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Regional Relative Price Disparities and Their Driving Forces

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This paper studies the long-run behavior of relative price dispersion among cities in Korea with a special emphasis on heterogeneous transitional patterns of price level dynamics. Formal statistical tests indicate considerable evidence for rejecting the null of relative price level convergence among the majority of cities over the sample period of 1985-2015. The analysis of gravity model suggests that the effect of transportation costs on intercity price level differentials is limited, while other socioeconomic factors, such as income, input factor prices, demographic structure, and housing price growth, play key roles in accounting for persistent regional price level disparities. Individual price levels are found to be better explained by a multiple-component model, and the deviations from PPP may be attributed to distinct stochastic common trends that are characterized by income and demographic structure.

Keywords: Relative Price Convergence, Purchasing Power Parity, Heterogeneous Transition, Factor Model, Multiple Stochastic Trends
JEL classification: C28, C38, E31, F22

I. INTRODUCTION

This paper studies relative price level convergence by utilizing panels of major cities in Korea. While substantial research continues to evaluate price level disparities in international context, there have been relatively lack of successful empirical studies investigating the validity of purchasing power parity (PPP) within a single currency area. To gain further insight for the sources of considerable and persistent

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price level dispersion, we employ formal statistical techniques to test whether intranational price level differentials tend to shrink over time with a special emphasis on their heterogeneous transitional behavior. Our empirical analysis explores potential explanations for why there is substantial deviation from PPP or markedly slow convergence by considering disaggregated CPI data classified according to consumption expenditure in addition to extant factors that are attributable to the PPP deviations, such as transportation costs, income, and input prices.

The importance of understanding both time-series and cross-sectional properties of price dispersion measures has been underscored by researchers as well as policymakers. Since PPP has been a key building block of most open-economy macroeconomic models as the link between exchange rate and relative price levels, empirical validity of PPP is a long-standing issue. Ever since Rogoff (1996) articulated the PPP puzzle, a large number of papers have studied price level convergence with international data and potential sources of PPP deviation or slow price level convergence.[1] This has also brought about interest in testing convergence in relative city price within a country to better understand difference in prices across locations, Beck, Hubrich, and Marcellino (2009), Cecchetti, Mark, and Sonora (2002), Parsley and Wei (1996), and Sonora (2008), to name a few. Unlike international data, it may be reasonable to conjecture that major cities of a country share relatively similar characteristics, and thus relative price dispersion is unlikely to be substantial. However, the conclusion regarding long-run patterns of price disparities across cities is somewhat mixed, whereas PPP clearly is violated in the short run in those studies. Interestingly, some studies argue that price level convergence rates within a country are somewhat longer than those estimated with international data (Cecchetti, Mark, and Sonora, 2002).

Despite the fact that the deviation from PPP is well documented in international data and even within a country, there has not been an extensive study rigorously investigating the possibility of PPP among major cities in Korea.[2] This motivates

[1] For an excellent survey of PPP puzzle, see Murray and Papell (2005) and Taylor and Taylor (2004), among others.

[2] Recently, in his paper, Moon (2017) studies relative price convergence among 6 metropolitan cities and 9 provinces over the period of 1990-2016 in Korea. Although the paper deals with somewhat similar issues, but the methodology employed in this study allows us to study a more general case of multiple common factors driving long-run PPP deviations.

us to examine the long-run behavior of relative price level dispersion with a special emphasis on heterogeneous transition dynamics of individual prices. In addition, with disaggregated CPI data, the paper scrutinizes dynamic patterns of price disparities for consumption expenditure categories classified according to purpose.[3] Our research has primarily three goals. First, we investigate whether there exist persistent regional price level disparities, and, if so, assess the extent of deviations from PPP. In addition, their dynamic patterns are also examined. Second, and more importantly, this paper aims to provide a better understanding of main factors that drive substantial price level disparities across cities. Third, as overall price divergence does not necessarily exclude the possibility of club convergence, we explore whether there is a subgroup of cities that share similar aspects in terms of socioeconomic variables and exhibit price level convergence among the member cities.

To draw attention to the importance of regional price level dispersion, we first document some salient features of intercity price differentials.[4] Some basic descriptive statistics of price differential variability and mean absolute log price differential indicate that there is little evidence of price level convergence. Relative price dispersion employed by Crucini, Telmer, and Zachariadis (2005) and Phillips and Sul (2007) also tells us somewhat similar stories and provides further evidence of heterogeneous transitional dynamics of individual prices. Given the PPP deviations or possibly slow convergence among cities in Korea obtained from our preliminary analysis, we introduce a formal statistical technique, time-varying factor model, to test whether relative price levels converge to a single common factor.[5] The log t convergence test by Phillips and Sul (2007) strongly rejects the null hypothesis of overall price level convergence during sample periods of 1985:M1-2015:M12 for

[3] Note that another approach to disaggregation that is equally popular in the literature is to deal with consumption expenditure by major type of product. The empirical analysis with this type of disaggregated CPI data yields largely the same conclusion.

[4] There has been no clear consensus about how best to measure price dispersion. Thus, in this paper, we introduce some commonly used measures of intercity price differentials in the literature (Canzoneri, Cumby, Diba, and Eudey, 2002; Imbs, Mumtaz, Ravn, and Rey, 2005; Parsley and Wei, 1996).

[5] A rapidly growing number of studies have stressed the importance of heterogeneity in dynamic panel regression models due to Stock and Watson (2002) and Bai (2003) in a variety of contexts, such as Kim and Rous (2012) and Phillips and Sul (2009).

10 major cities and 1990:M1-2015:M12 for a larger set of 30 cities.[6] Moreover, for none of individual consumption categories, there is little evidence of price convergence.

The apparent violation of PPP among cities in Korea motivates us to explore possible sources of regional price level disparities. As suggested by a number of studies, we employ extant factors of PPP deviations, such as distance as a proxy for unobservable transportation costs (Crucini and Yilmazkuday, 2014; Engel and Rogers, 1996; Obstfeld and Taylor, 1997; Parsley and Wei, 1996) and income (Bergin and Glick, 2007; Crucini, Telmer, and Zachariadis, 2005).[7] While much work has been undertaken to extend the analysis of the effects of those conventional variables, there have also been important developments that examine the role of non-traditional determinants such as other socioeconomic factors that possibly account for regional price disparities. Therefore, in this paper, we additionally utilize city-specific socioeconomic characteristics such as the composition of labor market and demographic structure (Maestas, Mullen, and Powell, 2016). To summarize our empirical findings, the analysis of gravity model indicates that the effect of transportation costs on intercity price differentials is limited, while other socioeconomic city-specific factors, such as income, input factor prices, demographic distribution, and housing price growth, play key roles in accounting for regional price level disparities. Our clustering analysis, in general, confirms that price levels are governed by a finite number of multiple common stochastic trends. Finally, multinomial logit regression analysis suggests that the deviation from PPP may be attributed to differences in income and demographic distribution, while the role of factors that are traditionally recognized as dominant forces of persistent price dispersion, for example transportation costs, is found to be limited.

The remainder of the paper is organized as follows. The next section discusses price dispersion measures and documents some salient features of intercity price

[6] As an alternative hypothesis, one can consider the case that the relative prices diverge from one another or real exchange rates between cities contain a stochastic trend. More interestingly. There is the possibility that a part of cities from the entire panel shares common stochastic trend, which can be interpreted as club convergence. This will be extensively discussed in Section 4.

[7] An intuition behind this approach introducing an income-related variable is that firm's mark-up decision is influenced by the level of income, commonly measured by per capita GDP (Rose and Engel, 2002). Other potential sources of price dispersion involve, for example, input factor prices (Crucini and Yilmazkuday, 2014; Parsley and Wei, 2001a; Rogers, 2007) and differences in opportunity cost of price search (Alessandria and Kaboski, 2011).

differential found in price level data. Section introduces a formal statistical technique to test whether price levels tend to converge over time. In addition, potential sources of PPP deviations are discussed in a number of dimensions. In Section 4, we study the possibility of multiple common stochastic trends in price levels and discuss characteristics of member cities in each price level convergence club. Concluding remarks are contained in Section 5.

II. REGIONAL PRICE DIFFERENTIAL: STYLIZED FACTS

This section documents some salient features of intercity price differential found in price level data. We begin with price level data with a special emphasis on their potential issues in empirical applications. In addition, price dispersion measures popularly employed in the literature are discussed. By utilizing price level data for major cities in Korea, this section provides preliminary findings with regard to the possibility of price level convergence.

1. Data and Some Related Issues

For the data on prices of individual goods and services, this paper employs panels of monthly observations on the Consumer Price Index (CPI) for some selected cities in Korea obtained from the Statistics Korea.[8] Due to data availability, sample period varies with the number of cities used in a panel. In this paper, we consider mainly two sets of cities: the former covers 10 major cities that are relatively homogeneous with the sample period spanning from 1985:M1 to 2015: M12, the latter contains a larger number of cities, 30 cities, but with a relatively short sample period, 1995:M1-2015:M12.[9] In addition to all-item CPI as a measure

[8] It is important to note that this paper studies price level convergence, not actual price of each individual item in a market basket.

[9] The cities and their corresponding abbreviations are as follows. For the sample of 10 major cities, Seoul (SEO), Busan (BUS), Daegu (DAE), Incheon (INC), Gwangju (GWA), Daejeon (DAJ), Suwon (SUW), Chuncheon (CHU), Cheongju (CHE), and Jeonju (JEO). In addition to these cities, the sample of 30 cities also contains Ulsan (ULS), Seongnam (SUN), Uijeongbu (UIJ), Bucheon (BUC), Wonju (WON), Gangneung (GAN), Chungju (CHJ), Cheonan (CHA), Boryeong (BOR), Gunsan (GUS), Namwon

of average cost of living for each city, detailed expenditure categories classified according to purpose are also utilized to investigate the possibility of price convergence for a particular item.[10]

Since the data for price level used in this paper are price indices, not actual prices, the conclusion of whether relative price disparities across cities shrink or not evidently depends on when the base year is. That is, for instance, if the base year is set to the end of time-series observations, T, all price indices, by construction, have the same value, $P_{i,t} = 100$ for all $i = 1, 2, \cdots, N$, where N is the number of cross sectional observations. However, this does not necessarily indicate that all price levels converge to a single point. To overcome this issue, following the suggestion by Phillips and Sul (2007), we take the first observation of a sample as the base year, $P_{i,t} = P_{i,t}/P_{i,1} \times 100$ for all $t = 1, 2, \cdots, T$, and throw out some initial observations from the sample to avoid base-year initialization effects.[11] Next, as this paper is aimed to study long-run dynamics of PPP deviations, we use the Hodrick-Prescott trend of price indices to remove cyclical components of the data.

2. Price Dispersion Measures and PPP Deviations

Before employing formal statistical techniques, it is useful to look at some summary statistics on intercity price dispersion and the dynamic pattern of price differential variability. The most popular measure of the intercity price differential, which is analogous to real exchange rate in international data, in the previous studies such as Canzoneri, Cumby, Diba, and Eudey (2002), Imbs, Mumtaz, Ravn,

(NAM), Mokpo (MOK), Yeosu (YEO), Suncheon (SUC), Pohang (POH), Gyeongju (GYE), Andong (AND), Gumi (GUM), Jinju (JIN), and Jeju (JEJ).

[10] The major expenditure categories involve "food and non-alcoholic beverages," "alcoholic beverages and tobacco," "clothing and footwear," "housing, water, electricity and other fuels," "furnishings, household equipment and routine household maintenance," "health," "transport," "communication," "recreation and culture," "education," "restaurants and hotels," and "miscellaneous goods and services."

[11] The number of observations that must be discarded may vary across price indices, all item CPI and CPI by consumption expenditure categories. For simplicity, however, we remove the same number of initial observations that are sufficient to shirk the initial effects for all price indices used in this paper.

and Rey (2005), and Parsley and Wei (1996), is the percentage difference in price of commodity k at time t between cities i and j. That is to say,

$$q_{ij,k,t} \equiv \ln(P_{i,k,t} - P_{j,k,t}) = p_{i,k,t} - p_{j,k,t}, \ i \neq j, \tag{1}$$

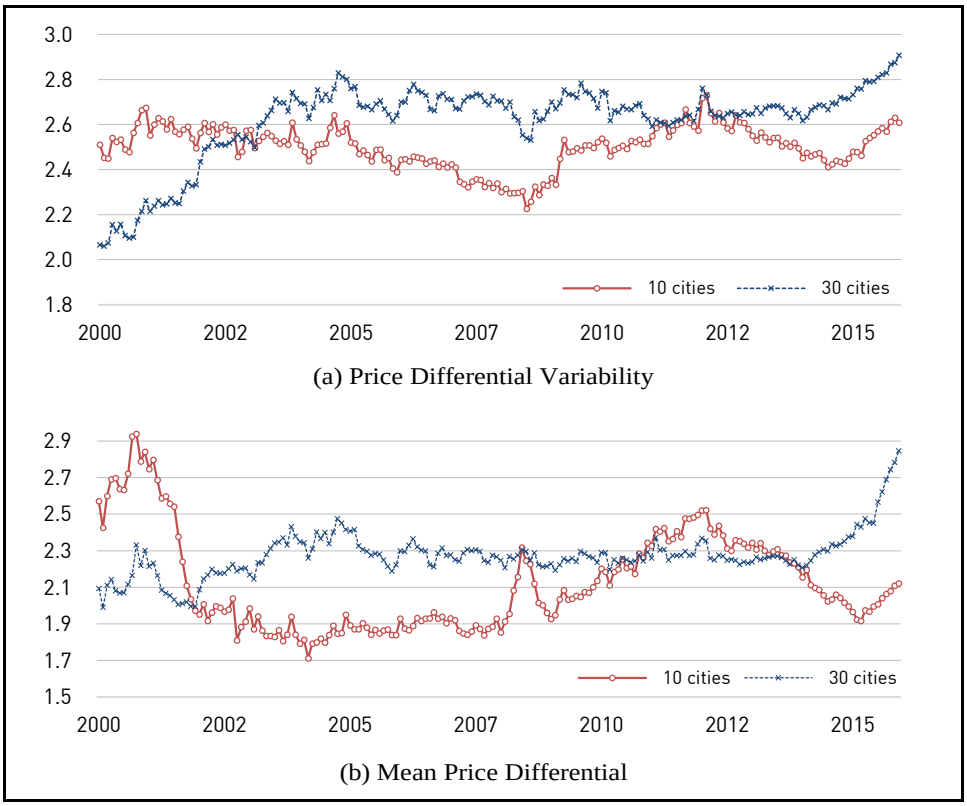
where $p_{i,k,t} \equiv \ln P_{i,k,t}$ as an example. Under the null of PPP as the natural benchmark, $q_{ij,k,t}$ is zero, but, in practice, prices in different locations are regularly found to differ mainly due to transportation costs, which is popularly substituted for distance.[12]

To yield a graphical impression of relative price convergence, we first compute intercity price differential, the log CPI in each city relative to the log CPI in Seoul as the benchmark city.[13] Price differential variability at each period t is then defined as the cross-sectional standard deviation of the price difference given in Eq. (1). Panel (a) of Figure 1 plots the percentage price differential variability during the sample period, 2000:M1-2015:M12 for both 10 cities and 30 cities in Korea. As apparent in the figure, cross-sectional standard deviations do not exhibit any pattern, and thus substantial intercity price differential may persist over time. Interestingly, the variability of price differential across 30 cities tends to rise. This suggests that, in Korea, it is not surprising that regional price disparities exist to some extent, but a more puzzling empirical issue is why PPP deviations appear to be greater over time. Alternatively, we also present mean absolute price differential, which is defined as the mean percentage absolute deviation of log prices between cities, $|p_{i,k,t} - p_{j,k,t}|$, where i is Seoul. The mean absolute price differentials shown in Panel (b) of Figure 1 tell somewhat similar stories. That is, there seems to be little evidence of price level convergence since PPP deviations measured by price indices tend to be greater over time, especially for a larger set of cities.

[12] For alternative measures of price dispersion based on this intercity price differential, see Parsley and Wei (2001b), for example.

[13] Note that in an international context, the conclusion of PPP tests is found to be somewhat sensitive to the choice of benchmark or numeraire currency. However, the choice of benchmark city has little influence for the tests for cities within a country including this paper.

Figure 1. Price Differential Variability and Mean Price Differential



As presented in Table 1, we investigate the dynamic patterns of price differential variability and mean average price differential for each group of individual items in CPI market basket for the comparison with all-item CPI.[14] There are mainly two approaches depending on how consumption expenditure is disaggregated, "consumption expenditure by major type of product" and "consumption expenditure according to purpose." The former is divided into two broad categories, "commodities" and "services," and the latter consists of 12 major components of CPI market basket classified according to the purpose of consumption expenditure. Some important implications directly emerge from the table. First, intercity price differentials for both commodities and services do not exhibit a tendency that diminishes during the

[14] To conserve on space, the results for 30 cities, which are qualitatively quite similar, are not presented (available from the author upon request).

sample period. Moreover, the log service price differences across major cities tend to rise over time. In addition, services have the higher mean average price differential while there is essentially no difference in price differential variability between the two categories. Second, none of categories classified by consumption expenditure purpose display the pattern that intercity price differentials diminish over time. From the table we observe that, of the 12 categories, "transport" and "education" have the highest mean price differential while "transport" exhibits the highest variability of price differential. Not surprisingly, "health" and "communication" appear to have the lowest intercity price differential.[15] These findings suggest that PPP deviation, if exists, is not simply explained by a single dominant factor, which motivates us to explore potential sources of why intercity price differentials persist over time.

Table 1. Descriptive Statistics of Intercity Price Differential

	Variability of price differential				Mean absolute price differential			
	2000-2015	2000-2005	2006-2010	2011-2015	2000-2015	2000-2005	2006-2010	2011-2015
Panel I: Major type of product								
Commodities	2.80	2.61	2.78	3.05	3.37	3.63	3.13	3.31
Services	2.82	2.40	2.82	3.32	2.57	2.30	2.31	3.16
Panel II: Consumption purpose								
Food and non-alcoholic beverages	4.45	4.01	4.50	4.93	5.31	5.53	4.66	5.67
Alcoholic beverages and tobacco	3.16	2.98	3.36	3.16	2.79	2.41	2.73	3.29
Clothing and footwear	3.79	3.82	3.82	3.73	4.46	4.37	4.37	4.67
Housing, water, electricity, gas and other fuels	8.18	7.29	8.48	8.97	7.65	6.24	7.67	9.31
Furnishings, household equipment and routine maintenance	6.76	6.63	6.72	6.95	5.90	5.69	5.89	6.17
Health	2.27	1.77	2.31	2.84	2.32	1.98	2.42	2.62
Transport	12.97	12.88	13.01	13.03	10.77	10.69	10.73	10.91
Communication	3.01	2.99	2.99	3.06	2.20	2.08	2.21	2.33
Recreation and culture	4.69	4.57	4.77	4.76	3.90	3.67	4.02	4.06
Education	6.66	5.51	7.00	7.69	10.29	10.00	10.04	10.90
Restaurants and hotels	5.31	4.89	5.20	5.94	3.96	3.85	3.77	4.27
Miscellaneous goods and services	6.44	5.60	6.66	7.24	5.06	4.45	5.04	5.83

Note: The numbers indicate time-series mean of standard deviation of percentage price differential and absolute deviation of log prices between cities during each subsample.

[15] Note that these findings must be interpreted with an extreme caution because our empirical analysis is based on disaggregated price data, not actual prices of individual items, although this analysis is well beyond the scope of the current paper.

Next, we consider an alternative measure of price dispersion, relative price dispersion, which becomes increasingly popular in the literature. Specifically, following Cecchetti, Mark, and Sonora (2002), Crucini, Telmer, and Zachariadis (2005), and Phillips and Sul (2007), among other, we first compute the deviation of log price from its mean,

$$h_{i,k,t} = \frac{p_{i,k,t}}{N^{-1}\sum_{i=1}^{N} p_{i,k,t}}. \tag{2}$$

That is, $h_{k,t}$ measures the extent how each price index in period t deviates from its cross sectional mean in that period.[16] As a benchmark, $h_{i,k,t}$ will asymptotically approach to one under the null of PPP. To investigate how $h_{i,k,t}$ evolves over time, we define a quadratic distance measure of cross sectional variance for log of each price index k, $p_{i,k,t}$, as

$$H_{k,t} = \frac{1}{N}\sum_{i=1}^{N}(h_{i,k,t} - 1)^2, \ \ \forall k. \tag{3}$$

Since $h_{i,k,t}$ will be converging to one for all i in the long run under the null of overall convergence, $H_{k,t} \rightarrow 0$ as $t \rightarrow \infty$.[17] Thus, by examining how $H_{k,t}$ evolves over time, we can examine whether PPP holds or not.

Figure 2 plots the cross-sectional variance for each price index, $H_{k,t}$ for 10 major cities in Korea.[18] Since H_t does not display any tendency to decline over time, price level disparities across cities do not shrink. Moreover, none of $H_{k,t}$, except for "clothing and footwear," exhibits a decreasing pattern during the sample period.[19]

[16] One of advantages using this price dispersion measure is that the dynamic pattern of $h_{i,k,t}$ can be interpreted as transition coefficient measuring how log price in city i behaves relative to the cross sectional mean.

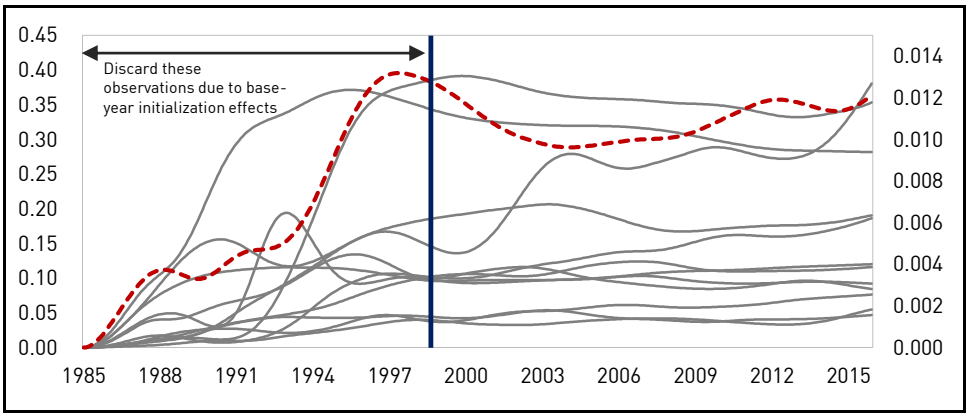
[17] However, when the overall convergence does not hold, $H_{k,t}$ will be some positive number as $t \rightarrow \infty$. Note that this does not necessarily suggest that some cities in a sample do not share a common trend. This issue will be rigorously discussed in Section 4.

[18] Die to base-year initialization effects, approximately the first half of observations are removed from the sample. Note also that the patterns of the cross-sectional variances in the sample of 30 cities are found to be qualitatively similar.

[19] Notice that the cross-sectional variance for "Housing, water, electricity, gas and other fuels" displays a marked upward trend, and hence this implies that intercity differences in overall prices might be due to this category.

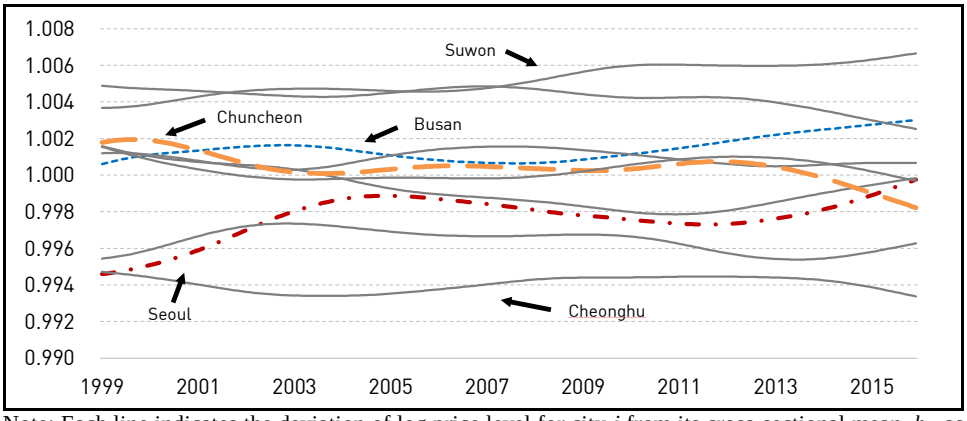
This is entirely consistent with findings from the intercity price differential presented in Figure 1 and Table 1. Therefore, our visual inspection suggests that PPP among major cities in Korea does not hold, but there seems to be no clear answer to the question of what drives the PPP deviation because any of disaggregated CPI data that has an increasing cross-sectional variance can be a potential source.

Figure 2. Cross-sectional Variances and Base-year Initialization Effects



Note: Each solid line (left scale) represents cross-sectional variance $H_{k,t}$ for the kth category of CPI classified according to expenditure purpose for k = 1, ⋯, 12 across 10 cities, and the dotted line (right scale) is H_t for all-item CPI.

Figure 3. Relative Transitional Coefficients of Price Level for 10 Major Cities



Note: Each line indicates the deviation of log price level for city i from its cross-sectional mean, $h_{i,t}$ as defined in Eq. 2.

One of empirical advantages using relative price dispersion measure over a simple intercity price differential is to allow us to explore dynamic behavior of each individual price from its cross-sectional mean. Figure 3 illustrates relative transition curves for 10 major cities in Korea, and some important implications immediately emerge. First, as apparent in the figure, relative price dispersion measures do not converge to the unity over the sample period, which implies a violation of PPP.[20] Second, there appear to be some heterogeneous transitional dynamics of price level data. Each transitional coefficient has a distinct dynamic path. For instance, Chuncheon and Busan have somewhat similar initializations, but their transition dynamics are considerably different. The transition path for Chuncheon involves shift from a high initial relative price to a low relative price, while the evolution of price level in Busan has the opposite manner. Next, Seoul and Chunchoen involve substantially different initial states, but their transitional curves tend to converge towards the same state over the sample period. Interestingly, some cities such as Suwon and Cheongju do not reveal a marked transitional dynamics.

III. CONVERGENCE TESTS AND EXPLANATIONS FOR PPP DEVIATION

In this section we first employ a formal statistical technique to test whether price level disparities tend to shrink over time. In addition, by utilizing disaggregated CPI data, we examine if there exists a potentially important factor that drives the observed intercity price differentials. Next, with city-specific characteristics in various dimensions, we investigate possible explanations for PPP deviations.

1. Tests of Relative Convergence

To test whether prices relative to their cross-sectional mean tend to decrease during sample period, we begin with the assumption that prices are generated from

[20] Each individual price categories has the same pattern (available from the authors upon request).

a single component model.[21] Alternatively, for instance, log price level in city i is assumed to be given by

$$p_{it} = \delta_{it}\theta_t, \tag{4}$$

where θ_t is a single common component that individual price levels share and δ_{it} is time-varying factor loading coefficient, which measures relative transitional effects from θ_t.[22] Under the null of relative convergence, cross-sectional price disparities decrease over time or, equivalently, $H_{k,t} \to 0$ as $t \to \infty$.

Following Phillips and Sul (2007), the empirical specification of price convergence test takes the form,

$$\log\frac{H_{k,1}}{H_{k,t}} - 2\log(\log t) = a + \gamma \log t + \varepsilon_t, \text{ for } t = rT, rT+1, \cdots, T, \tag{5}$$

where $r \in [0.2, 0.3]$. Under this representation, the null and alternative hypothesis are

$$H_0 : \gamma \geq 0 \quad \text{and} \quad H_A : \gamma < 0. \tag{6}$$

Thus, by estimating the slope coefficient of this log t regression model, one can test the null hypothesis that all prices have a tendency toward a common factor with one-sided t test of $\gamma \geq 0$.[23] It is worth noting that the log-t convergence test has no advantage over conventional time-series unit-root tests, if there is indeed a single common factor. Nonetheless we utilize this convergence concept, which does not depend on any particular assumptions on (non)stationarity in the common component, to deal with possible multiple common factors in the price data.

[21] This assumption does not necessarily imply that intercity price level differentials contain a single stochastic trend.

[22] Note that, in this paper, the time-varying factor loading coefficient δ_{it} is modeled by $\delta_{it} = \delta_i + \mathrm{L(t)}^{-1} t^{-\alpha_i}$, where $L(t)$ is a slow moving function, such as log t. For a detailed discussion about the concept of relative convergence and the log-t convergence test, see Phillips and Sul (2007).

[23] The alternative hypothesis involves that, at least, one price diverges from the common stochastic trend. Therefore, relative convergence test based on the log t convergence does not rule out the possibility of club convergence. This issue will be discussed in some detail in the following section.

Table 2. Relative Convergence Test Results

	r-value in log *t* regression				
	r = 0.200	*r* =0.225	*r* =0.250	*r* =0.275	*r* =0.300
Panel I: 10 cities (1985:M1−2015:M12)					
All items	-0.63	-0.64	-0.65	-0.66	-0.67
	(-70.7)	(-126.8)	(-321.0)	(-506.5)	(-583.3)
Goods	-0.61	-0.63	-0.65	-0.67	-0.68
	(-71.2)	(-65.4)	(-80.5)	(-119.2)	(-219.4)
Services	-0.68	-0.67	-0.66	-0.66	-0.65
	(-199.8)	(-163.8)	(-188.7)	(-259.6)	(-363.2)
Panel II: 30 cities (1990:M1−2015:M12)					
All items	-0.38	-0.38	-0.38	-0.38	-0.38
	(-15.8)	(-13.5)	(-11.9)	(-11.0)	(-10.5)
Goods	-0.38	-0.38	-0.38	-0.38	-0.39
	(-51.2)	(-37.4)	(-43.9)	(-71.9)	(-163.5)
Services	-0.49	-0.49	-0.49	-0.49	-0.50
	(-81.7)	(-74.9)	(-71.6)	(-70.2)	(-66.4)

Note: The numbers are slope coefficient estimate $\hat{\gamma}$ and the corresponding *t* statistics calculated with the heteroskedasticity and autocorrelation consistent (HAC) estimator for the covariance of γ are in parenthesis.

Table 2 presents the log *t* convergence test results for panels of log price levels for 10 cities and 30 cities with a variety of *r* values. First, the conclusion regarding relative convergence does not depend on the choice of *r* value. Next, the first row of each panel in the table indicates that overall convergence in regional price level is strictly rejected as $\hat{\gamma}$ is statistically significantly less than zero. This finding implies that PPP clearly does not hold in Korea.[24] Third, as Alessandria and Kaboski (2011), Engel (1999), and Chari, Kehoe, and McGrattan (2002), to name a few, argue that deviations from the law of one price in tradable goods play a key role in explaining PPP violation across countries, we investigate price convergence within each major product type, "goods" and "services" that represent tradable and non-tradable category, respectively. Both panels show that there is little evidence of price convergence among cities for both categories.

[24] Since some components of CPI market basket is evidently subject to regulation preventing prices from adjusting, we remove those categories, "alcoholic beverages and tobacco" and "communication" from the sample, but the main conclusion is found to be the same.

Table 3. Relative Convergence Test Results: Disaggregated CPI by Consumption Purpose

	r-value in log *t* regression				
	r = 0.200	*r* = 0.225	*r* = 0.250	*r* = 0.275	*r* = 0.300
Food and non-alcoholic beverages	-0.62	-0.62	-0.63	-0.64	-0.65
	(-213.9)	(-251.8)	(-216.7)	(-206.5)	(-230.5)
Alcoholic beverages and tobacco	-0.49	-0.47	-0.43	-0.41	-0.38
	(-20.4)	(-17.6)	(-12.1)	(-8.3)	(-5.9)
Clothing and footwear	-0.32	-0.31	-0.30	-0.29	-0.27
	(-18.1)	(-18.3)	(-18.8)	(-19.7)	(-21.8)
Housing, water, electricity and other fuels	-0.57	-0.56	-0.55	-0.56	-0.58
	(-26.6)	(-17.6)	(-15.3)	(-15.0)	(-15.6)
Furnishings, household equipment and routine household maintenance	-0.33	-0.33	-0.34	-0.35	-0.37
	(-28.2)	(-24.2)	(-32.8)	(-67.4)	(-130.1)
Health	-0.34	-0.33	-0.31	-0.30	-0.29
	(-46.4)	(-54.8)	(-68.3)	(-83.9)	(-86.5)
Transport	-0.38	-0.37	-0.37	-0.36	-0.36
	(-609.1)	(-422.2)	(-277.6)	(-203.6)	(-151.2)
Communication	-0.60	-0.60	-0.60	-0.60	-0.60
	(-2721.3)	(-2545.2)	(-3060.7)	(-2664.1)	(-1097.3)
Recreation and culture	-0.43	-0.41	-0.38	-0.35	-0.32
	(-18.2)	(-15.5)	(-15.5)	(-18.7)	(-28.5)
Education	-0.76	-0.76	-0.76	-0.76	-0.76
	(-662.4)	(-657.3)	(-591.5)	(-526.3)	(-474.5)
Restaurants and hotels	-0.30	-0.31	-0.34	-0.36	-0.39
	(-51.7)	(-26.6)	(-17.4)	(-15.8)	(-17.4)
Miscellaneous goods and services	-0.20	-0.21	-0.23	-0.26	-0.30
	(-3.7)	(-3.8)	(-5.7)	(-10.3)	(-20.2)

Note: The numbers are slope coefficient estimate $\hat{\gamma}$ and the corresponding *t* statistics calculated with the heteroskedasticity and autocorrelation consistent (HAC) estimator for the covariance of γ are in parenthesis.

Despite obvious PPP deviations in Korea, it is not quite clear which components of CPI market basket potentially explain the failure of price level convergence with those broad product categories. A natural response to overcome this issue is to utilized more disaggregated CPI components. The log *t* convergence test results for 12 price indices according to consumption expenditure purpose are presented

in Table 3.[25] Surprisingly, none of prices relative cross-sectional mean does not display a tendency to decrease over time, which is in line with visual inspection shown in the previous section. That is, the estimates of log *t* regression model, $\hat{\gamma}$ are consistently less than zero for any of the disaggregated price data. Further empirical analysis with a more detailed price items in CPI market basket, which is not reported in this present paper, also suggests that there is no particular CPI component that dominates the dynamic pattern of persistent regional disparities in overall price level.[26]

2. Factors Driving Intercity Price Differentials

For both panels of 10 major cities and 30 cities in Korea, the log *t* convergence test consistently suggests that price levels do not converge to their cross-sectional mean. In addition, since disaggregated CPI data indicates that any of individual prices for items included the CPI market basket does not exhibit a convergence pattern, the sources of the apparent PPP deviations may not be quite clear. Therefore, this motivates us to investigate possible explanations for regional price level disparities by employing a variety of city-specific socioeconomic factors rather than individual consumption expenditure categories.

To uncover explanations for why there exist substantial and persistent PPP deviations, a number of empirical studies have suggested potential sources of relative price level dispersion in an international context. First, distance, as a proxy for unobservable transportation costs, probably the most popular factor used in the literature.[27] Many empirical findings, such as Crucini and Yilmazkuday (2014), Engel and Rogers (1996), Obstfeld and Taylor (1997), and Parsley and Wei (1996),

[25] The test statistics are obtained from the sample of 10 major cities. Notice that the test results for 30 cities have the same conclusion.

[26] Investigating sources of intercity price differentials for each price category should prove useful. However, this analysis is well beyond the scope of the current paper, and thus we leave this for future research.

[27] Despite the fact that whether PPP hold on a pre-tax or tax adjusted basis might be an important empirical issue, we did not consider tax adjustment price data in this paper. This is because it is hard to imagine trade barriers such as tariffs play a key role in explaining PPP deviation within a country. Moreover, it is plausible that consumers care more about post-tax prices when purchasing goods and services, but there is little different in tax rate across cities in Korea.

suggest that the distance between two cities appears to be positively associated with the intercity price differentials with the effect being the strongest among traded goods. Thus the introduction of transaction costs into a model may help understand real exchange rate dynamics.[28] Next, as one of the most compelling explanations for overall price level divergence, some studies attribute much of persistent PPP deviations to the presence of nontraded-goods prices. Empirical tests routinely have found that the deviations from PPP tend to be greater and last longer for services (Beck, Hubrich, and Marcellino, 2009; Glushenkova and Zachariadis, 2016).

In addition to these possible explanations for the PPP deviations, empirical studies have employed a variety of variables to capture city-specific effects on the deviations from PPP. These include main demand and supply shifters that influence prices, such as income (Bergin and Glick, 2007; Crucini, Telmer, and Zachariadis, 2005) and wage (Crucini and Yilmazkuday, 2014; Parsley and Wei, 2001a; Rogers, 2007). An intuition behind this approach introducing an income-related variable is that firm's mark-up decision influenced by the level of income, commonly measured by per capita GDP, although the direction of how those are associated may differ across types of products.[29] However, it is worth noting that the use of income to account for regional price level disparities is somewhat problematic due to a possible endogeneity of income and the price level. Thus, in this paper, some well-known proxies for income will be experimented. Next, prices set by suppliers are primarily determined by the prices of input factors, for example wages, rents, and return to capital. In particular, wage as a measure of labor costs is frequently used for proxy for non-tradable components of CPI market basket.[30] Moreover, empirical studies, e.g., Beck and Weber (2003), have suggested that price dispersion appears to be larger as labor markets are less integrated.[31] Finally, Alessandria (2009) and Alessandria and Kaboski (2011), among others, point out that differences in opportunity cost of

[28] To examine whether the distance effect differs across different product groups, a squared distance in addition to distance is commonly employed (Parsley and Wei, 2001b).

[29] Some studies, e.g., Rose and Engel (2002), relate price convergence to market integration patterns in which the role of comovement of income variations is emphasized.

[30] Note that differences in wage differences can in part be attributable to the failure of income convergence (Engel and Rogers, 2004).

[31] However, the role of wage difference in accounting for PPP deviation becomes weaker labor mobility increases (Crucini and Yilmazkuday, 2014).

price search, which in turn depends on local wage, may help understand price disparities due to search frictions. In sum, those city-specific variables widely used in the literature allow us to account for possible heterogeneity that potentially leads to persistent intercity price level differentials.

To yield potential explanations for why relative prices do not converge over time or possibly why convergence is so slow, we introduce a number of variables including those discussed above to uncover the sources of persistent PPP deviations. Our approach is to investigate factors influencing intercity price differentials by considering a simple linear gravity model. In general, the gravity model utilizes gravitational force concept as an analogy to account for the volume of trade, international capital flow, and price dispersion. For instance, in an international context, gravity models establish a baseline for price dispersion as determined by GDP, population, and distance.[32] Following Cecchetti, Mark, and Sonora (2002), Engel and Rogers (1996), and Parsley and Wei (1996), we begin by introducing the most popular factors representing arbitrage costs used in this type of empirical analysis.[33] These costs involve distance between city locations that are positively associated with transportation costs and the presence of non-tradable goods and inputs, and would increase variations of relative prices. First, to explain the effects of market segmentation, we estimate a simple price gravity model by regressing intercity price differentials on distance measures.[34] As we present in columns I and II of Table 4, we examine whether intercity price level differentials defined as Eq. (1) can be explained by transportation costs measured by the logarithm of distance between cities together with a squared distance to explore a possible non-linearity in this relationship for both panels of cities. For a set of major 10 cities that are relatively more homogeneous and have integrated market than other smaller cities, transportation costs do not play a role in explaining price dispersion across cities.

[32] The use of a linear gravity model is to compare our empirical results with those suggested in the previous studies. It is worth noting that there may be some theoretical reasons of nonlinear dynamic behavior of relative prices, although this analysis is well beyond the scope of the current paper.

[33] For a theoretical justification of price gravity regression models, see Engel and Rogers (1998). Note that, for the variability of real exchange rate, most studies include a border dummy to evaluate the so-called "border effect."

[34] The data for all explanatory variables used in this paper are obtained from Statistics Korea. For a detailed description of the variables and their summary statistics are available from the authors.

However, when we add other cities to the sample, distance between cities has some ability to account for PPP deviations, but the distance effect does not display convexity feature.[35] This finding does not come to surprise as Korea is relatively a small country and markets are highly integrated.

Next, we add several commonly used variables such as income, input prices, and market integration, to the price gravity model to examine economic influences on the distance effects.[36] As we discussed earlier in this paper, income is measured by education level, a fraction of individuals with a college degree, due to possible endogeneity problem. Since wage data is not available, land price growth rate is employed as an effective proxy for input costs. To measure the extent of market integration and city size, the logarithm of population is used. The estimation results are presented in Column III of the table. Most importantly, after controlling for those factors, the price gravity model suggests that there is little evidence of distance effects even for the panel of 29 cities.[37] For the case of 10 major cities, the estimated coefficients for those explanatory variables are not significantly different from zero, except for education. On the other hand, all three factors are found to be important sources of intercity price level differentials with the correct signs of the estimates suggested by theories. The higher income measured by education level and land price growth rate are, the higher cities have general price levels. Since product market becomes more integrated as the size of city increases measured by population (Engel and Rogers, 2004), a city with relatively less integrated market appears to have a higher price level.

Since our preliminary analysis of relative price disparities among cities in Korea suggests there exist substantial heterogeneities across the cities, we introduce a number of potentially important variables representing city-specific characteristics

[35] As some studies, for example Parsley and Wei (1996), document that the non-linear distance effects differ across product groups, it may be useful to examine the role of transaction costs for each consumption expenditure categories. We leave this issue for a future research direction.

[36] Note that all explanatory variables employed in our empirical analysis are differences in the variables between cities.

[37] For the data availability, Jeju is removed from the sample of 30 cities for this analysis.

in addition to commonly used factors for PPP deviations in the literature.[38] Controlling for those factors, the price gravity model estimation results presented in columns IV of Table 4 yield somewhat common stories for both panels.[39] As in model specification III, transportation costs have little impact on the price level disparities. By adding other socioeconomic factors into the model specification, the conventional explanations for PPP deviations become increasingly important since the estimates for education, land price growth, and log population are consistently significant even at the 1% level for both 10-city and 29-city panels. The additional variables employed in this paper indicate that the socioeconomic characteristics of cities play a key role in accounting for the deviations from PPP. Notably, the composition of labor market influencing firms' markup decision and input factor prices is found to be a dominant driving force of regional price disparities. The higher is net labor inflow growth reflecting faster labor force growth, the lower producers increase their prices reflecting relatively lower price level. Moreover, a city with demographic structure of higher population ages 65 and above growth tends to have a relatively higher price level. This result may be consistent with the fact that older population appears to have the largest real wealth level among age groups in Korea. There also exists ample microeconomic evidence, e.g., Kaplan, Menzio, Rudanko, and Trachter (2016), that relative price dispersion stems from in part sellers' attempts to discriminate between types of buyers due to price search costs (Alessandria and Kaboski, 2011), which in turn may depend on the buyers' demographic factors, such as age and gender. According to spatial equilibrium models, a shift in labor supply in a city is largely a function of its amenities, and thus we employ EQ-5D index measuring the quality of life in a city. Since the coefficient of EQ-5D index is significantly different from zero, relative price dispersion may come from the differences in life quality across cities. Finally, as we mentioned earlier, the sizable portion of PPP deviation can be explained by different housing price growth rates.

[38] Those variables that are not reported in our empirical results because they have little power to account for intercity price differential include, for example, population density, industry structure, electricity usage, Jeonse price, birth rate, tax revenue, and modern market ratio.

[39] Despite the potential endogeneity issue, we also include estimation results with income data, per capita GRDP, in model specification V to compare our empirical findings with the previous studies with income data.

Table 4. Explanations for Intercity Price Differentials

	10 cities					29 cities				
	I	II	III	IV	V	I	II	III	IV	V
Log distance	-0.16	-5.93	-3.32	0.19	1.05	0.75***	4.99*	4.33*	2.06	0.58
	(0.57)	(6.92)	(7.13)	(3.18)	(4.19)	(0.26)	(2.83)	(2.58)	(2.47)	(2.27)
Log distance squared		0.61	0.32	-0.06	-0.21		-0.44	-0.39	-0.15	-0.02
		(0.72)	(0.75)	(0.34)	(0.44)		(0.29)	(0.26)	(0.25)	(0.23)
Education			0.05	0.09***				0.06***	0.04***	
			(0.03)	(0.02)				(0.01)	(0.01)	
Per capita GRDP					0.14					0.07***
					(0.11)					(0.01)
Land price growth			0.09	2.79***	2.30***			0.57***	0.84***	1.12***
			(0.45)	(0.35)	(0.50)			(0.15)	(0.15)	(0.13)
Log population			-0.41	-8.02***	-6.92***			-0.81***	-1.07***	-0.86***
			(0.55)	(0.91)	(1.24)			(0.14)	(0.17)	(0.16)
Net labor inflow growth				-17.6***	-15.4***				-0.51**	-0.07
				(1.53)	(2.06)				(0.21)	(0.19)
EQ-5D index				1.39***	2.56***				0.37**	0.86***
				(0.45)	(0.51)				(0.16)	(0.13)
Population ages 65 and above growth				0.83***	0.63***				0.06***	0.06***
				(0.11)	(0.14)				(0.01)	(0.01)
Housing price growth				1.88***	1.33***				-1.09***	-1.46***
				(0.33)	(0.43)				(0.20)	(0.18)
Constant	0.56	13.8	8.69	1.97	1.50	-2.41*	-12.5*	-10.4*	-4.84	-1.17
	(3.01)	(16.1)	(16.3)	(7.24)	(9.55)	(1.34)	(6.86)	(6.26)	(5.99)	(5.48)
Number of observations	45	45	45	45	45	406	406	406	406	406
R^2	0.00	0.02	0.10	0.86	0.76	0.02	0.03	0.20	0.30	0.42

Note: ***, **, and * denote statistical significance at the 1%, 5% and 10% levels respectively.

IV. MULTIPLE STOCHASTIC TRENDS OF PRICE LEVEL AND THEIR DETERMINANTS

This section scrutinizes the possibility that individual prices are governed by multiple stochastic common trends by utilizing a clustering algorithm. Next, we estimate the number of common components, and investigate explanations for why there exist some distinct trends that cause apparent PPP deviations. In addition, we discuss characteristics of member cities in each price level convergence club.

1. Clustering Common Trends of Prices

Our empirical analysis successfully suggests that PPP does not hold among cities in Korea as price disparities between cities, in general, do not tend to decrease over time. However, this conclusion suggested under the assumption that all prices are governed by a single stochastic common trend does not necessarily imply that all of price levels are diverging from the common component. Even in a benchmark case that only price level of city *i* diverges from the trend, while all other price levels share the common component, the log *t* convergence test will reject the null of overall convergence in price level. Therefore, in this section, we first consider a more general factor representation allowing for a finite number of common trends. That is, instead of the simple component model given by Eq. (4), individual price levels in a panel can be modelled by

$$p_{it}\begin{cases} \delta_{1,it}\theta_{it} & \text{for} \quad \lim_{t\to\infty}\delta_{1,it} = \delta_{1,} \qquad i \in C_1 \\ \vdots & \qquad\qquad\qquad\qquad\qquad\qquad \vdots \\ \delta_{M,it}\theta_{it} & \text{for} \quad \lim_{t\to\infty}\delta_{M,it} = \delta_{M,} \qquad i \in C_M \end{cases} \tag{7}$$

Here C_j is the *j*-th price level convergence subgroup for $j = 1, 2, \cdots, M$, where M is the number of common trends, and $\lim_{t\to\infty}\delta_{j,it} = 0, if \;\; i \notin C_j$.

To investigate the possibility of price level convergence among a part of cities in the entire panel that are relatively more homogeneous, at the outset, it is useful to divide the data into some arbitrary groups.[40] Although it is not reported in this paper to conserve on space, we consider a variety of subsamples in terms of city size, geographic neighborhood, and population density, but there is little evidence of price level convergence for any of these presumed classifications. As a consequence, we employ a clustering algorithm developed by Phillips and Sul (2007), which utilizes the log *t* convergence test subsequently. That is, the stepwise application

[40] In the analysis of real exchange rate, some studies, e.g., Parsley and Wei (1995), consider subsample of countries, such as OECD countries, to examine the extent of deviations from PPP.

of the log *t* convergence tests has the ability to separate out individual prices from a common trend.[41]

The empirical results of clustering analysis for price level measured by all-item CPI are presented in Table 5. There exist three convergence clubs for both 10-city and 30-city panels. Albeit their different sample periods, it is worth noting that club convergence classification for 10 major cities is nested by that of 30 cities, as the 10 cities classified from the clustering analysis with 30 cities in bold face are the same in those found in Panel I of Table 5. For each convergence club, the slope coefficient $\hat{\gamma}$ is statistically greater than or equal to zero implying that PPP deviations among member cities tend to shrink over time as price levels within a club converge toward their own common trend. Each convergence club displays very distinctive pattern of price level change. The first convergence club can be classified as high price level, while cities in club 3 appear to have a relatively low price level.

Table 5. Convergence Club Classifications

	$\hat{\gamma}$	$t_{\hat{\gamma}}$	Member cities
Panel I: 10 cities (1985:M1-2015:M12)			
Club 1 [2]	-0.03	-0.30	Busan, Suwon
Club 2 [6]	0.35	5.03	Seoul, Daegu, Gwangju, Daejeon, Chuncheon, Jeonju
Club 3 [2]	1.36	3.51	Incheon, Cheongju
Panel II: 30 cities (1990:M1-2015:M12)			
Club 1 [4]	0.30	17.65	**Busan**, **Suwon**, Seongnam, Uijeongbu
Club 2 [16]	0.05	1.98	**Seoul**, **Daegu**, **Gwangju**, **Daejeon**, Gunsan, Ulsan, Bucheon, **Chuncheon**, Wonju, Cheonan, Boryeong, **Jeonju**, Namwon, Mokpo, Yeosu, Suncheon
Club 3 [10]	0.00	0.15	**Incheon**, Gangneung, **Cheongju**, Chungju, Pohang, Gyeongju, Andong, Gumi, Jinju, Jeju

Note: Entries in square brackets indicate the number of member cities. $\hat{\gamma}$ and $t_{\hat{\gamma}}$ represent the slope coefficients of Eq. (5) and corresponding *t*-statistics, respectively.

There should be some reasonable explanations for why the groups of cities have persistently different price levels. However, at this point, it is not quite clear which

[41] Specifically, after a subgroup of cities having the highest price level is chosen to form a core group, the number of cities in the core group is determined. Next, a series of log *t* convergence tests allow us to decide which cities are to be included in club 1, and the rest of cities will form the second group. If relative convergence holds for group 2, there are two convergence clubs. If not, repeat the steps above to check if the second group can be divided into other convergence clubs. For a detailed instruction on clustering algorithm and club-merging tests, see Phillips and Sul (2007) and Phillips and Sul (2009).

factors may drive those distinctive stochastic common trends. Before formally investigating possible explanations for the different common trends, we apply the clustering analysis to each of consumption expenditure categories. Convergence club classifications for 10 major cities presented in Table 6 suggest some important implications. First and most importantly, none of the clustering results is compatible with price level club convergence classification. This implies that there is no single dominant factor that drives persistent PPP deviations. Second, as the patterns of price dispersion across countries considerably differ across individual expenditure categories especially in terms of club member cities, further microeconomic studies are inevitable to better understand long-run dynamic behavior of prices.

Table 6. Convergence Club Classification: 12 Consumption Expenditure Categories

	$\hat{\gamma}$	$t_{\hat{\gamma}}$	Member cities
Food and non-alcoholic beverages			
Club 1 [3]	3.05	121.16	Busan, Gwangju, Jeonju
Club 2 [7]	-0.03	-1.12	Seoul, Daegu, Incheon, Daejeon, Suwon, Chuncheon, Cheongju
Alcoholic beverages and tobacco			
Club 1 [5]	0.01	0.30	Busan, Daegu, Gwangju, Daejeon, Chuncheon
Club 2 [2]	1.81	1.44	Incheon, Suwon
Club 3 [3]	0.57	2.90	Seoul, Cheongju, Jeonju
Clothing and footwear			
Club 1 [2]	-0.12	-1.20	Daejeon, Cheongju
Club 2 [4]	0.24	4.73	Daegu, Suwon, Chuncheon, Jeonju
Club 3 [2]	0.24	16.88	Incheon, Gwangju
Club 4 [2]	0.34	25.43	Seoul, Busan
Housing, water, electricity and other fuels			
Club 1 [2]	0.00	-0.03	Seoul, Suwon
Club 2 [5]	0.27	4.40	Busan, Daegu, Incheon, Daejeon, Jeonju
Club 3 [2]	-2.22	-0.77	Gwangju, Cheongju
Group 4 [1]	–	–	Chuncheon
Furnishings, household equipment and routine household maintenance			
Club 1 [5]	0.11	29.60	Busan, Daejeon, Suwon, Chuncheon, Cheongju
Club 2 [3]	0.88	3.22	Seoul, Daegu, Jeonju
Group 3 [2]	-1.52	-37.57‡	Incheon, Gwangju
Health			
Club 1 [3]	3.46	23.34	Incheon, Daejeon, Chuncheon
Club 2 [5]	0.09	7.42	Seoul, Busan, Gwangju, Suwon, Jeonju
Group 3 [2]	-6.10	-6.28‡	Daegu, Cheongju

Table 6. Continued

	$\hat{\gamma}$	$t_{\hat{\gamma}}$	Member cities
Transport			
Club 1 [2]	2.75	1.92	Busan, Chuncheon
Club 2 [4]	0.06	3.37	Seoul, Suwon, Cheongju, Jeonju
Club 3 [4]	0.17	0.85	Daegu, Incheon, Gwangju, Daejeon
Communication			
Club 1 [2]	-0.08	-0.70	Seoul, Jeonju
Club 2 [2]	3.37	16.11	Incheon, Chuncheon
Group 3 [6]	-0.56	-694.06‡	Busan, Daegu, Gwangju, Daejeon, Suwon, Cheongju
Recreation and culture			
Club 1 [4]	0.32	63.96	Gwangju, Daejeon, Suwon, Chuncheon
Club 2 [4]	0.01	0.12	Seoul, Busan, Cheongju, Jeonju
Club 3 [2]	-2.12	-1.31	Daegu, Incheon
Education			
Club 1 [2]	0.00	0.00	Suwon, Chuncheon
Club 2 [3]	0.67	3.81	Busan, Daegu, Gwangju
Club 3 [5]	0.11	13.95	Seoul, Incheon, Daejeon, Cheongju, Jeonju
Restaurants and hotels			
Club 1 [7]	0.03	8.90	Busan, Daegu, Incheon, Daejeon, Suwon, Chuncheon, Cheongju
Club 2 [2]	0.15	1.50	Seoul, Jeonju
Group 3 [1]	–	–	Gwangju
Miscellaneous goods and services			
Club 1 [3]	0.47	4.20	Busan, Incheon, Chuncheon
Club 2 [7]	-0.08	-0.82	Seoul, Daegu, Gwangju, Daejeon, Suwon, Cheongju, Jeonju

Note: ‡ denote statistical significance at 1% level. Entries in square brackets represent the number of cities in each subgroup.

2. Determinants of Stochastic Common Trends

Identifying driving forces that characterize three convergence clubs of price level is clearly of interest. Thus, we investigate other important factors that drive the observed clustering patterns of individual price levels. By considering potential drivers of intercity price level differentials suggested in our empirical studies in the previous section, we examine the interaction between those variables and price level. To estimate the likelihood that a city is found to be a member of each convergence club, a multinomial logit regression model is utilized. Specifically, when club m is the base club, the probability P_j for $j = 1, 2, \cdots, m\text{-}1$ that a city is a member of convergence club C_j is given by

$$P_j = P(C_j|X) = \frac{\exp(X'\gamma_j)}{\left[1+\sum_{j=1}^{m-1}\exp(X'\gamma_j)\right]} \ , \tag{8}$$

where Cj is convergence club, X is a vector of characteristics, and γ_j is the vector of coefficients related to club j. Since the probability of being the base club is

$$P_m = \frac{1}{\left[1+\sum_{j=1}^{m-1}\exp(X'\gamma_j)\right]} \ , \tag{9}$$

the log odds ratio of being in club j relative to the base club is $\ln(P_j/P_m) = X'\gamma_j$.

Table 7. Multinomial Logit Estimates of Price Level Club

	Base=Club 1		Base=Club 2
	Club 2	Club 3	Club 3
Population ages 65 and above growth	-0.15	-0.31**	-0.16**
	(0.14)	(0.15)	(0.08)
Log population	0.73	1.19	0.45
	(1.19)	(1.38)	(0.75)
Education	-0.10	-0.18*	-0.08
	(0.07)	(0.09)	(0.06)
Net labor inflow growth	-0.42	-0.62*	-0.20
	(0.33)	(0.35)	(0.13)
Housing price growth	3.79	5.79**	1.99
	(2.41)	(2.69)	(1.26)
Constant	1.41	3.40	1.99
	(11.0)	(13.6)	(8.34)
Log-likelihood = -19.56			
LR χ^2= 19.31			
Pseudo R^2 = 0.33			

Note: Entries in parentheses are t-values. ** and * denote statistical significance at the 5% and 10% levels, respectively.

The data set used to estimate this model is 29 cities after removing Jeju from the sample due to data availability. Explanatory variables that we consider include population ages 65 and above growth, the logarithm of population, education level as a proxy for income, net labor inflow growth for input factor costs, and housing price growth. These variables are chosen because they appear to play a significant

role in explaining intercity price dispersion in the gravity model in Section 3. Other variables were found to be very limited support for the observed clustering patterns. Multinomial logit regression coefficients and their *t*-values are reported in Table 7.[42] For instance, the estimated coefficient shown in column 2 reflects the effect of an explanatory variable on the likelihood of being in club 2 relative to the reference group, club 1. In general, the model fits the data reasonably well, as a few explanatory variables account for roughly 33% of the variation in the model. Some variables reported in Table 7 are statistically significant factors that drive different common trends of price level. The signs of the coefficients on the variables are consistent with previous research. In particular, education and population ages 65 and above growth have significant positive effects on the movement to higher long-run price level. Therefore, our empirical finding implies that the deviation from PPP may be attributed to differences in income and demographic distribution. Likewise, cities appear to be converging to their own steady states, which in turn are determined by those variable.

V. CONCLUDING REMARKS

To explore possible sources of regional price level disparities in Korea, we utilize a variety of data sets with regard to consumption expenditure categories and cities. Despite the fact that the deviation from PPP is well documented even within a country, there have not been any studies rigorously investigating the possibility of PPP among major cities in Korea. This motivates us to study the long-run behavior of relative price level dispersion with a special emphasis on heterogeneous transition dynamics. In addition, with disaggregated CPI data, the paper scrutinizes dynamic patterns of price disparities across cities for consumption expenditure categories classified according to purpose. Given the fact that PPP deviations or possibly slow convergence, we investigate main factors that drive the price level disparities across cities.

To summarize our empirical findings, the log *t* convergence test strongly rejects the null hypothesis of overall price level convergence during sample periods of

[42] Note that the multinomial logit regression model with per capita income (GRDP), instead of education level, yields a very similar result.

1985:M1-2015:M12 for 10 major cities and 1990:M1-2015:M12 for a larger set of 30 cities. Moreover, for none of individual consumption categories, there is little evidence of price convergence. The analysis of gravity model indicates that the effect of transportation costs on intercity price differentials is limited, while other socioeconomic city-specific factors, such as income, input factor prices, demographic distribution, and housing price growth, play key roles in accounting for regional price level disparities. Our clustering analysis, in general, confirms that price levels are governed by a finite number of multiple common stochastic trends that are characterized notably by income and the growth rate of older population.

Obviously, there are some fruitful further issues that are worth pursuing. Some degree of complications in empirical analysis may improve the fit of gravity model to explain why price level differs substantially across cities otherwise similar in many respects. A promising direction would be to utilize more detailed consumption expenditure categories and to incorporate nonlinearity in relative price dynamics. In addition, as we briefly discussed in this paper, the apparent heterogeneous transitional patterns across cities suggest that it should prove useful to investigate factors driving some evolution in convergence clubs over time.

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