}^{\dagger}$ where $\hat{u}_{it}^{\dagger} = y_{it}^{\dagger} - \underline{z}_{it}\hat{\underline{\phi}}^{\dagger}$. Use these residuals to construct the error covariance matrix $\hat{\mathbf{V}}_u$.

Lastly, estimate (B.1) by GLS using $\hat{\mathbf{V}}_u$ to get the RGLS estimator of ρ, and estimate (B.2) by GLS to get the RGLS estimator of $\underline{\phi}$.

Appendix C. Shintani's nonlinear based persistence measure

Consider the following nonlinear AR(1) model

$$q_t = m(q_{t-1}) + \varepsilon_t \tag{C.1}$$

where $m(q_{t-1})$ denotes a nonlinear conditional mean function $E(q_t|q_{t-1})$. Using the properties that the first derivative of $m(q_{t-1})$ is proportional to the one step ahead nonlinear IRF for small δ,

$$Dm(q_0) = \lim_{\delta \to 0} \frac{m(q_0 + \delta) - m(q_0)}{\delta} = \lim_{\delta \to 0} \frac{IRF_1(q_0, \delta)}{\delta},$$

and that ρ in the linear AR(1) model of $q_t = \mu + \rho q_{t-1} + \varepsilon_t$ can be viewed as the first derivative of the conditional mean function, a local half-life at q_0 is defined by

$$h(q_0) = \frac{\ln 0.5}{\ln |\mathrm{Dm}(q_0)|}.$$

Then a summary measure of persistence is constructed by averaging the local speed of convergence

$$h^* = \frac{\ln 0.5}{\lambda}$$

where λ represents the Lyapunov exponent of time series

$$\lambda \equiv \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} \ln\left|\mathrm{Dm}(q_{t-1})\right|$$

which is uniquely determined regardless of mean-reversion as well as independent of the initial value q_0.

To estimate h^* from data, Shintani (2005) employs the so-called local polynomial regression estimator such that

$$\hat{h}^* = \frac{\ln 0.5}{T^{-1}\sum_{t=1}^{T} \ln|D\widehat{m(q_{t-1})}|}$$

where $D\widehat{m(q_{t-1})}$ denotes a nonparametric estimator of the first derivative of $m(q_{t-1})$ in equation (C.1) and T is the sample size. According to Shintani (2005), $\hat{h}^*$ becomes a consistent estimator of h^* and converges to a well-defined, half-life-like measure of persistence when λ is estimated by consistent nonparametric estimators. Given the monthly frequency of data used in our study, we consider autoregressive order higher than one and thus the derivative is replaced by Jacobian.

Appendix D. The Bai–Perron's method for structural break detection

Bai and Perron's (1998, 2003, BP) propose a two stage method to estimate unknown multiple structural breaks in dynamic linear regression models. The first stage pertains to estimating the number of unknown structural breaks. To this end BP suggest a couple of testing procedures: double maximum tests and a test for l versus $l+1$ breaks. The former tests are constructed under the null hypothesis of no structural break against the alternative of an unknown number of breaks given some upper bound, while the latter, labeled $\sup F_T(l+1|l)$, involves testing the null of l breaks against the alternative of $l+1$ breaks. BP recommends to apply double maximum tests first to see whether at least one break exists. If the tests suggest the presence of at least one break, then the number of breaks is decided based on a sequential examination of the $\sup F_T(l+1|l)$ statistics. According to BP, this approach leads to the best results and hence is recommended for empirical applications.

Once the number of break is identified, the second stage of BP method involves estimating breakpoints as well as coefficients of interest using the least squares principle. To illustrate, consider a linear regression model with $m-1$ breaks (provided that m regimes are identified in the first stage),

$$y_t = \delta^{(j)} + \varepsilon_t, \quad t = T_{j-1}+1, T_{j-1}+2, \ldots, T_j,$$

for $j = 1, \ldots, m$ where $\delta^{(j)}$ is the mean level of the series in the jth regime. To estimate breakpoints, we consider every possible m-partition of T, $(T_1, \ldots, T_m)$. For each m-partition, the regression coefficients ($\delta^{(j)}$s) are estimated by minimizing

$$\sum_{j=1}^{m} \sum_{t=T_{j-1}+1}^{T_j} \left[y_t - \delta^{(j)}\right]^2.$$

Let $S_T(T_1, \dots, T_m)$ be the sum of squared residuals such that

$$S_T(T_1, \dots, T_m) = \sum_{j=1}^{m} \sum_{t=T_{j-1}+1}^{T_j} \left[y_t - \hat{\delta}^{(j)}\right]^2.$$

Then the breakpoints $(\hat{T}_1, \dots, \hat{T}_m)$ are estimated by choosing the m-partition that has minimal $S_T(T_1, \dots, T_m)$ such that

$$\left(\hat{T}_1, \dots, \hat{T}_m\right) = \underset{T_1, \dots, T_m}{\operatorname{argmin}} S_T(T_1, \dots, T_m).$$

With these breakpoint estimates, the associated regression parameters are obtained subsequently. BP developed an efficient algorithm for the minimization problem based on the principle of dynamic programming.

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