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ISSUES WITH A CHAINED-TYPE PRICE INDEX: AN ANALYSIS WITH THE PRODUCER PRICE INDEX

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Regarding the recent switch from the fixed base price index to the chained-type price index in many countries, we examine important issues including the selection of the weight to produce more accurate chained-type price indices and to maintain statistical consistency in the time series of a price index in this study. We determine that the actual weight from year t-3 data better produces a more correct chained-type producer price index at t between two available methods of selecting the weights. This weighting method also provides generally better statistical consistency and stability for the chained-type producer price index. We also compare the MAE and RMSE of the price equations of the fixed base and chain indices. Both the unit root test and comparison of the model performance evaluation reveal no critical difference, thus confirming a stability over the two indices. In particular, the substitutability of the chain index for the fixed base index is highly obtained, regardless of the time horizon. Overall, we can confidently assert that the chain index provides a statistical consistency and stability over a fixed base index.

Keywords: Chained-type Price Index, Weight to Produce Price Index, Producer Price Index, Accuracy, Statistical Consistency and Stability
JEL classification: C82, E31, E01

1. INTRODUCTION

As stabilization of price levels is the most important objective for central banks, the measurement of an accurate price index is a critical task for them. However, it has been determined that existing price indices based on the Laspeyres method have an upward bias resulting from the fixed weight for every five years. As a consequence, many

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advanced countries have adopted chained-type indices to attenuate the problem presented by the Laspeyres method.

As a chained-type price index re-sets the base year each year, it can mitigate the upward bias problem in the Laspeyres index, which becomes increasingly serious as the timing of the price index moves further and further away from the base year, and can reflect drastic fluctuations of prices in a more timely manner.[1] Additionally, re-organizing price indices via the chained-type method can provide organizational consistency with Gross Domestic Production (GDP), which has already adopted the chained-type indexation method in many countries. Thus, the proper method of computing a chained-type price index is a critical issue for central banks or government agents, which measure and report price indices.

In order to generate more accurate chained-type price indices, however, many points must be considered when a chained-type price index is adopted. Those include the following: i) Although it is ideal to use the previous year's weights for the computation of the chained-type index, the use of the previous year's weights is not possible due to the time required for the collection and management of the data for the weights. As a result, central banks must select a feasible base year for the weights among the options available. ii) Since different weights are employed for the *t*-1 year's December and *t* year's January, there tends to be a jump in the series of a chained-type price index between December and January, which may not be related to price fluctuations over those two months. This problem is frequently referred as the step problem. iii) As a method to compute price index changes from the Laspeyres index to the chained-type index, the statistical properties of the price index may also change. Even though these problems are important issues in the production of an accurate chained-type price index, it is surprising that few studies have addressed these issues. A few exceptions to the rare consideration of chained-typed indices are the studies of Lee (2002) and Lee (2009). Lee (2002) experimentally compiled real GDP of Korea using the chain weighted method before its official introduction and assessed the relevance of chain-weighted real GDP. He attempted to determine whether major revisions of growth rate due to introduction of chain-typed GDP altered the patterns of economic fluctuation and economic co-movement. Lee (2009) assessed structural changes in business cycle after the introduction of chain-typed GDP and its statistical consistency over the fixed base GDP.

[1] The Laspeyres index and the chained-type index can be expressed mathematically as follows: The Laspeyres index can be written as $P^L_{(o,t)} = \dfrac{\sum p_t q_0}{\sum p_0 q_0}$. The chained-type index can be written as $P^C_{(o,t)} = P^L_{(0,1)} \times P^L_{(1,2)} \times \ldots \times P^L_{(t-1,t)}$, where $P^L_{(t-1,t)} = \dfrac{\sum p_t q_{t-1}}{\sum p_{t-1} q_{t-1}}$.

He concluded that the chained-type GDP could be substituted for fixed base GDP. However Lee (2002, 2009) did not mention a chain-typed price deflator.

In this study, we investigate the above-mentioned issues, such as the selection of weight to produce a more correct chained-type price index and to maintain statistical consistency in a price index series using the producer price index. Among many price indices, providing an accurate producer price index is particularly important because the producer price index helps central banks correctly perceive the current economic status, and helps private firms and producers make rational decisions for forward contracts or unit cost computation. In this study we attempt to determine the best method to compute the weights among feasible options (the actual weights in year t-3 and the estimated weights in year t-2) in measuring the producer price index, how to mitigate the step problem, and whether the time series characteristics of the producer price index are influenced by the transition from the Laspeyres producer price index to the chained-type producer index. In order to answer these questions, the paper is organized as follows. Section 2 compares the accuracy of the chain-typed producer price index when the actual weights in year t-3 are used and when the estimated weights in year t-2 are used, employing the Diebold-Mariano test statistics. Section 3 examines whether the time series characteristics of the producer price index are affected when the chained-type index is introduced. Section 4 provides concluding remarks.

2. COMPARISON OF METHODS TO COMPUTE THE CHAINED-TYPE PRODUCER PRICE INDEX

Many advanced countries have already employed the chained-type producer index to substitute for the Laspeyres producer index, and many developing countries are interested in such switching in computing the producer price index. Although it is the optimal method for using the previous year’s weights for the computation of the chained-type index, the use of the previous year’s weights is infeasible due to the time required for the collection and management of the data for the weights. As a consequence, central banks need to consider the best method of selecting the weights among feasible options. Table 1 shows the list of OECD countries that have already employed the chained-type producer index and two currently adopted ways to determine the weights. One of these ways involves the use of the actual weights in year t-3, and the other involves using the estimated weights in year t-2. As is shown in Table 1, the former method is employed by most countries, such as Japan and Sweden, whereas the latter method is used in Norway. Even if there are two distinct ways to compute the chained-type producer price index depending on which weights are employed, it is surprising to see that no rigorous studies have been conducted to determine which weight can generate more accurate producer price indices. This section addresses this question by comparing the accuracy of the two different chained-type producer indices according to the weights.

Table 1. List of OECD Countries with Chained-Type Producer Price Index

Countries which have already adopted the chained type producer price index		Countries which plan to adopt the chained-type producer price index in 2010
t-3 Actual Weights	*t*-2 Estimated Weights	
Austria, Australia, Belgium, Hungary, Iceland, Japan, Turkey, Sweden	Norway	Italy, France

We designate as Method 1 the method used to compute the chained-type producer price index in year t using the actual weights in year *t*-3, and designate Method 2 the method used to compute the chained-type producer price index in year *t* using the estimated weights in year *t*-2.[2] Additionally, we set the *ex post* chained-type producer price index computed by the use of actual weights in year *t*-2 as the benchmark case. Note that the benchmark case is not feasible in practice due to the time required for the collection and management of the data. Our strategy to compare those two methods is to determine which method is relatively closer to the benchmark case. In other words, we compare the average gap between Method 1 and benchmark case with the average gap between Method 2 and benchmark case.

2.1. Data

We use the time series data for the producer price index in this analysis. That is, we use the chained-type producer price index computed by the benchmark methodology, the chained-type producer price index computed by Method 1, and the chained-type producer price index computed by Method 2. The sample period is 2005.1 - 2010.8 and the starting time is dictated by the availability of the above series by the Bank of Korea.[3] In an effort to overcome drawbacks from the relatively short time series data, we utilize not only the aggregate producer price index but also the indices for sub-division items which are constituents of the aggregate producer price index. The lists of sub-division items at various division levels are provided in Tables 2, 3, and 4.

[2] The Bank of Korea extends quantity results in Mining and Manufacturing Survey using surveyed growth rates in Monthly Survey of Mining and Manufacturing. That is, the values based on these two surveys are used as the estimated weights in Method 2.

[3] All data series in this study are provided by the Bank of Korea.

Table 2. Classification for Aggregate Producer Price Index, 1 Digit, and 3 Digit Level Producer Price Indices at Bank of Korea

Digit Level	Digit Code	PPI
Aggregate Producer Price Index	W	All
1 Digit	2	Mining Products
	3	Industrial Products
3 Digit	201	Mineral Fuels
	202	Non-metallic Mineral Products
	301	Food Products, Beverages & Tobacco
	302	Textile Products & Apparel
	303	Leather Products & Footwear
	304	Wood & Wood Products
	305	Pulp, Paper Products & Publications
	306	Coke & Petroleum Products
	307	Chemical Materials & Products
	308	Drugs & Pharmaceuticals
	309	Rubber & Plastic Products
	310	Non-metallic Mineral Products
	311	Basic Metal Products
	312	Processed Metal Products
	313	Electronic Components, Computers, Radio, Television & Communication Equipment
	314	Medical Appliances, Precision & Optical Instruments
	315	Electric Instruments
	316	Other Machinery & Equipment
	317	Motor Vehicles & General Transportation Equipment
	318	Other Furniture & Industrial Products

Table 3. Classification at 4 Digit Level PPI at Bank of Korea

Digit Code	PPI	Digit Code	PPI
3011	Prepared Foods	3111	Basic Iron & Steel
3012	Beverages	3112	Basic Non-ferrous Metal Products
3013	Feeds	3113	Cast Metal Products
3014	Tobacco Products	3121	Structural Metal Products
3021	Yarns & Threads	3122	Forged, Stamped & Pressed Metal Products
3022	Textile Fabrics	3123	Hand Tools & General Hardware
3023	Textile Fabric Products	3124	Metal Fasteners & Screws
3024	Other Textile Products	3125	Wire Products

3025	Apparel	3126	Metal Springs
3031	Leather & Leather Products	3127	Metal Cans & Containers
3032	Footwear	3128	Others
3041	Wood	3131	Semi-conductors
3042	Wood Products	3132	Electronic Components
3051	Pulp, Paper & Paper Products	3133	Computers and Peripherals
3052	Publications	3134	Communication Equipment & Apparatus
3061	Coke Oven Products	3135	Video & Audio Apparatus
3062	Petroleum Products	3141	Medical Appliances & Instruments
3071	Basic Chemicals	3142	Measuring, Testing & Navigational Instruments
3072	Fertilizers	3143	Eyeglass, Photographic Equipment & Optical Instruments
3073	Synthetic Rubber & Plastic Materials	3144	Watches & Clocks
3074	Soaps, Detergents & Toiletries	3151	Electric Motors, Generators & Transformers
3075	Other Chemical Products	3152	Batteries & Accumulators
3076	Man-made Fibers	3153	Insulated Wires & Cables
3081	Human Pharmaceuticals	3154	Electric Lamps & Lighting Equipment
3082	Veterinary Drugs	3155	Household Appliances
3083	Other Drugs Pharmaceuticals	3156	Other Electric Devices
3091	Rubber Products	3161	General Purpose Machinery
3092	Plastic Products	3162	Special Purpose Machinery
3101	Glass & Glass Products	3171	Motor Vehicles
3102	Ceramic Ware	3172	Other Transportation Equipment
3103	Structural Clay Products	3181	Furniture
3104	Cement & Lime Products	3182	Other Industrial Products
3105	Other Non-metallic Minerals		

Table 4. Classification at 5 Digit Level PPI at Bank of Korea

Digit Code	PPI	Digit Code	PPI
20101	Anthracite	30926	Plastic Household Products
20102	Briquets & Natural gas	30927	Other Plastic Products
20201	Stone, Sand & Clay	31011	Basic & Processed Glass Products
20202	Other Non-metallic Mineral Products	31012	Glass Containers
30111	Processed Meat Products	31041	Cement
30112	Processed Marine Products	31042	Lime

30113	Processed Fruits & Vegetables	31043	Cement & Concrete Products
30114	Oils & Fats	31111	Iron & Steel Materials
30115	Dairy Products	31112	Semifinished Steel Products
30116	Cerealflour, Starches, Sugar & Sweeteners	31113	Hot-rolled Steel Products
30117	Bakery Products, Sweets & Noodles	31114	Cold-rolled Steel Products
30118	Condiments & Food Additives	31115	Steel Wire
30119	Other Prepared Foods	31116	Steel Pipes
30121	Alcoholic Beverages	31117	Coated or Otherwise Surface-treated Steel
30122	Non-alcoholic Beverages	31121	Non-ferrous Metal Materials
30131	Compound Feeds	31122	Rolled, Drawn & Extruded Products of Copper
30132	Miscellaneous Feeds	31123	Rolled, Drawn & Extruded Products of Aluminum
30211	Cotton Yarns	31131	Cast Iron & Steel Products
30212	Worsted & Woolen Yarns	31132	Non-ferrous Cast Metal Products
30213	Synthetic Fiber Yarns	31211	Metal Doors & Related Articles
30214	Threads	31212	Other Structural Metal Products
30221	Synthetic Fiber Fabrics	31221	Forged Metal Products
30222	Cotton Fabrics	31222	Pressed & Stamped Metal Products
30223	Worsted & Woolen Fabrics	31311	Electronic Integrated Circuits
30224	Other Textile Fabrics	31312	Semi-conductors
30231	Knitted Fabrics& Articles	31321	Liquid Crystal Display
30232	Other Textile Fabric Products	31322	Printed Circuit Boards
30251	Men's Apparel	31323	Electronic Tubes
30252	Women's Apparel	31324	Electronic Capacitors
30253	Children's Apparel	31325	Electronic Resistors
30254	Underwear	31326	Other Electronic Components
30255	Other Shirts & Working Clothes	31331	Computers
30256	Leather Garments	31332	Computer Memory Storage
30257	Fur Garments	31333	Computer Input Output System
30258	Apparel Accessories	31341	Wire Telecommunication Instruments
30311	Leather	31342	Wireless Telecommunication Instruments
30312	Leather & Leather Products	31351	Television Receivers
30321	Leather Footwear	31352	Sound Recoder & Player
30322	Other Footwear	31353	Radio Receivers
30411	Lumber	31354	Other Radio & Television Receiving Equipment, Audio & Video Apparatus
30412	Surface Processed Wood Products	31511	Electric Motors & Generators
30421	Plywood & Reconstituted Wood	31512	Transformers
30422	Other Wood Products	31513	Switching, Protecting & Connecting Apparatus

30511	Pulp	31514	Electricity Distribution & Control Boards
30512	Paper & Paperboard	31515	Other Electric Switch Apparatus
30513	Paper & Paperboard Containers	31541	Electric Bulbs & Lamps
30514	Paper Products For Office Use	31542	Lighting Equipment, Office & Commercial Use
30515	Sanitary Paper Products	31543	Lighting & Electrical Equipment For Vehicles
30516	Other Paper Products	31551	Household Electric Appliances
30521	Books	31552	Non-Electric Domestic Heater
30522	Newspapers & Periodicals	31553	Non-Electric Domestic Cooker
30523	Reproductions of Recorded Media	31611	Internal Combustion Engines & Motors
30621	Refined Petroleum Products	31612	Oil Pressure Machinery
30622	Liquefied Petroleum Gas	31613	Mechanical Power Transmission Equipment
30623	Lubricating Oils & Greases	31614	Industrial Furnace
30624	Other Petroleum Products	31615	Industrial Lifting and Handling Equipment
30711	Basic Petrochemicals	31616	Industrial Refrigerators & Refrigerating Equipment
30712	Other Basic Organic Chemicals	31617	Air-conditioning Equipment
30713	Basic Inorganic Chemicals	31618	Other Office Machinery
30714	Nuclear Fuel	31619	Other General Purpose Machinery
30715	Industrial Gases	31621	Agricultural Machinery
30716	Dyestuffs & Pigments	31622	Machine Tools
30731	Synthetic Rubber	31623	Construction & Mining Machinery
30732	Synthetic Resin	31624	Textile Machinery
30741	Soaps & Detergents	31625	Semiconductor Machines
30742	Cosmetics	31626	Other Special Purpose Machinery
30751	Agricultural Chemicals	31711	Passenger Cars
30752	Paints	31712	Buses
30753	Others(Other Chemical Products)	31713	Trucks & Special Purpose Motor Vehicles
30761	Synthetic Fibers	31714	Motor Vehicle Parts and Accessories
30911	Tires & Tubes	31811	Chairs for Transportation Equipment
30912	Other Rubber Products	31812	Wood Furniture
30921	Plastics in Primary Form	31813	Metal Furniture
30922	Construction Plastic Products	31821	Musical Instruments & Athletic Gears
30923	Packaging Plastic Products	31822	Dolls & Other Toys
30924	Industrial Plastic Products	31823	Others(Other Industrial Products)
30925	Foamed Plastic Products		

2.2. Econometric Methodology

The basic idea underlying the selection of a method to generate a relatively more accurate chained-type producer price index involves the comparison of the gap between the chained-type producer price index from Method 1 and benchmark case with the gap between the chained-type producer price index from Method 2 and benchmark case. Hence, we denote the difference between Method 1 and benchmark case for the chained-type producer price index of sub-division item *i* at time *t* as $e_{1,it}$, the difference between Method 2 and benchmark case for the chained-type producer price index of sub-division item *i* at time *t* as $e_{2,it}$. Also, let z_{it} denote the loss differential between two competing methods. That is, $z_{it} = f(e_{2,it}) - f(e_{1,it})$. If the loss function is quadratic, then $z_{it} = (e_{2,it})^2 - (e_{1,it})^2$. If the loss function is absolute, then $z_{it} = |e_{2,it}| - |e_{1,it}|$. z_{it} can be decomposed as $z_{it} = \alpha_i + \varepsilon_{it}$, where α_i is the sample mean of z_{it} for item level *i*.[4] Then, the null hypothesis to address which method is relatively closer to the benchmark case can be tested by examining whether $\overline{\alpha}$ (the average loss differential across smaller items) is significantly different from zero. As a result, the null hypothesis and the alternative hypothesis can be expressed as:

$$H_0 : \overline{\alpha} = 0 \quad \text{and} \quad H_1 : \overline{\alpha} \neq 0,$$

where $\overline{\alpha}$ is the average of α_i.

To overcome the short sample size, we utilize not only the aggregate producer index series but also the panel data of the producer price indices for sub-division levels. Hence, the null hypothesis can be tested by constructing the following test statistics which is a variant of the Diebold-Mariano (1995) test statistics to compare the forecast ability of time series models:

$$\overline{DM} = \frac{z}{\sqrt{V(\overline{z})}} \sim N(0,1), \tag{1}$$

where $\overline{z} = m^{-1}\sum_{i=1}^{m}\overline{z}_i$, $\overline{z}_i = \frac{1}{T}\sum_{t=1}^{T} z_{it}$, and $V(\overline{z})$ is the variance of $\overline{z}$. Although $\overline{z}$ can be straightforwardly computed, the computation of $V(\overline{z})$ requires careful consideration

[4] For the aggregate producer price index, we can omit the subscript *i* which indicates a sub-division item level.

due to possible serial correlations or cross-sectional correlations in ε_{it}.[5] In our analysis, serial correlations in ε_{it} may arise when Method 1 has consistently smaller/larger gap with the benchmark case as compared to Method 2. Also, cross-sectional correlations in ε_{it} may arise when common indicators across *i* are employed to estimate weights in Method 2. As a result, we allow serial correlations or cross-sectional correlation in ε_{it} as much as possible.

More specifically, we allow serial correlations in ε_{it} for the aggregate producer price index, 1 digit level producer price indices (producer price index for mining products and producer price index for industrial products), 3 digit level producer price indices, and 4 digit level producer price indices. We did not allow cross-sectional correlations for producer price indices at these levels because no common indicator is employed for the 1 digit level producer indices and only one common indicator is used for the 3 digit level indices.[6] Although 5 common indicators are used for 65 producer price indices at the 4 digit level, we assume no cross-sectional correlation because the number of observations over time exceeds the number of observations across sub-division items at this level. That is, we allow serial correlations but assume no cross-sectional correlations when $T>m$. This assumption means that we implicitly assume that the law of large numbers works in the direction where greater number of observations are utilized in the analysis. Under the assumption that only serial correlations are allowed, $V(\bar{z})$ is computed as follows:

$$V(\bar{z}) = \left(\frac{1}{mT}\right)\left(m^{-1}\sum_{i=1}^{m}\hat{\sigma}_i^2\right), \tag{2}$$

where $\hat{\sigma}_i^2 = \left[\dfrac{2\pi\hat{h}_i(0)}{T}\right]$, and $h_i(0)$ is the spectral density function at frequency zero for sub-division item level *i*.[7] The truncation lag in computing $h_i(0)$ is chosen according to Andrews (1991).

[5] Pesaran *et al*. (2009) constructs a panel Diebold-Mariano test statistics assuming $\varepsilon_{it} \sim iid(0, \sigma_i^2)$.

[6] This is shown in Table 5. The 3 digit producer price indices for which a common indicator is used to estimate year *t*-2 weights are '30924 industrial plastic products' and '31543 lighting & electrical equipment for vehicles'.

[7] The spectral density function at frequency zero for sub-division *i* is an alternative representation of the variance of the sample mean of loss differentials for sub-division *i* because the spectral density function at frequency zero is equivalent to the autocovariance-generating function at the unity.

Table 5. 5 Digit PPI Using Common Indicators in Method 2

Code/Item Name	PPI code	PPI
Compound Feeds (10807200)	30131 30132	Compound Feeds Subsidiary Feeder*
Synthetic Fiber Yarns (13109600)	30213 30214	Synthetic Fiber Yarns Threads
Knitted Underwear (14312800)	30231 30254	Knitted Fabrics & Articles Underwear
Sawnwood (16114700)	30411 30412	Hemlock Lumber Wood Floor Boards
Manufacture of Pulp, Paper and Paperboard (17100000)	30512 30513 30516	Paper & Paperboard Paper & Paperboard Containers Other Paper Products
Kraft Paper (17116100)	30512 30513	Paper & Paperboard Paper & Paperboard Containers
Manufacture of Basic Chemicals (20100000)	30711 30712 30713 30714 30715 30716	Basic Petrochemicals Other Basic Organic Chemicals Basic Inorganic Chemicals Nuclear Fuel* Industrial Gases Dyestuffs & Pigments*
Synthetic Rubber (20327500)	30731 30732	Synthetic Rubber Synthetic Resin
Beauty Soap (20430400)	30741 30742	Soaps & Detergents Beauty Soap
Manufacture of Plastic Products (22200000)	30921 30923 30924 30926	Plastics in Primary Form Packaging Plastic Products Industrial Plastic Products Plastic Household Products
Plastic Parts and Accessories for Motor Vehicle (22234800)	30924 31543	Industrial Plastic Products Lighting & Electrical Equipment For Vehicles
Cement, Lime, and Plastic, etc (23300000)	31042 31043	Lime* Cement & Concrete Products
Primary Steel Products (24100000)	31111 31117	Iron & Steel Materials Coated or Otherwise Surface-treated Steel
Bar Steel (24139400)	31113 31114	Hot-rolled Steel Products Cold-rolled Steel Products
Steel Pipes (24141200)	31116 31117	Steel Pipes Coated or Otherwise Surface-treated Steel
Casting (24343800)	31131 31132	Cast Iron & Steel Products Non-ferrous Cast Metal Products*

Manufacture of Other Metal Products; Metal Working Service Activities (25900000)	31212 31222	Other Structural Metal Products Pressed & Stamped Metal Products
Manufacture of Computers and Peripheral Equipment (26300000)	31332 31333	Computer Memory Storage Computer Input Output System
Liquid Crystal Display (26351900)	31326 31333	Other Electric Components Computer Input Output System
Manufacture of Telecommunication and Broadcasting Apparatuses (26400000)	31341 31342	Wire Telecommunication Instruments Wireless Telecommunication Instruments
Mobile Phone(CDMA) (26453500)	31331 31342	Computers Wireless Telecommunication Instruments
Manufacture of Electronic Video and Audio Equipment (26500000)	31353 31354	Radio Receivers Other Radio & Television Receiving Equipment, Audio & Video Apparatus
Transformers (28158300)	31512 31515	Transformers Other Electric Switch Apparatus
Fluorescent Lamp (28461200)	31541 31542	Electric Bulbs & Lamps Lighting Equipment, Office & Commercial Use*
Manufacture of Domestic Appliances (28500000)	31551 31552	Household Electric Appliances Non-electric Domestic Heater
Manufacture of General Purpose Machinery (29100000)	31616 31617	Industrial Refrigerators & Refrigerating Equipment Air-conditioning Equipment
Manufacture of Special-Purpose Machinery (29200000)	31623 31626	Construction & Mining Machinery Other Special Purpose Machinery
Parts and Accessories for Motor Vehicle Bodies (30374400)	31713 31714	Trucks & Special Purpose Motor Vehicles Motor Vehicle Parts and Accessories
Chairs (32077000)	31812 31813	Wood Furniture Metal Furniture
Wardrobe (32076600)	31812 31813	Wood Furniture Metal Furniture

Note: * indicates 5 digit sub-division items which use only one code for their weights.

For 5 digit level producer price indices, we allow cross-sectional correlations for ε_{it}. As the number of observations across items is far greater than that over time at 5 digit level, we assume that the law of large numbers is working in the dimension of cross-sections rather than the time dimension. Hence, we allow for cross-sectional correlation but assume no serial correlation when $m>T$. In order to implement this idea, we adjust the order of sub-division item producer price indices at 5 digit level such that indices using a common indicator are adjacently located. This ordering makes the cross-sectional correlation dependent on the distance of indices in the order. Table 5 shows the list of common indicators and sub-division indices which employ those common indicators. After adjusting the order of indices, $V(\bar{z})$ is computed similarly to that in Equation (2).

$$V(\bar{z}) = \left(\frac{1}{mT}\right)\left(T^{-1}\sum_{t=1}^{T}\hat{\sigma}_t^2\right), \tag{3}$$

where $\hat{\sigma}_t^2 = \left[\frac{2\pi\hat{h}_t(0)}{m}\right]$, and the truncation lag of $h_t(0)$ is also determined by the method in Andrews (1991).

Since $z_{it} = f(e_{2,it}) - f(e_{1,it})$, a significantly negative (positive) value in $\overline{DM}$ shows that Method 2 (Method 1) generates a significantly more accurate index. Finally, $\overline{DM}$ will have the standard normal distribution asymptotically.

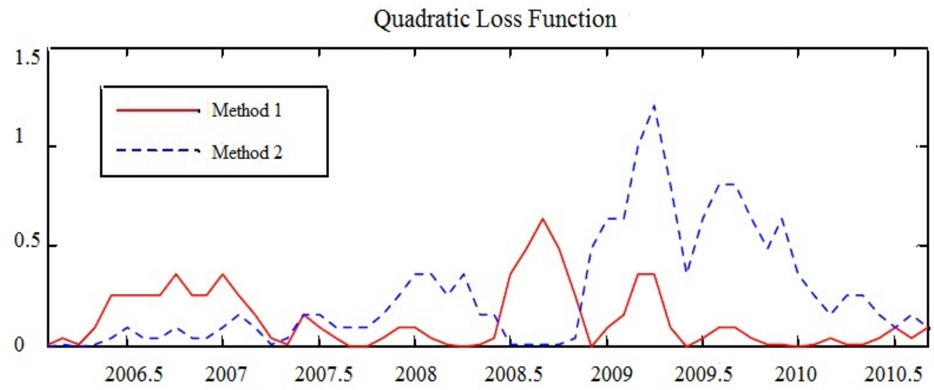
2.3. Empirical Results

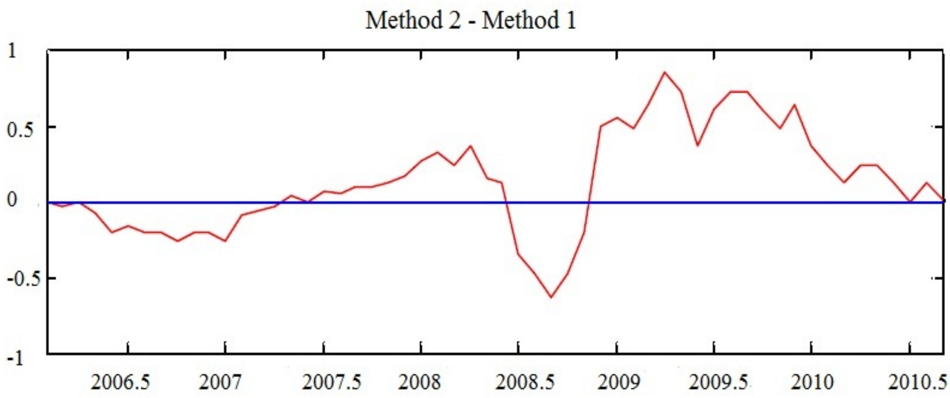
Table 6 presents the empirical results. The first row demonstrates that $\overline{DM}$ for the aggregate producer price index equals 1.4522 (1.5091) under the quadratic loss function (the absolute loss function). The null hypothesis that both methods have equal accuracy cannot be rejected in either of these loss functions. Movements of z_t from the aggregate producer price index under both loss functions are plotted in Figure 1. Figure 1 suggests that z_t has some serial correlations which is consistent with our assumption in the previous sub-section.

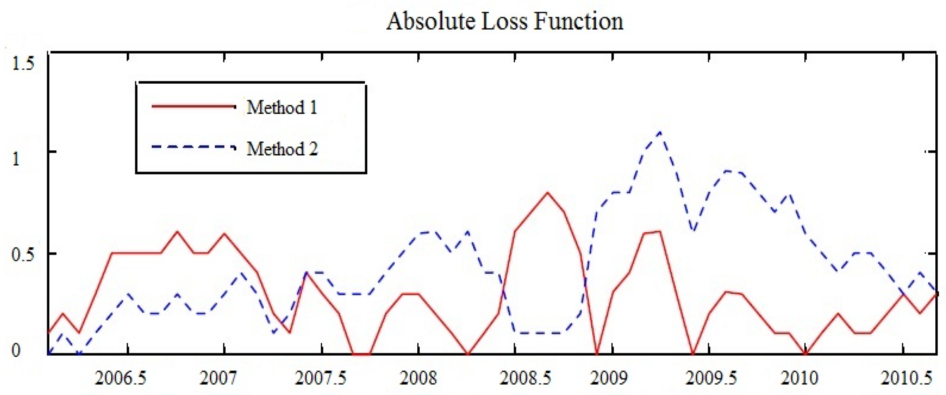
Table 6. Comparison of Method 1 and Method 2 at Various Levels

	Quadratic Loss Function	Absolute Loss Function
Aggregate PPI	1.4522	1.5091
1 Digit Level PPI	1.6749*	1.7928*
3 Digit Level PPI	0.8610	0.7666
4 Digit Level PPI	0.0942	0.2294
5 Digit Level PPI	0.5769	0.6955

Notes: This table shows the Diebold-Mariano test statistics with the producer price indices at various levels. *, **, *** indicates that the null hypothesis of equal accuracy can be rejected at the 10%, 5%, and 1% significance level, respectively.


Quadratic Loss Function
Method 1
Method 2
1.5
1
0.5
0
2006.5
2007
2007.5
2008
2008.5
2009
2009.5
2010
2010.5


Method 2 - Method 1
1
0.5
0
-0.5
-1
2006.5
2007
2007.5
2008
2008.5
2009
2009.5
2010
2010.5


Absolute Loss Function
Method 1
Method 2
1.5
1
0.5
0
2006.5
2007
2007.5
2008
2008.5
2009
2009.5
2010
2010.5

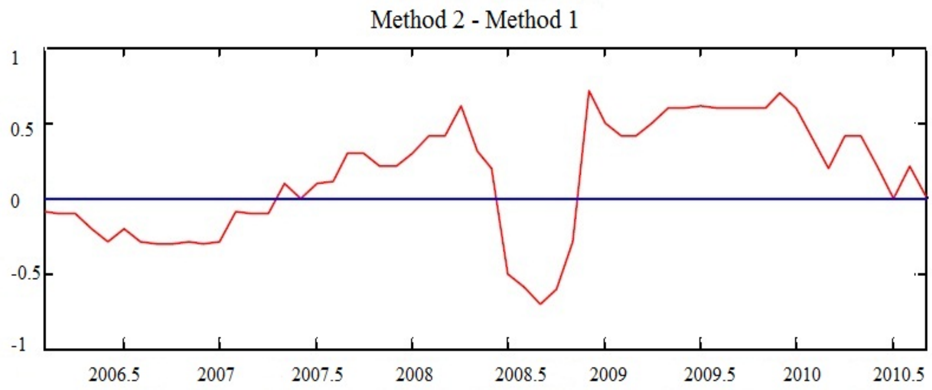


Figure 1. Loss Differentials for Aggregate PPI

When the 1 digit level producer price indices are examined (that is, when the aggregate producer index is categorized further into the price index for mining products and the price index for industrial products), $\overline{DM}$ becomes significantly positive at the 10% level, which indicates that Method 1 generates significantly more accurate indices. This result is shown in the second row of Table 6. If we test the null hypothesis using the price index for mining products and the price index for industrial products separately, then *DM* becomes significantly positive at the 1% level with the price index for mining products, whereas *DM* is insignificant with the price index for industrial products. The results are robust to the use of the loss functions and imply that the significant $\overline{DM}$ with 1 digit level producer price indices results from the mining products as opposed to the industrial products.

The third row of Table 6 shows the results with 3 digit level producer price indices. $\overline{DM}$ statistics is not sufficiently high to reject the null hypothesis of equal accuracy in either of the loss functions. Again, when we run the same test with price indices for mining products (the price index for mineral fuels and the price index for non-metallic mineral products), we are able to obtain significantly positive $\overline{DM}$ from both loss functions at the 1% level. However, $\overline{DM}$ is not significant at all with price indices for industrial products. When we conduct the same hypothesis test with the price index for mineral fuels and the price index for non-metallic mineral products separately, we obtain a significant *DM* with the price index for mineral fuels only. This again suggests that Method 1 generates significantly more accurate indices for mining products (particularly for the price index for mineral fuels), while no significant difference is detected between two methods for industrial products.

The fourth row of Table 6 demonstrates that $\overline{DM}$ is insignificant with 4 digit level price indices by both loss functions.[8] Finally, the fifth row of Table 6 shows that $\overline{DM}$ is not significant with 5 digit level price indices. As cross-sectional dependence is allowed for the 5 digit level price indices, σ_t^2 is calculated for each t first and then averaged. As a result, it is impossible to separate the price indices for sub-division item levels at 5 digit level price indices.

In summary, no significant overall difference is noted between Method 1 and Method 2 in terms of accuracy. However, Method 1 is significantly better at generating more accurate price indices for mineral products.

3. THE STEP PROBLEM AND STATISTICAL CONSISTENCY TEST OF CHAINED INDEX

3.1. Step Problem

The chain base method provides some profound advantages to economists and businessmen. It helps them to know the extent of change that has arisen in the current year as compared to the previous year. The construction of the chain index, however, raises the problem of different weight usage between the last month of the previous year and the January of the current year. This problem is the so-called step problem. Theoretically, no step problem arises with a Divisia Integral Index which constructs a price index via the integration of a continuous flow of price information. However, it is impossible to shorten the base period frequency below one year, say, by one month or one day. We will discuss two types of chain method among others belonging to overlapping methods. The first one is the annual overlapping method, and the second one is the one month overlapping method. The selection criterion among the two methods involves the reduction of a step bias from the chain method.

The first method caused a step problem in the index level since the January price index is calculated using the previous average annual price. However, in the second one, the January price is based on the price of the previous month, i.e., the December of the previous year, which has a smoother index than the annual overlapping methods. For example, the chained-type producer price index for January 2006 based on the annual overlapping method using the t-3 actual weight can be expressed as

[8] The difference between the 3 digit level price indices and 4 digit level price indices is a finer classification for industrial products. Hence, we did not conduct the test for mining products and industrial products separately.

$$PPI_{0601} = \frac{\sum P_{05}^{i} Q_{02}^{i}}{\sum P_{05}^{i} Q_{02}^{i}} \times \frac{\sum P_{0601}^{i} Q_{03}^{i}}{\sum P_{05}^{i} Q_{03}^{i}} ,$$

where P_{05}^{i} is the average price for good *i* in 2005, P_{0601}^{i} is the average price for good *i* in January 2006, and Q_{t}^{i} is the quantity of good *i* in year *t*. The chained-type producer price index for January 2006 based on the one month overlapping method using the *t*-3 actual weight can be expressed as

$$PPI_{0601} = \frac{\sum P_{0512}^{i} Q_{02}^{i}}{\sum P_{05}^{i} Q_{02}^{i}} \times \frac{\sum P_{0601}^{i} Q_{03}^{i}}{\sum P_{0512}^{i} Q_{03}^{i}} .$$

Let us consider an example to demonstrate the difference between the two methods. Let us consider a world containing two goods, say, TVs and PCs (personal computer). The TV represents a lower price elasticity good and the PC represents a higher price elasticity good. Let us imagine the volume change in the year-to year base. In Table 7, we know that there are 60 TVs in 2005 and 80 TVs in 2006 and 40 PCs in 2005 and 120 PCs in 2006.

Table 7. The Change of Volume Weights

	2005	2006
TV	60	80
PC	40	120

The price of a TV in January 2005 is $1,000 and increases by 3.0% every month, but the price of a PC does not change as of January 2005, when it is $500.

From this setting, we know that step bias arises from the annual overlapping method. However, the price index from the one month overlapping method is smoother than the one generated by the annual overlapping method. From Table 8 and Figures 2 and 3, we can see that the fixed base index and two chain indices have the same number in 2005. However, in 2006, the annual overlapping method has a step problem in the price level, as we can observe a big step from December 2005 to January 2006. The percentage change on a-month-ago basis was 2.5% in November and December of 2005. It falls in January of 2006 by 0.6%, but returned to 2.0% in the February of 2006, although the individual price of TV and PC does not change much.

We see a smoother index in the one month overlapping method.[9] From the example above, the chain index using the one month overlapping method shows a percentage change of 2.4% in November and December of 2005 and 1.9%, 2.0% in January and February of 2006 respectively. Unlike what is observed in the annual overlapping method, the price index does not evidence a step problem in the one month overlapping method.

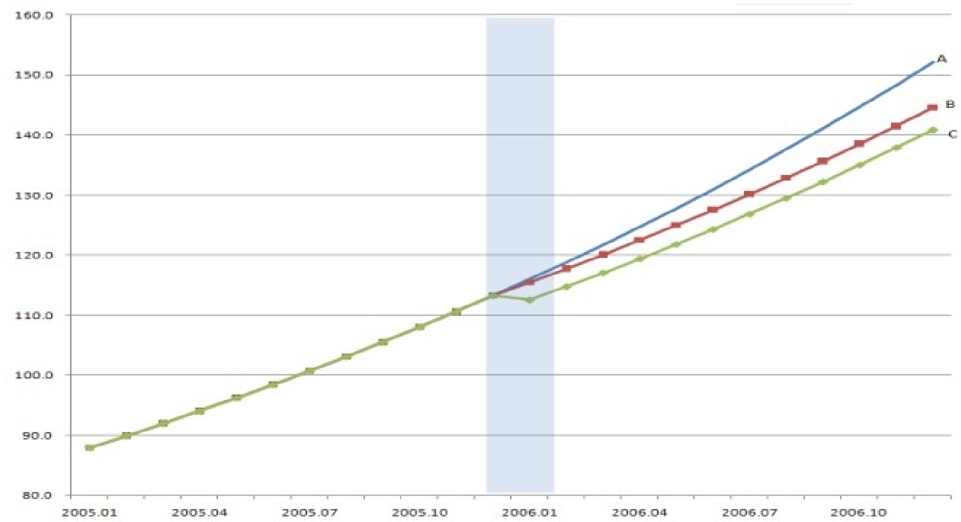
The figure showed this pattern more clearly. As the price of a PC remains constant and the price of a TV is increasing, the price index of the annual overlapping method falls overall. However, we do not have this kind of problem with the one month overlapping method.[10]

Table 8. Example of Step Problem

			05.01	05.02	…	05.11	05.12	06.01	06.02	06.03
Price	TV		100.0	103.0	…	134.4	138.4	142.6	146.9	151.3
	PC		50.0	50.0	…	50.0	50.0	50.0	50.0	50.0
Price Index	Fixed Base Index		88.0	89.9	…	110.6	113.3	116.0	118.9	121.8
	Chain Index	One Month Overlapping	88.0	89.9	…	110.6	113.3	115.5	117.8	120.1
		Annual Overlapping	88.0	89.9	…	110.6	113.3	112.6	114.8	117.1
Growth Rate (%)	Fixed Base Index			2.3	…	2.4	2.4	**2.4**	2.4	2.4
	Chain Index	One Month Overlapping		2.3	…	2.4	2.4	**1.9**	2.0	2.0
		Annual Overlapping		2.3	…	2.4	2.4	**-0.6**	2.0	2.0

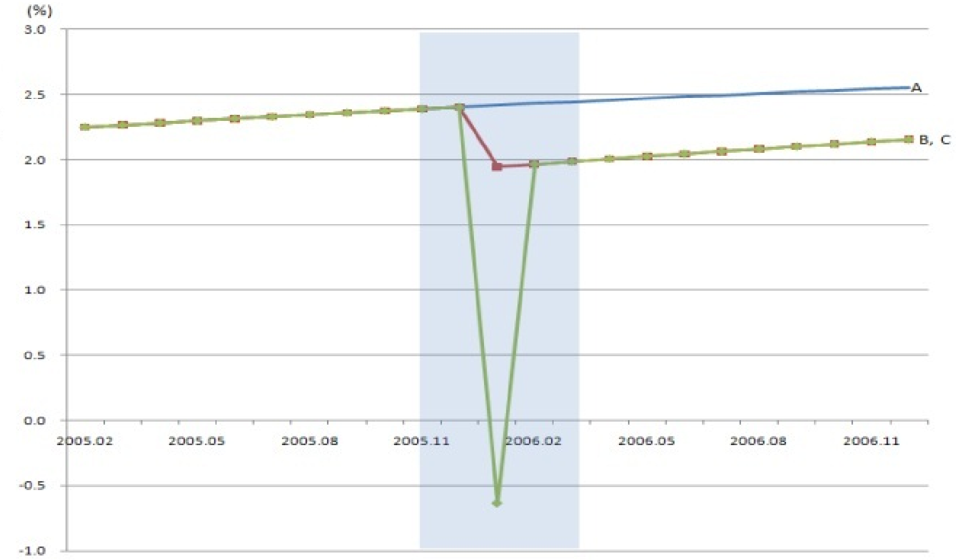
[9] IMF (2001) showed that the one month overlapping method is known to have the smoothest transition among the link relatives.

[10] Because of this reason, all analyses in other sections of this study are conducted with the producer price index constructed from the one month overlapping method.



Note: A denotes fixed base PPI, B month specific method, and C annual overlapping method, respectively.

Figure 2. Fixed Base Index and Two Chain Indices (Level)



Note: A denotes fixed base PPI, B month specific method, and C annual overlapping method, respectively.

Figure 3. Fixed Base Index and Two Chain Indices (Growth Rate)

3.2. Test of Statistical Consistency

The chain base method provides a marked advantage to economists and businessmen. It helps them to know the extent of change that has arisen in the current year as compared to the previous year. However, chain index does not guarantee the statistical continuity with the fixed base index.[11] To explore this consistency we make a series of tests, as below.

The priority is to test the unit roots in the price index. The unit root test is known to distinguish the stationarity of the time series. Next, we estimate the producer price index (PPI) equation using both price indices. By so doing, we can determine whether the newly constructed chain index provides stability and consistency over the fixed base index. Therefore, we estimate the PPI equation with dependable variables such as the chain index and fixed base index PPI, and compared each equations' predictability via MAE (Mean Absolute error, %) and RMSE (Root Mean Squared Error, %). We employ two sample types. The first type is in the period from 2005~2010 (type I). The second type extends the type I sample back to the year of 1996 linking the fixed base year to the chain index (type II).

3.2.1. The Unit Root Test of Chain Index

Three price indices are tested. Here we have two types of chain index according to the weight usage. The first uses the actual volume weight of three years ago (method 1). The other uses the estimate of actual volume weight of two years ago (method 2). We test the aggregate price index, and the time span of the test is from January of 2005 to June of 2010.

We employ the ADF(Augmented Dickey Fuller) unit root test in Engle and Granger (1987) as specified in (4). The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher-order correlation by assuming that the time series follows an AR(p) process, and adding the p-lagged difference terms of the dependent variable to the right-hand side of the test regression.

$$\Delta Y_t = \beta_0 + \beta_1 Y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-i} + \varepsilon_t \,, \tag{4}$$

$$H_0 : \beta_1 = 0, \quad H_1 : \beta_1 < 0 \,, \tag{5}$$

[11] The reason why we need to test statistical consistency between the two indices is to give a researcher assurance of the usage of chain type index as a substitute of the fixed base one.

$$t_{\beta_1} = \frac{\widehat{\beta}_1}{s.e.(\hat{\beta}_1)} . \tag{6}$$

This augmented specification is then employed to test (5) using the *t*-ratio (6). An important result obtained by Fuller is that the asymptotic distribution of the *t*-ratio for $\widehat{\beta}_1$ is independent of the number of lagged first differences included in the ADF regression. Moreover, while the assumption that follows an autoregressive (AR) process may appear somewhat restrictive, Said and Dickey (1984) demonstrate that the ADF test is asymptotically valid in the presence of a moving average (MA) component, provided that sufficient lagged difference terms are included in the test regression. We also employ the DFGLS (Dickey Fuller Generalized Least Squares) test in Elliott *et al*. (1996) and PP (Phillips Perron) test in Phillips and Perron (1988).

Table 9 shows the results of the ADF, DFGLS, and PP tests. We report the test results as the level and growth rate of each. The last panel of Table 9 shows the evaluation of the time series as to whether it is stationary, I(0), or nonstationary, I(1).

The test result shows that all of the PPI are I(1) in level term, but I(0) in growth rate term.

Table 9. The Unit Root Test Results

Variable	Test	Level		Growth rate		I(0)/I(1)
		Statistics	*p*-value	Statistics	*p*-value	
Fixed Base Index	ADF	-1.425	0.565	-3.737	0.006	I(1)
	DFGLS	-1.042	0.301	-3.703	0.000	I(1)
	PP	-0.845	0.800	-3.853	0.004	I(1)
Method 1	ADF	-1.631	0.461	-3.599	0.008	I(1)
	DFGLS	-1.395	0.168	-3.545	0.001	I(1)
	PP	-00975	0.757	-3.776	0.001	I(1)
Method 2	ADF	-1.600	0.477	-3.693	0.006	I(1)
	DFGLS	-1.382	0.172	-3.637	0.000	I(1)
	PP	-0.972	0.759	-3.859	0.001	I(1)

3.2.2. The Estimation of Price Equation

The conventional long-run determinants of PPI are the wage, nominal effective exchange rate, and oil import price. In the short-run, the lagged term variables, unit import price, and nominal interest rate also contribute the determination of PPI together with long-run factors. We need an estimation of the PPI equation, since we compare the forecasting errors of each PPI equation and evaluate the continuity between the chain index and fixed base index. As discussed previously, we employ the fixed base index and chain index as dependable variables for the 2005~2010 period (type I) and the hybrid sample for the 1996~2010 period (type II) to estimate the PPI equation.

The long-run PPI equation is estimated with Equation (7) and the short-run Equation with (8).

$$\log(PPI_t) = \alpha_0 + \alpha_1 \log(PPI_{t-1}) + \alpha_2 \log(NEER_t) + \alpha_3 \log(OIL_t) + \alpha_4 \log(PMGS_t) + \alpha_5 D2008 + \varepsilon_t, \quad (7)$$

$$d\log(PPI_t) = \beta_0 + \beta_1 d\log(NEER_t) + \beta_2 d\log(OIL_t) + \beta_3 d\log(PMGS_t) + \beta_4 diff(YCB_t) + \beta_5 d\log(WAGE_t) + \beta_6 E\_PPI_{t-1} + \mu_t, \quad (8)$$

where PPI is the producer price index, NEER is the nominal effective exchange rate, OIL is the oil import price, PMGS is the unit import price, D2008 is the dummy variable for the 2008 global financial crisis, YCB is the yield on 3-year corporate bonds, WAGE is the average wage of manufacture industries, and E_PPI is the error correction term from the estimation of Equation (7).

We employ two data-sets. The first is the type I data set for the period from January of 2005 to June of 2010. The other is the type II data set, which extends the PPI time series back to 1996. As the chain index PPI does not exist prior to 2005, we simply extend the time series by adding the growth rate of the fixed base index to the chain index level. Fgures 4 and 5 depict the trend of both PPI indices.

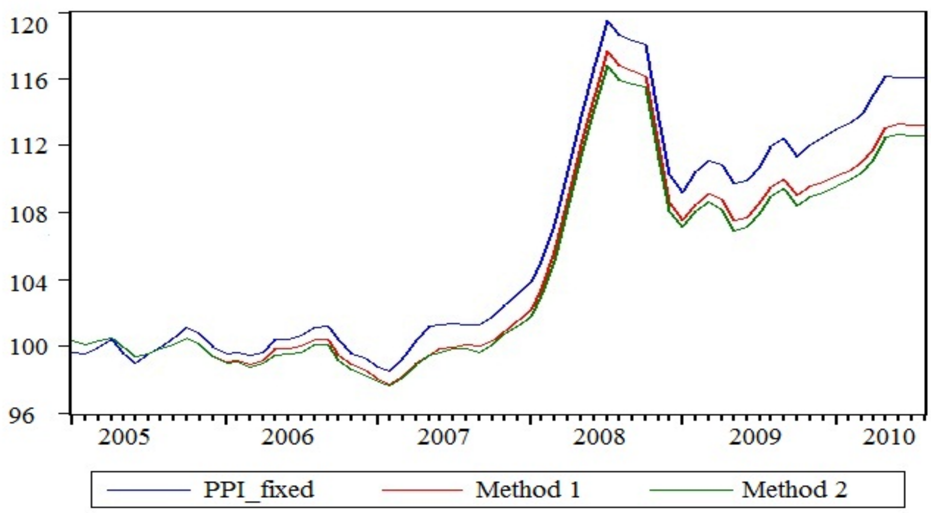


Figure 4. The Trend of PPI Index: Type I

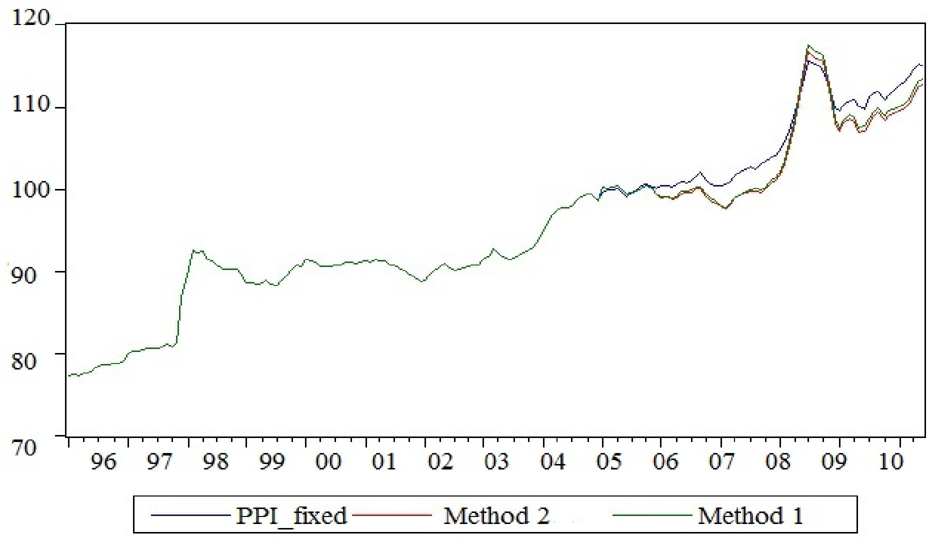


Figure 5. The Trend of PPI Index: Type II

The explanatory variables are similar to the one described by Shin (2005). In Equations (7)~(8), WAGE is the average monthly wage of manufacturing and mining industries. NEER denotes the nominal effective exchange rate and is from International Finance Statistics (IFS). OIL denotes Western Texas Intermediate (WTI)'s barrel price from Petronet of the Korea National Oil Corporation. PMGS is the unit import price from the Bank of Korea (BOK) and is a constant price in 2005. The interest rate we employ is the 3-year corporate bond yield. We include D2008, the 2008 global financial crisis dummy variable in the type I regression, but we add D1997, the 1997 currency crisis dummy variable, to capture both economic crises. Table 10 reports the technical statistics of the explanatory variables.

Table 10. The Technical Statistics

	WAGE	NEER	OIL	PMGS	YCB
Average	2,542,476	94.06	67.17	109.74	5.48
Median	2,478,002	94.53	63.81	107.45	5.33
Maximum	3,812,769	110.35	133.91	153.40	8.56
Minimum	1,864,450	68.66	34.23	85.50	3.73
Standard Deviation	396,059	12.73	22.16	15.32	0.97
Number of Observation	78	78.00	78.00	78.00	78.00
Source	Min. of Employment and Labor	IMF	Petronet	BOK	BOK

Table 11 reports the regression results of the long-run PPI Equation based on (7). The coefficients of the explanatory variables show the expected sign and statistical significance. Both the fixed base index and chain index show similar results. The method 1 chain index provides better estimates than method 2, in that it is similar to the fixed base one.

Table 11. Long-run PPP Equation Regression (Type I)

	Fixed Base Index	Chain Index	
		Method 1	Method 2
Constant	1.007**	0.863**	0.842**
	(0.334)	(0.368)	(0.388)
Lagged Variable	0.790***	0.813***	0.818***
	(0.061)	(0.067)	(0.071)
NEER	0.078***	0.063***	0.060***
	(0.020)	(0.020)	(0.020)
OIL	0.027**	0.025**	0.024**
	(0.011)	(0.010)	(0.011)
PMGS	0.045	0.039	0.037
	(0.029)	(0.026)	(0.027)
D2008	-0.023**	-0.022**	-0.021**
	(0.009)	(0.009)	(0.009)
$\overline{R}^2$	0.989	0.988	0.987
F-statistics	1154.6	998.0	889.1
Durbin-Watson Statistics	1.620	1.527	1.549
Prob (F-statistic)	0.000	0.000	0.000

Notes: 1) ( ) represents White corrected heteroskedasticity standard error. 2) ***, **, * denotes 1%, 5%, 10% statistical significance respectively.

Table 12 reports the regression results of the short-run PPI equations based on Equation (8). The equation transforms the variables into the first difference form and add the YCB variable and error correction term from the long-run regression. In the short-run regression, we obtain satisfactory results in terms of the coefficient's sign and statistical significance.

Table 12. Short-run PPP Equation Regression (Type I)

	Fixed Base Index	Chain Index	
		Method 1	Method 2
Constant	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
NEER	0.101***	0.110***	0.108***
	(0.034)	(0.033)	(0.032)
OIL	0.022*	0.023*	0.022*
	(0.012)	(0.012)	(0.012)
PMGS	0.199***	0.193***	0.185***
	(0.051)	(0.051)	(0.051)
YCB	-0.005	-0.006	-0.005
	(0.005)	(0.005)	(0.005)
WAGE	-0.007*	-0.006*	-0.006*
	(0.003)	(0.003)	(0.003)
E_PPI	-0.029	0.035	0.033
	(0.151)	(0.169)	(0.168)
$\overline{R}^2$	0.481	0.507	0.481
F-statistics	9.112	9.794	8.817
Durbin-Watson Statistics	1.323	1.294	1.342
Prob (F-statistic)	0.000	0.000	0.000

Notes: 1) ( ) represents White corrected heteroskedasticity standard error. 2) ***, **, * denotes 1%, 5%, 10% statistical significance respectively.

Next, we run an identical regression for the type II data set. For long-run and short-run regression results, its performance is superior to the type I dataset, since the sample size becomes larger in both the fixed base and chain indices. Table 13~14 depicts the results of this regression .

Table 13. Long-run PPP Equation Regression (Ttype II)

	Fixed Base Index	Chain Index	
		Method 1	Method 2
Constant	0.835***	1.021***	1.021***
	(0.148)	(0.152)	(0.155)
Lagged Variable	0.847***	0.814***	0.815***
	(0.026)	(0.027)	(0.027)
NEER	0.064***	0.008***	0.077***
	(0.011)	(0.010)	(0.011)

OIL	0.019***	0.021***	0.021***
	(0.003)	(0.004)	(0.004)
PMGS	0.019*	0.024***	0.021***
	(0.006)	(0.008)	(0.008)
D2008	0.009*	0.007	0.008*
	(0.005)	(0.004)	(0.005)
$\overline{R}^2$	-0.013***	-0.017***	-0.016**
F-statistics	(0.005)	(0.007)	(0.007)
Durbin-Watson Statistics	0.997	0.996	0.996
Prob (F-statistic)	9778	6923	6632

Notes: 1) ( ) represents White corrected heteroskedasticity standard error. 2) ***, **, * denotes 1%, 5%, 10% statistical significance respectively.

Table 14. Short-run PPP Equation Regression (Type II)

	Fixed Base Index	Chain Index	
		Method 1	Method 2
Constant	0.002***	0.002***	0.002***
	(0.0004)	(0.001)	(0.001)
NEER	0.096***	0.121***	0.120***
	(0.032)	(0.037)	(0.021)
OIL	0.011	0.017*	0.016**
	(0.007)	(0.010)	(0.007)
PMGS	0.056**	0.097***	0.093***
	(0.024)	(0.029)	(0.024)
YCB	0.001	0.0004	0.0004
	(0.001)	(0.002)	(0.001)
WAGE	-0.003	-0.004*	-0.004
	(0.002)	(0.003)	(0.003)
E_PPI	0.267*	0.188	0.184*
	(0.153)	(0.142)	(0.0945)
$\overline{R}^2$	0.379	0.388	0.382
F-statistics	18.45	19.04	18.58
Durbin-Watson Statistics	1.308	1.165	1.19
Prob (F-statistic)	0.000	0.000	0.000

Notes: 1) ( ) represents White corrected heteroskedasticity standard error. 2) ***, **, * denotes 1%, 5%, 10% statistical significance respectively.

3.2.3. Evaluation of Model Performance with Chain Index

Based on estimation results with the type I and type II samples, we evaluate the performance of the model whose dependable variable is either the fixed base index or chain index. This method was originally fitted to a macroeconometric model, the performance of which is evaluated with the forecast error between the predicted value and actual value.

The criterion of the evaluation is the size of MAE (Mean Absolute Error) or the RMSE (Root Mean Squared Error). We compare the MAE or RMSE of the sample regression results with a variety of dependent variables. We also compared the static simulation and dynamic simulation results.[12]

The MAE and RMSE is defined as follows;[13]

$$MAE(\%) = 100\sum_{t=1}^{T}\frac{1}{T}\left|\frac{\hat{Y}_t - Y_t}{Y_t}\right|, \tag{9}$$

$$SE(\%) = 100\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{\hat{Y}_t - Y_t}{Y_t}\right)^2}, \tag{10}$$

where Y_t is an endogenous variable and $\hat{Y}_t$ is the predicted variable.

[12] The static simulation refers that the values of the endogenous variables up to the previous period are used each time the model is solved. A static solution is typically used to produce a set of one-step ahead forecasts over the historical data so as to examine the historical fit of the model. A static solution cannot be used to predict more than one observation into the future. On the other hand, a dynamic simulation method refers that only values of the endogenous variables from before the solution sample are used when forming the forecast. A dynamic solution is typically the correct method to use when forecasting values several periods into the future (a multi-step forecast), or evaluating how a multi-step forecast would have performed historically. See more Eviews 6 manual.

[13] An anonymous referee indicates that RMSE can be decomposed into two: RSB (root squared bias) and RV (root variance). i.e., $RMSE^2 = RSB^2 + RV^2$.

$$RMSE = 100\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{\hat{Y}_t - Y_t}{Y_t}\right)^2}\ ;\ RSB = 100\sqrt{\left(\frac{1}{T}\sum_{t=1}^{T}\frac{\hat{Y}_t - Y_t}{Y_t}\right)^2}\ ;\ RV = 100\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{\hat{Y}_t}{Y_t} - \frac{1}{T}\sum_{t=1}^{T}\frac{\hat{Y}_t}{Y_t}\right)^2}.$$

Intuitively, RMSE is a measure of the overall quality of the estimator, RSB is a measure of the accuracy, and RV is a measure of the stability. This decomposition allows us to study the relative contributions of the bias and the variability. We appreciate the referee for this point.

Table 15 displays the long-run and short-run MAE and RMSE of the type I sample with all values below 5%. The static MAE and RMSE show the overall model fitness, and the dynamic ones show the model predictability.[14]

From Tables 15~16 and various graphs, we know that the performance of the chain index is slightly better than the fixed one in the static simulations, but this is reversed in the comparison of the dynamic simulation. With regard to the chain index performance, the method 1 chain index evidences performance superior to that of method 2. We can check this in the graphs of Figures 6 and 7. The result of type II is similar to the type I results.

We can conclude that both the fixed base index and chain index evidence stability in model specification and time series property. This means that when we estimate a price equation as to whether it is a long-run or short-run relationship it does not matter whether we select the fixed base index or the chain index. This implies that we have a high level of substitutability between the fixed base index and chain index. Method 1 is a better measure of the chain index than method 2, since its MAE and RMSE are smaller than that of method 2. This can be intuitively explained in that method 1 uses the actual weight of the data (t-3), whereas method 2 employs an estimated weight (t-2). Overall we can conclude that the chain index substituting a fixed base index provides assurance regarding the stability of price equation estimation and statistical consistency.

Table 15. The Performance of Model (Type I)

(a) Long-run Equation

Dependent Variable	Static		Dynamic	
	MAE(%)	RMSE(%)	MAE(%)	RMSE(%)
Fixed Base Index	0.480	0.683	0.730	1.001
Chain Index: Method 1	0.459	0.654	0.820	1.088
Chain Index: Method 2	0.461	0.664	0.842	1.102

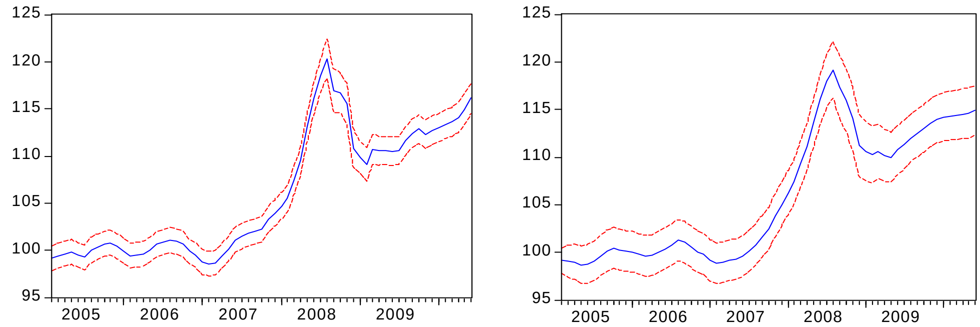
(b) Short-run Equation

Dependent Variable	Static		Dynamic	
	MAE(%)	RMSE(%)	MAE(%)	RMSE(%)
Fixed Base Index	0.576	0.857	2.690	3.415
Chain Index: Method 1	0.542	0.818	2.927	3.614
Chain Index: Method 2	0.552	0.821	2.914	3.582

[14] The dynamic MAE and RMSE are larger than the static ones since the errors between the simulated values and actual ones are accumulated as time goes on from the starting points. For more about this, see Shin (2005).

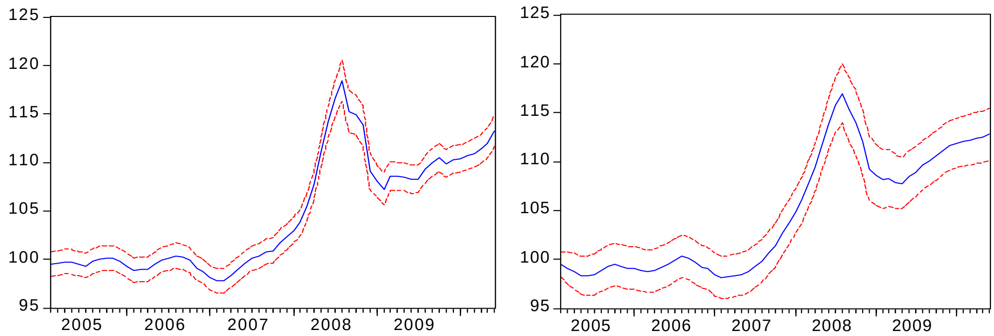
Table 16. The Performance of Model (Type II)

Dependent Variable	Static		Dynamic	
(a) Long-run Equation				
	MAE(%)	RMSE(%)	MAE(%)	RMSE(%)
Fixed Base Index	0.406	0.533	1.103	1.315
Chain Index: Method 1	0.448	0.628	1.139	1.451
Chain Index: Method 2	0.450	0.629	1.152	1.457
(b) Short-run Equation				
	MAE(%)	RMSE(%)	MAE(%)	RMSE(%)
Fixed Base Index	0.446	0.629	2.058	2.660
Chain Index: Method 1	0.507	0.733	2.677	3.305
Chain Index: Method 2	0.505	0.730	2.726	3.318



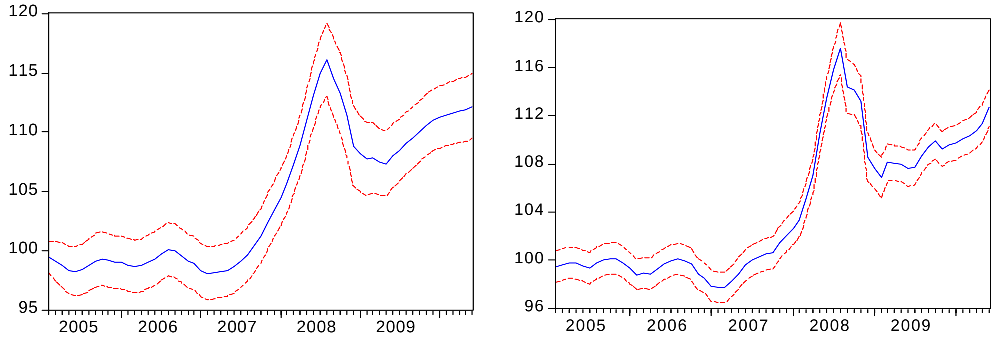
(a) Static (b) Dynamic

Figure 6.1. The Prediction of Long-run Equation of Price Index: Fixed Base Index



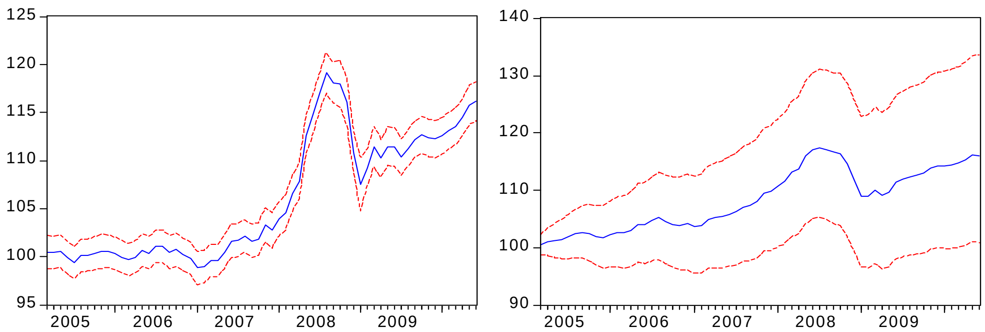
(a) Static (b) Dynamic

Figure 6.2. The Prediction of Long-run Equation of Price Index: Chain Index Method 1



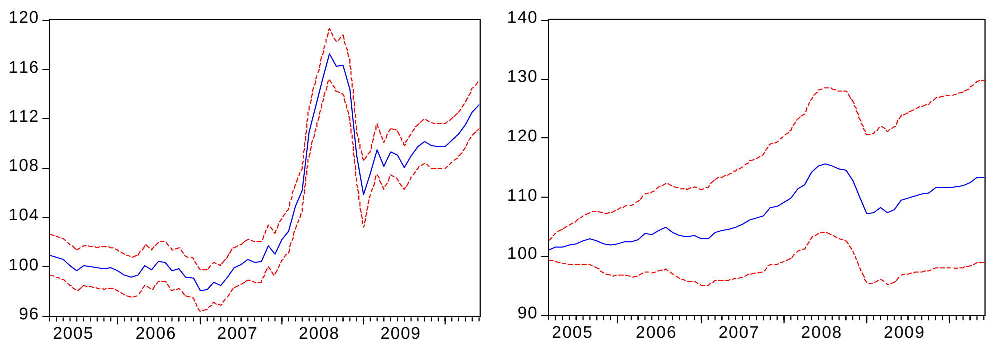
(a) Static (b) Dynamic

Figure 6.3. The Prediction of Long-run Equation of Price Index: Chain Index Method 2



(a) Static (b) Dynamic

Figure 7.1. The Prediction of Short-run Equation of Price Index: Fixed Base Index



(a) Static (b) Dynamic

Figure 7.2. The Prediction of Short-run Equation of Price Index: Chain Index Method 1

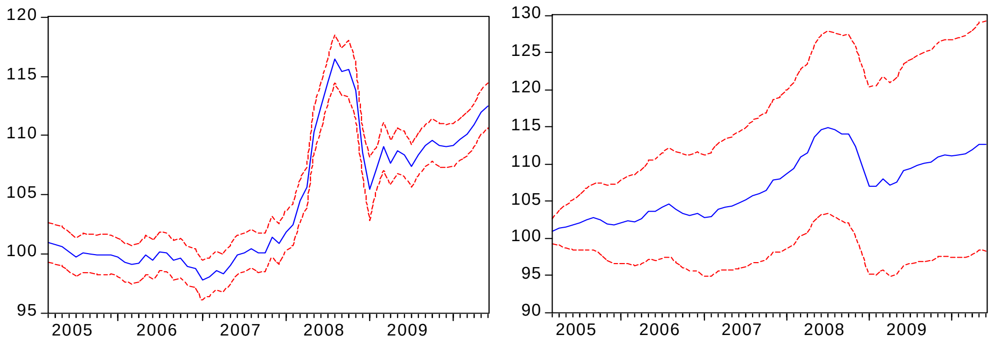


Figure 7.3. The Prediction of Short-run Equation of Price Index: Chain Index Method 2

4. CONCLUDING REMARKS

This study examined various problems when the BOK alters the methodology of the producer price index calculation. While investigating these issues, first of all, we test the statistical accuracy of two alternative chain index methods with the Diebold-Mariano test. Secondly we examined the step problem. Finally, we conducted the unit root test and evaluated the price equation performance between the fixed based and chain indices.

Our results are summarized as follows. The Diebold-Mariano tests demonstrated that method 1 did not differ significantly from method 2 at the aggregate level or lower level, but the former has a relatively smaller error than the latter. This can be intuitively explained by the fact that method 1 uses the actual weight of the data (*t*-3) whereas method 2 employs an estimated weight (*t*-2). By this reason, we can conclude that method 1 is slightly better than method 2 among the chain indices.

Secondly, we compare the MAE and RMSE of the price equations of the fixed base and chain indices. Both unit root test and the comparison of the model performance evaluation reveal no critical difference, thus confirming a stability over the two indices. In particular, the substitutability of the chain index for the fixed base index is highly obtained, regardless of the time horizon. As similar as the DM test results are in section 2, method 1 is clearly better than method 2 in the statistical consistency test. Overall, we can confidently assert that the chain index provides statistical consistency and stability over the fixed base index.

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