The Korean Economic Review
Volume 31, Number 1, Summer 2015, 145-176.

Disaggregated Approach to Measuring Core Inflation*

Hyok Jung Kim** · Young Se Kim***

To distinguish inflation signal from transient noise, monetary policymakers have long used core inflation measures. Using disaggregate CPI data for Korea, this paper reviews extant measures of core inflation and documents several important empirical features of the measures. Our theoretical analysis demonstrates that the stylized facts on the extant measures are not compatible with a single stochastic trend, and our empirical findings strongly support this view. Motivated by price divergence, we model disaggregate prices in multiple-component structure and find there are four persistent components together with a group of diverging items. Having identified distinct common components, we employ a new core inflation measure based on a limited influence estimator for each convergence club. The new core inflation dominates the extant measures in its ability to account for central tendency of price distribution and for generating low variance of price changes. In addition, it forecasts the underlying trend of headline CPI inflation more accurately than the extant core inflation indicators do.

JEL Classification: C33, C38, E31, E37, E50
Keywords: Core Inflation, Time-varying Common Factor Model, Clustering Analysis, Divergence

I. Introduction

While monetary policymakers have long used core inflation to account for the current inflation rate and where it is headed, there is no consensus about the definition of core inflation. This paper is motivated by the long-standing interest in

---

Received: Sept. 17, 2014. Revised: Jan. 21, 2015. Accepted: March 2, 2015.
* This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2012S1A5A8023703).
** Department of Economics, Sungkyunkwan University, 53 Myeongnyun-dong 3-ga, Jongno-gu, Seoul 110-745, Korea; E-mail: hyokzzang@gmail.com
*** Corresponding Author, Associate Professor, Department of Economics, Sungkyunkwan University, 53 Myeongnyun-dong 3-ga, Jongno-gu, Seoul 110-745, Korea; E-mail: youngsekim@skku.edu.

measuring core inflation, and compares conventional measures of core inflation in their ability to consistently estimate the underlying trend of inflation and to generate low volatility. Using disaggregate Consumer Price Index (CPI) data for Korea, we attempt to document several salient features of core inflation measures and their potential drawbacks under price divergence. To overcome serious shortcoming of extant core measures, we employ a new measure of core inflation based on a multiple-component model and explore whether it dominates the extant measures in terms of standard statistical criteria.

Notwithstanding its importance, a clear definition of core inflation has been rarely provided.[1] However, a common conclusion that economists agree is that a proper measure of core inflation must exhibit low volatility and have an ability to predict the underlying trend of inflation. In accordance with these fundamental ingredients, several measures of core inflation have been suggested to remove a great deal of high frequency noise in overall inflation. Why do forecasters and monetary policymakers focus on core inflation?[2] Intuitively, core inflation is regarded as a useful measure in tracking future inflation since it eliminates transitory shocks that monetary policy does not want to react to. That is, they want to know not only what current headline inflation is, but also, and more importantly, where headline inflation is expected to be headed. A common argument for filtering out some transitorily volatile components is that these prices are quickly reversed, and thus often do not require a policy response, while they have substantial effects on headline inflation.[3] Moreover, shocks on certain components of CPI basket, such as food and energy, affect the level of their prices, but not necessarily their mid- or long-run inflation rates. In particular, since the early 1990s, it has become increasingly crucial to have consistent measure of inflation as a number of central banks have adopted inflation targeting.[4]

On the contrary, the other line of research, e., Bullard (2011), suggests dropping

---

[1] One of main reasons is that core inflation can differ across monetary policy regimes (Smith, 2005).

[2] Note that researchers have often pointed out the limited role of core inflation particularly for inflation targeters in recent years. However, this does not necessarily imply that the notion of core inflation *per se* is no longer useful. In practice, most central banks also monitor the core inflation as a guide in setting policy that is appropriate to achieve the inflation target in the future. The core measures are often used as operational guides for monetary policy in pursuit of the target for headline inflation in the absence of corrective policy action. For a detailed discussion with regard to the role of core inflation under inflation targeting, see Smith (2005).

[3] In his speech, Mishkin (2007) also said that “what central bankers are truly concerned with—both for the purposes of internal deliberations and for communications with the public—is the underlying rate of inflation going forward, and core inflation can be a useful proxy for that rate. Thus, focusing on core inflation can help prevent a central bank from responding too strongly to transitory movements in inflation.”

[4] For example, Svensson (1997) argues that strict inflation targeting implies inflation forecast targeting, and core inflation can be the optimal intermediate target for monetary policy.

the emphasis on core inflation, especially on the excluded-item measure.[5] There are several arguments against a focus on core inflation in monetary policy discussion. By removing historically volatile components, monetary policymakers may not take account of what households indeed care about. For instance, despite the fact that households pay for food and energy items almost every day, some prominent core measures deliberately exclude those components. Second, it is possible for monetary policymakers to miss potentially important early signals of inflation, if their prices are, by construction, excluded. Lastly, as we will discuss in detail in Section 2, not all food and energy prices are volatile.[6] By removing all food and energy items, monetary policymakers may restrict themselves and do not fully utilize all available information on prices when forecasting future inflation.

To overcome the potential drawbacks of excluded-item measures, alternative measures of core inflation have been proposed.[7] These measures are customarily constructed using a cross-sectional filter, which eliminates outliers of disaggregate prices in CPI components. Instead of excluding certain fixed components, Bryan and Cecchetti (1994), Smith (2004), and Dolmas (2005), among others, suggest using limited influence estimators, such as median and trimmed mean. A limited influence estimator removes components with price changes in the tails of the distribution, and thus excluded components are allowed to vary over time. A number of empirical studies on evaluation of core measures routinely document that a limited influence estimator outperforms excluded-item measures in terms of volatility and forecastability. However, this approach is also not free of the unrealistic assumption that all individual prices can be modeled by a single stochastic trend, which presumably ignores the possibility of some diverging prices from the common factor.[8]

Motivated by the possibility of price divergence that affects the effectiveness of core measures, this paper first explores some salient features of conventional core inflation measures, such as median, trimmed mean, and excluded-item measures, during the sample period, 1985-2013. All extant core inflation measures are found to be less volatile than headline CPI inflation, but they tend to underestimate the underlying trend of inflation even in the long run. We also document that some food and energy items are much less volatile and exhibit substantial persistence.

---

[5] Nonetheless, this measure is the most commonly used measure of core inflation by monetary authorities since it is simple and easy to communicate with the public (Wynne, 1999; Clark, 2001).

[6] For example, most of the volatilities of energy prices come from the variations in prices of fuels and lubricants for personal transport equipment, with much less price volatility in other energy categories, such as gas and electricity.

[7] In practice, a simple way of reducing outlier effects is to average data over periods longer than one month and, as a consequence, central banks do not respond to a single monthly inflation rate.

[8] Recently, Greenaway-McGrevy, Kim, and Sul (2014) also show that, under price divergence which is apparent in the US data, any extant measure would no longer be the consistent estimator of core inflation, and individual prices can be better explained by a multiple-component model.

This suggests conventional excluded-item measures may excessively remove high-price items to smooth out headline inflation. Next, surprisingly, the disparity between the measures does not shrink over time for any pair of extant core measures. Since the extant measures of core inflation are virtually based on a single-component model, this empirical finding is not compatible with the assumption of price convergence in the model. One possible explanation why there exist differences in core inflation measures in the long run is to allow some individual prices to diverge from the common factor. Our empirical finding from the log-t convergence test due to Phillips and Sul (2007) suggests that there is strong evidence against overall price convergence. Thus this points out that the conventional attempts to measure core inflation did not take the possibility of price divergence into consideration.

Thus, in this paper, we consider more general case where individual prices are modeled in a multiple-component structure, where price changes for the CPI items within each convergence club share the same persistent component. We analytically show that the multiple-component model is compatible with the stylized facts of core inflation estimators regarding volatility and disparities among the measures. Our empirical application also supports the theoretical results as there exist four distinct persistent components. Following Greenaway-McGrevy, Kim, and Sul (2014), we introduce a new measure of core inflation for Korea based on the multiple-component structure. That is, given overall price divergence, a limited influence estimator can be used to estimate the common component within each convergence club. A consistent estimator of core inflation is obtained by taking a weighted average of the limited influence estimators. Our empirical analysis demonstrates that the new core inflation exhibits lower volatility and predicts headline inflation more accurately than the conventional measures of core inflation considered in this paper.

The rest of the paper is organized as follows. Section II reviews the definitions of core inflation and commonly used core inflation measures. By investigating time-series properties of extant core inflation measures, the section also describes stylized facts and potential limitations of the measures. In section III, we consider single-component model to examine whether the extant measures of core inflation are compatible with price divergence. By generalizing the single-component model to permit multiple persistent factors, section IV estimates the number of common trends in disaggregate prices and discusses characteristics of convergence clubs as well as diverging CPI items. In section V, we employ a new measure of core inflation based on our clustering analysis and compare this to the extant core measures with regard to volatility and forecastability. Our conclusions are discussed in section VI.

II. Extant Core Inflation Measures: Facts and Limitations

This section reviews definitions of core inflation. In addition, we discuss conventional core measures with a special emphasis on their potential drawbacks. Some important time-series properties of the core inflation rates with regard to central tendency and volatility will be rigorously explored.

2.1. Definitions of Core Inflation

Due to lack of a precise definition of core inflation, researchers disagree about how best to measure core inflation.[9] For instance, Bryan and Cecchetti (1994) and Cogley (2002) define core inflation as "the component of price changes that is expected to persist over medium-run horizons of several years." In line with this definition, Dolmas (2005) and Mishkin (2007) also define it as "a measure of inflation that excludes the rate of increase of prices for certain volatile components in price indexes."[10] This class of definitions relies on the presumption that headline measures of inflation including all items in market basket are inherently noisy and cannot be used as an appropriate indicator of the future movement of underlying inflation that monetary authority should focus on. Thus, a proper measure of core inflation should be able to smooth volatile movements in particular prices in order to distinguish the inflation signal from the temporary noise component.[11] Another important ingredient that a measure of core inflation must possess is its ability to predict the path of future inflation. Blinder (1982, 1997) and Smith (2004), among others, define core inflation as "the best forecaster of inflation." In sum, despite the fact that there is no clear definition of core inflation, a number of discussions of core inflation suggest that a good measure of core inflation must be less volatile than headline inflation and has an ability to forecast future inflation.

2.2. Extant Measures of Core Inflation

The core inflation is conventionally measured by using the data on prices of individual items in consumer's consumption basket. The preferred measure of core inflation in many countries is an excluded-item measure by removing some components of price indices that are historically highly volatile, such as food and

[9] The concept of core inflation was first introduced by Gordon (1975) for political purposes. Later, Eckstein (1981) defined core inflation as "the trend increase in the cost of the factors of production."

[10] Similarly, Bryan, Cecchetti, and Wiggins (1997) use a definition of core inflation, "a measure of inflation that excludes the rate of increase of prices for certain volatile components in price indexes."

[11] As an alternative approach based on monetary neutrality, Quah and Vahey (1995) define core inflation as "the component of measured inflation that has no (medium- to) long-run impact on real output." However, implementing this definition based on the long-run neutrality of inflation requires a structural model, which is hard to formulate and to evaluate (Bryan and Cecchetti, 1994).

energy.[12] The rational for excluding food and/or energy is that those items are frequently subject to high frequency price change that are unlikely to be related to the underlying trend in inflation. Moreover, non-monetary aspects, such as weather and seasonal factors, generally drive much of the price variation. In addition, this measure is probably the most widely used by monetary authority mainly due to the fact that it is simple and easy to communicate with the public (Wynne, 1999; Clark, 2001). In particular, the Bank of Korea (BOK) also uses this type of core inflation measure, the less agricultural products and oil Consumer Price Index (CPI) inflation.[13]

[Table 1] Volatility and Persistence of CPI Components

CPI component	Standard Deviation	Persistence rank (1=highest)
Vegetables & seaweeds †	68.54	65
Other fuels and energy †	46.19	64
Fruit †	40.50	49
Fuels and lubricants for personal transport equipment †	34.53	50
Food products n.e.c. †	31.58	53
Telephone and telefax equipment	31.47	44
Footwear	30.26	67
Tobacco	27.55	58
Gas †	25.68	21
Hospital services	24.79	63
Pre-primary and primary education	24.09	1
Personal effects n.e.c.	24.05	43
Passenger transport by air & sea and inland waterway	23.09	57
Newspapers and periodicals	22.76	56
Meat †	22.13	52
Passenger transport by railway	20.82	59

[12] In the US, the Federal Reserve has used the less food and energy Personal Consumption Expenditure (PCE) as its preferred measure since February 2000. Japanese core CPI inflation removes food but does include energy prices. The Bank of Japan also publish core-core measure of CPI inflation excluding both food and energy prices, which is the same as the US core inflation. Other countries exclude other components besides food and energy. For example, the Bank of Canada excludes the eight most volatile components. The Reserve Bank of New Zealand removes credit services and interest charges while the Bank of England excludes mortgage interest payments.

[13] Note that, as an alternative indicator of core inflation, the BOK also releases data on the less food and energy CPI inflation excluding a larger set of items than the less agricultural products and oil CPI. Both measures display the same systematic pattern. However, the less agricultural products and oil Consumer Price Index (CPI) inflation appears to be relatively more persistent and thus performs better in tracking the underlying inflation trend.

Oils and fats †	20.80	20
Coffee, tea and cocoa †	20.47	11
Equipment & spare parts and accessories for information processing	20.16	34
Other services	19.54	19
Domestic services and household services	18.79	7
Milk, cheese and eggs †	18.66	46
Secondary education	18.39	33
Postal services	18.20	61
Other recreational items and equipment, gardens and pets	17.38	66
Sugar, jam, honey, chocolate and confectionery †	16.46	18
Water & Sewage disposal charge	15.50	29
Outpatient services	15.49	45
Fish and seafood †	14.77	48
Passenger transport by road	14.61	41
Accommodation services	14.27	60
Telephone and telefax services	12.94	62
Tertiary education	12.71	4
Furniture and furnishings, carpets and other floor coverings	12.47	55
Audio-visual equipment	12.22	8
Cleaning, repair and hire of clothing	11.98	5
Non-durable household goods	11.98	27
Hairdressing salons and personal grooming establishments	11.85	37
Other services in respect of personal transport equipment	11.58	28
Garment for men	11.55	39
Electricity †	11.49	40
Maintenance and repair of the dwelling	11.42	22
Other major durables for recreation and culture	11.26	54
Garment for women	10.54	9
Private institutions for adults & other education	10.19	23
Household electronic appliance & Household appliances	10.14	51
Books	10.03	47
Stationery	9.93	14
Garment for children & infants	9.79	38
Bread and cereals †	9.57	25
Other services relating to the dwelling n.e.c.	9.37	30
Household textiles	9.17	10
Private institutions and supplementary education	8.80	12

Mineral waters, soft drinks, fruit and vegetable juices †	8.61	13
Alcoholic beverages	8.43	35
Casual wear	8.41	24
Glassware, tableware and household utensils	8.34	26
Purchase of vehicles	8.30	42
Tools and equipment for house and garden	7.17	31
Electric appliances & other appliances, articles and products for personal care	6.71	32
Medical products and therapeutic appliances	6.71	16
Pharmaceutical products	6.60	36
Catering services	6.09	3
Recreational and sporting services	5.39	6
Cultural services	4.76	17
Other articles of clothing and clothing accessories	4.69	15
Actual rentals for housing	3.66	2

Note: The sample period is 1986:M1-2013:M6. For each component, standard deviation is calculated for annualized month-to-month inflation rate. Standard deviation for headline CPI inflation rate is 4.10. Persistence is estimated as the first-order autocorrelation coefficient. † denotes CPI component excluded in calculating the less food and energy CPI inflation.

One serious shortcoming of excluded-item measures of core inflation is that households almost daily pay for food and energy items, which are by definition omitted from the measure, and thus monetary policymakers do not take account of what households indeed do care about. Next, even if the overall food and energy price components are regarded as being highly volatile, the analysis of disaggregated CPI data routinely confirms that certain food and energy items exhibit much less volatility and substantial persistence than other items in CPI basket, whereas some non-food and non-energy prices appears to be remarkably volatile and less persistent.[14] Table 1 evidently shows that some specific food and energy items appear to be much less volatile than others, such as electricity, mineral waters, soft drinks, fruit and vegetable juices, bread and cereals, and fish and seafood. At the same time, telephone and telefax equipment, footwear, hospital services, and pre-primary and primary education are listed as some of the most variable non-food and non-energy components.[15] In addition, some volatile food and energy items, such

[14] Accordingly, using US disaggregate CPI data, Clark (2001) develops CPI excluding the eight most volatile components as a measure of core inflation—fuel oil and other household fuel commodities; motor fuel; meats, poultry, fish, and eggs; fruits and vegetables; infants' and toddlers' apparel; public transportation; used cars; and other apparel commodities.

[15] The BOK commonly uses CPI excluding agricultural products and oil as the core inflation measure, but using this definition requires a higher level of disaggregation. Thus we consider the less food and energy CPI inflation for this analysis. Note also that a similar result was found for 12-month

as gas and oil and fats, display substantial persistence. Those components are likely to provide useful information about the underlying inflation trend, and thus it is better not to exclude. Finally, it is worth pointing out that a certain set of components that are excluded are not volatile all the time which makes excluded-item measures not suitable measure of core inflation. Table 2 presents 10 most frequently listed CPI components in the left and right tails of the distribution. Even for the most volatile food and energy components, more than a half of the sample period, they are not in the lowest and highest 10% of the distribution. Moreover, some non-food and non-energy items, such as equipment & spare parts and accessories for information processing, telephone and telefax equipment, and pre-primary and primary education, frequently belong to the group of outlying CPI components.[16]

[Table 2] Outlying CPI Components

CPI component	Frequency (%)
Panel I: Components in the lowest 10%	
Vegetables & seaweeds †	44.2
Equipment & spare parts and accessories for information processing	41.5
Fruit †	36.1
Audio-visual equipment	32.4
Fuels and lubricants for personal transport equipment †	30.3
Telephone and telefax equipment	30.3
Personal effects n.e.c.	28.2
Oils and fats †	27.6
Meat †	25.8
Other recreational items and equipment, gardens and pets	23.9
Panel II: Components in the highest 10%	
Vegetables & seaweeds †	42.1
Fruit †	35.8
Other fuels and energy †	30.0
Fuels and lubricants for personal transport equipment †	26.7
Meat †	25.8
Fish and seafood †	25.5
Food products n.e.c. †	24.5
Personal effects n.e.c.	21.5
Pre-primary and primary education	20.9
Domestic services and household services	20.0

Note: The sample period is 1986:M1-2013:M6. The number for each CPI component represents the frequency of month-to-month inflation rate that belong in the highest or lowest 10% of the distribution. † denotes CPI component excluded in calculating the less food and energy CPI inflation.

inflation rates.

[16] In Section 4, our clustering analysis suggests some of outlying components are found to be diverging from a common factor that must be excluded in estimating core inflation.

Next, instead of using the same fixed set of components from overall CPI, another important line of approaches to core inflation is to remove items with price change in the tails of the distribution and thus excluded items are permitted to change periodically. According to the menu-cost model of firm-level pricing behavior by Ball and Mankiw (1995) in which firms setting their prices face a one-time cross-sectional shock, only firms whose shocks are sufficiently large decide to change their prices ahead of schedule. As a result, when the shocks are asymmetrically distributed, the conventional mean price level will temporarily change because the tails of the distribution are no longer average out properly. For example, negative skewness of the distribution causes a transitory decrease in inflation. To calculate the persistent component of aggregate inflation reflecting the underlying trend in inflation, Bryan and Cecchetti (1994) and Bryan, Cecchetti, and Wiggins (1997), among others, propose to use limited influence estimators that average the central part of a distribution after truncating the outlying observations. Examples of limited influence estimators include (weighted) median (Bryan and Pike, 1991; Bryan and Cecchetti, 1994; Smith, 2004) and trimmed mean (Bryan, Cecchetti, and Wiggins, 1997; Dolmas, 2005).[17] By construction, a limited influence estimator as a measure of core inflation is less volatile than headline inflation since it is less sensitive to skewness of the distribution.[18] In addition, by excluding transient component of price changes, limited influence estimators tend to display relatively substantial persistence.

One of important common features of extant core inflation measures discussed in this paper is that they utilize cross-sectional filters, whereby some items are removed before averaging individual price changes.[19] As a consequence, the measures of core inflation can be described by a single-component model,

$$\pi_{it} = \pi_t^c + \pi_{it}^o, \quad i = 1,2,\cdots,N \quad \text{and} \quad t = 1,2,\cdots,T, \tag{1}$$

where π_{it} is inflation rate for the ith item of CPI market basket at time t, π_t^c is common component across all items in the basket and thus can be interpreted as a measure of core inflation. Finally, π_{it}^o is transitory or idiosyncratic component for the ith item.[20] An important property of this model having a single common

[17] The median is a special case of trimmed mean as it is a 50% symmetric trimmed mean. Dolmas (2005) suggests asymmetric trimmed mean and the amount of being trimmed is calibrated to match ex-post long-term trend of inflation.

[18] Similarly, excluded-item measures discussed earlier also exhibit lower volatility since the excluded items are commonly present in the tails of the distribution.

[19] Despite the fact that a simple high frequency filter, e.g., Cogley (2002), also has an ability to yield a measure of core inflation that is less volatile than headline inflation and to predict the path of future inflation, Bryan and Cecchetti (1994) point out that such measures are untimely from the policy-making perspective.

[20] Note that asymmetry in the distribution of $\{\pi_{it}^o\}_{i=1}^N$ is the main source of transitory volatility in

stochastic trend is that year-to-year variations in π_{it} can be dominated by π_{it}^{o}, but, over the long periods of time, the variation in headline inflation comes from π_t^c. Thus when individual prices have a tendency to converge over time, any of limited influence estimators can be a consistent measure of core inflation. That is, under price convergence, differences between the extant measures of core inflation must shrink over time.

What if prices in the CPI market basket do not converge over time? In other words, can the single-component model of Eq. (1) be a proper model accounting for dynamic patterns of aggregate inflation? In the presence of multiple persistent components, the extant core inflation measures become biased even in the long run. Let's consider a simple case where headline inflation is governed by two common stochastic trends, $\pi_t^{c_1}$ and $\pi_t^{c_2}$, as shown in Greenaway-McGrevy, Kim, and Sul (2014),

$$\pi_{it} = \begin{cases} \pi_t^{c_1} + \pi_{it}^{o} & \text{for } i \in S_1 \\ \pi_t^{c_2} + \pi_{it}^{o} & \text{for } i \in S_2 \end{cases}, \tag{2}$$

where S_j is a subgroup of individual items dominated by the common factor $\pi_t^{c_j}$ for $j = \{1,2\}$ and $\pi_t^{c_1} - \pi_t^{c_2} \neq 0$ on average under price divergence. Accordingly, a consistent estimator of core inflation is an weighted mean of common factors given by

$$\pi_{it} \equiv \omega_1 \pi_t^{c_1} + \omega_2 \pi_t^{c_2}, \tag{3}$$

where $\omega_j = N_j / N$ denotes the relative weight between two subgroups based on the number of items in subgroup j, N_j. It is easy to show that any of limited influence estimator becomes biased. For example, if $\pi_t^{c_1} > \pi_t^{c_2}$ and $\omega_1 > \omega_2$, the median estimator or any symmetric trimmed mean estimator becomes closer to $\pi_t^{c_1}$ than to $\pi_t^{c_2}$ and thus overstate the underlying inflation trend.[21] Thus, before modeling disaggregate inflation, it is inevitable to explore whether individual prices in the CPI market basket display overall convergence.

2.3. Time-Series Properties of Extant Core Inflation Measures

To evaluate core inflation measures, we first establish some important time-series properties of commonly used core measures in Korea: (i) the less agricultural products and oil CPI inflation published by the BOK (π_t^{excl}), (ii) the median CPI

aggregate inflation in Ball and Mankiw (1995) model.

[21] Similarly, this result holds for excluded-item measure. For a detailed discussion, see Greenaway-McGrevy, Kim, and Sul (2014).

inflation (π_t^{med}), and (iii) a trimmed mean CPI inflation (π_t^{trim}).[22] While the CPI excluding agricultural products and oil CPI inflation is publicly available, neither the median CPI inflation nor a trimmed mean CPI inflation is officially released.[23] We construct the median and trimmed mean measures of core inflation using disaggregate CPI components obtained from the Statistics Korea. Despite the fact that the most disaggregate level of the CPI (481 components) may be ideal for this analysis, we use 67 CPI components to construct the limited influence estimators to achieve a sufficiently large number of time-series observations mainly due to data availability.[24]

Table 3 presents some descriptive sample moments of the core inflation measures together with aggregate CPI inflation. Both annualized month-to-month and 12-month inflation rates are considered for full sample period, 1986:M1-2013:M6, as well as for five different sub-samples. A couple of important findings are as follows. First, in accordance with the concept of core inflation, any measure of core inflation exhibits lower volatility than headline inflation. In particular, the median CPI inflation consistently displays the lowest standard deviation. Second, surprisingly, all three measures of core inflation do not show central tendency as their time-series means are persistently smaller than headline inflation over full sample or any sub-samples considered.[25] These two stylized facts are well illustrated in Figure 1.[26] The extant measures of core inflation are much smoother than overall CPI inflation and tend to under estimate the trend of underlying inflation.

[22] Following Bryan and Cecchetti (1994), we use a 10% symmetric trimmed mean estimator. Empirical results with an alternative amount of truncation are available from the authors upon request.

[23] For this analysis, without loss of generality, we consider simple measures of core inflation in the sense that expenditure share is identical across CPI components. Note that, although expenditure-weighted measures are also widely used in practice, we found that the introduction of expenditure weight does not have no qualitatively different implications with regard to the stylized facts discussed in this paper.

[24] The list of 67 individual items is presented in Table 1.

[25] This downward bias of extant core measures can be due to the fact that there exist certain CPI components displaying long-term downward trend for their prices that should be removed to define an appropriate indicator of underlying inflation. This issue will be extensively discussed in Section 4.

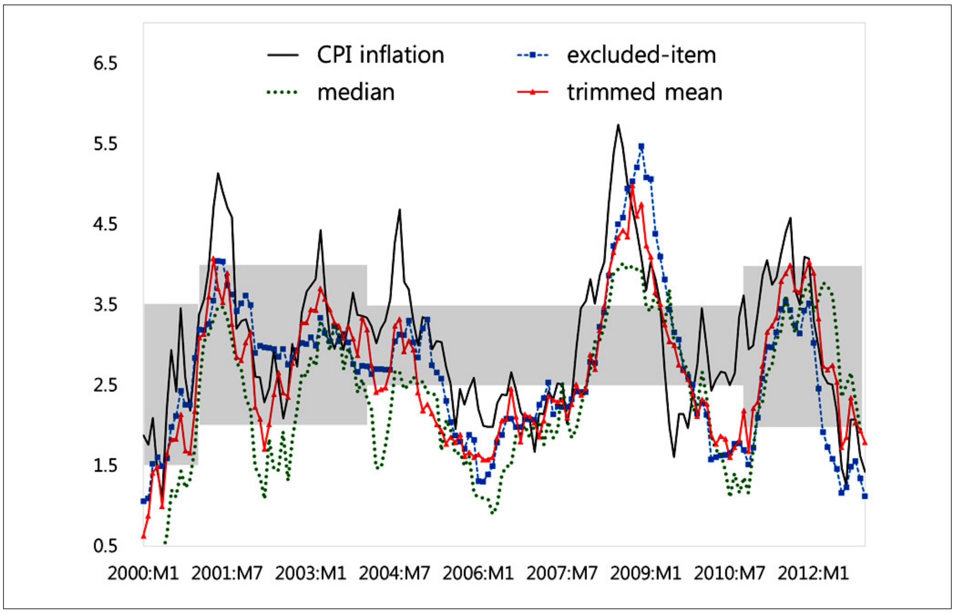
[26] This figure plots 12-month CPI and the core inflation rates during the period of inflation targeting regime in Korea, 2003-2013. The main results do not change for either month-to-month inflation rate or sample period.

[Table 3] Descriptive Statistics for Core Inflation Measures

	Time-series mean						Time-series standard deviation					
	Full sample	86-90	91-95	96-00	01-05	06-13	Full sample	86-90	91-95	96-00	01-05	06-13
Panel I: month-to-month inflation												
π_t^{CPI}	4.10	5.64	5.74	3.79	3.16	2.82	4.48	5.28	3.97	6.03	2.94	2.99
π_t^{excl}	3.78	5.50	5.68	2.99	2.77	2.54	3.36	4.25	3.41	3.67	1.69	1.94
π_t^{med}	2.09	2.39	2.94	1.80	1.59	1.87	1.40	1.34	1.21	2.21	0.76	0.78
π_t^{trim}	3.11	4.33	4.57	2.30	2.26	2.41	2.37	2.29	2.40	3.20	1.15	1.31
Panel II: 12-month inflation												
π_t^{CPI}	4.15	5.27	6.02	3.89	3.28	2.89	2.09	2.36	1.71	2.34	0.71	1.05
π_t^{excl}	3.82	5.30	5.70	3.25	2.94	2.54	1.96	1.95	1.33	2.09	0.49	1.08
π_t^{med}	2.98	3.26	4.21	2.89	2.35	2.46	1.46	1.08	1.36	2.14	0.64	0.92
π_t^{trim}	3.75	4.96	5.77	3.13	2.77	2.65	1.96	1.74	1.81	2.11	0.64	0.91

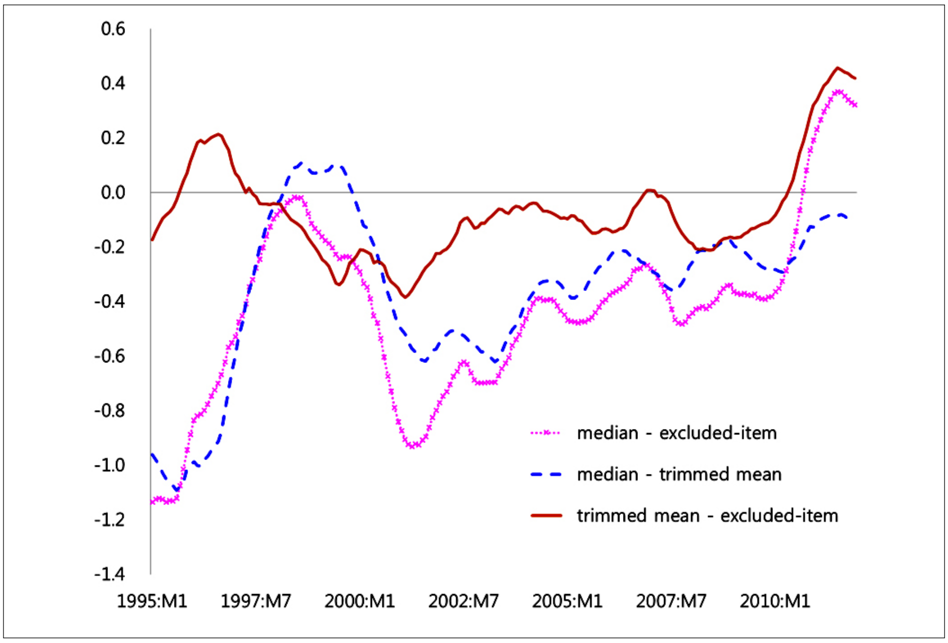
Note: For month-to-month inflation, time-series mean and standard deviation are calculated from annualized monthly inflation rates.

[Figure 1] 12-month Headline CPI and the Core Inflation Rates



Note: The shaded areas represent inflation target band. The BOK uses mid-term target band based on the less agricultural products and oil CPI inflation over the period of 2004-2007.

[Figure 2] Disparities between the Core Inflation Measures



Note: This figure plots differences between 12-month core inflation rates (3-year centered moving average).

Another important finding from sub-sample analysis is that, for a given sub-sample, time-series means vary considerably across the measures of core inflation. Moreover, as shown in Figure 2, disparities among the measures do not tend to diminish over the long period of time. Accordingly, the extant core measures do not converge over time, and thus none of the indicators may not be a consistent estimator of core inflation. Following Greenaway-McGrevy, Kim, and Sul (2014), we consider a regression model testing whether the disparities disappear over time,

$$y_t^a - y_t^b = \alpha + \beta t + \varepsilon_t, \text{ where } y_a, y_b \in \{\pi^{excl}, \pi^{med}, \pi^{trim}\}. \tag{4}$$

To investigate if any pair of core measures has a tendency of convergence, we test $H_0 : \alpha = \beta = 0$.[27] Empirical results are presented in Table 4. Except for month-to-month inflation gap between π_t^{med} and π_t^{trim}, all core measures appear to be diverging over time as $\hat{\beta}$ is significantly different from 0 even at the 1% level.

[Table 4] Divergence between Core Inflation Measures

	month-to-month		12-month	
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{\beta}$
	-3.165	0.009	-2.019	0.007
$\pi_t^{med} - \pi_t^{excl}$	(0.437)	(0.002)	(0.265)	(0.001)
	$F = 40.34$		$F = 217.91$	
	-1.893	0.005	-1.784	0.006
$\pi_t^{med} - \pi_t^{trim}$	(0.231)	(0.001)	(0.217)	(0.001)
	$F = 1.20$		$F = 202.96$	
	-1.272	0.004	-0.235	0.001
$\pi_t^{trim} - \pi_t^{excl}$	(0.282)	(0.001)	(0.143)	(0.001)
	$F = 11.26$		$F = 10.18$	

Note: The numbers in parentheses are standard errors. F denotes F statistic for $H_0 : \alpha = \beta = 0$.

III. Testing Overall Convergence of Disaggregate Prices

In this section we first consider the single-component model given by Eq. (1) to discuss the properties of the excluded-item measure and limited influence estimator of core inflation. Next, by utilizing log-t convergence test, the empirical validity of the single-component model is examined.

[27] As a special case, two measures have distinct paths, when $\alpha \neq 0$ but $\beta = 0$.

3.1. Single-Component Model

Under the single-component model or homogeneous factor loading representation, individual price changes are assumed to have two independent elements, the common factor (π_t^c) and transitory factor (π_{it}^o). By assuming an equal expenditure share, a simple cross-sectional mean can be treated as headline inflation,

$$\pi_t = \pi_t^c + N^{-1}\sum_{i=1}^{N}\pi_{it}^o . \tag{5}$$

The extant measures of core inflation regard $N^{-1}\sum_{i=1}^{N}\pi_{it}^o$ as the primary source of short-term variations in headline inflation. In terms of factor-loading representation, let π_{it}^o be given by

$$\pi_{it}^o = t^{\alpha_i^*}\zeta_{it}, \quad \text{where} \quad \zeta_{it} \sim iid(0,\sigma_i^2) . \tag{6}$$

If $\alpha_i^* > 0$ for some i , then the transitory component becomes increasingly volatile over time because $\pi_t^o = O_p(t^{\alpha^*}N^{-1/2})$, where $\alpha^* = \max\{\alpha_i^*\}$, implying the variance of π_{it}^o is homogeneous.[28] That is, for any t ,

$$V(\pi_t \mid \pi_t^c) = (\pi_t^c)^2 + V(\pi_t^o) = (\pi_t^c)^2 + O_p(t^{2\alpha^*}N^{-1}) . \tag{7}$$

Recall that, as shown in Section 2, conventional core inflation measures are all less volatile than headline inflation in the data. Under (5) and (6), however, limited influence estimators can be as volatile as headline inflation, which clearly violate the stylized fact. For example, if the distribution of π_{it}^o is symmetric, cross-sectional median estimator, π_t^{med} , will be the same as cross-sectional mean estimator,[29] and hence

$$V(\pi_t^{med}) = (\pi_t^c)^2 + O_p(t^{2\alpha^*}N^{-1}) . \tag{8}$$

In addition, since the distribution of π_{it}^o is assumed to be symmetric, all extant measures must estimate the core inflation, π^c , $N-$asymptotically. That is,

[28] For a more general case where the variance of π_{it}^o is heterogenous across i , see Greenaway-McGrevy, Kim, and Sul (2014).

[29] Similarly, a symmetric trimmed mean estimator will have the same bound as long as the amount of truncation is time invariant. On the other hand, given this empirical specification, an excluded-item measure, π_t^{excl} , display less volatility than headline inflation.

$$\underset{N\to\infty}{\text{plim}}\,\pi^{med} = \underset{N\to\infty}{\text{plim}}\,\pi^{trim} = \underset{N\to\infty}{\text{plim}}\,\pi^{excl} = \pi^{c}\,. \tag{9}$$

Apparently, this is not consistent with the salient feature of the data, persistent deviations between core inflation measures, even in the long run.

Next, we now consider a more general case, time-varying factor loading representation.[30] Following Phillips and Sul (2007), we model individual log prices in CPI market basket as

$$p_{it} = \delta_{1,it}\theta_{1t} + \cdots + \delta_{M,it}\theta_{Mt} + \epsilon_{it} = \sum_{m=1}^{M}\delta_{m,it}\theta_{mt} = \delta_{it}\theta_{t}\,, \tag{10}$$

where $\delta_{it} \equiv \theta_t^{-1}\sum_{m=1}^{M}\delta_{m,it}\theta_{mt} + \theta_t^{-1}\epsilon_{it}$.[31] The common component is given by θ_t and M denotes the number of the common factors. In particular, δ_{it} measuring relative transitional effects from θ_t can be modeled by

$$\delta_{it} = \delta_i + L(t)^{-1}t^{-\alpha_i} \tag{11}$$

where $\psi_{it} \sim iid(0,\sigma_i^2)$ and $L(t)$ is a slow moving function. This implies that individual prices converge to θ_t when $\delta_i = \delta = 1$ and $\alpha_i \geq 0$ for all i. For instance, if p_{it} follows a quasi-trend stationary process given by $\pi_{it} = a_i t^{\tau} + p_{it}^{o}$, where $\tau = \alpha_i^{*}$, and $p_{it}^{o} = \psi_{it}$, then, under the null of overall convergence, all individual prices will share the same stochastic trend so that

$$\pi_{it} = \pi_t^{c} + \Delta p_{it}^{o} + O_p(t^{-1})\,, \tag{12}$$

which is asymptotically equivalent to the homogeneous factor loading representation, Eq. (1). Again, all conventional core inflation measures become consistent for any τ, which is not consistent with what we can observe in the data.

3.2. Log-t Convergence Test

As we have shown analytically, a single-component model does not account for some stylized facts of the extant core inflation measures. In particular, our analysis

[30] A number of theoretical and empirical studies have stressed the importance of individual heterogeneity that are often found in panels. To account for the heterogeneous transitional behavior of individuals, a variety of factor models consisting of a common factor structure and idiosyncratic effects have been developed, such as Stock and Watson (2002), Bai (2003), and Bai and Ng (2006).

[31] Note that this nonlinear stochastic process of p_{it} can be applied to a linear stochastic process. More importantly, since inflation rate of the ith component is $\pi_{it} = \delta_{it-1}\Delta\theta_t + \Delta\delta_{it}\theta_{t-1}$, all individual inflation rates can be dominated by the common factor, $\Delta\theta_t$.

suggests that persistent discrepancy between the core measures is not compatible with a single-component model. This is because that if the core measures can be represented by Eq. (1), they will share the same stochastic trend in the long run. Thus examining whether a single-component model is a proper model for individual prices is equivalent to test overall price convergence. In terms of the time-varying factor representation given by (10) and (11), the null of overall convergence is

$$H_0 : \delta_i = \delta \quad \text{and} \quad \alpha_i \geq 0 \tag{13}$$

and the alternative hypothesis is given by

$$\begin{aligned} H_A : &\{\delta_i = \delta \quad \text{for all} \quad i \quad \text{with} \quad \alpha_i < 0\} \quad \text{or} \\ &\{\delta_i \neq \delta \quad \text{for some} \quad i \quad \text{with} \quad \alpha_i \geq 0 \quad \text{or} \quad \alpha_i < 0\}. \end{aligned} \tag{14}$$

We employ log- t regression model by setting $L(t) = \log t$ in Eq. (11) suggested by Phillips and Sul (2007) to test the null hypothesis,

$$\log \frac{\Gamma_1}{\Gamma_t} - 2\log(\log t) = a + b \log t + \varepsilon_t, \quad \text{for} \quad t = rT, rT+1, \cdots, T, \tag{15}$$

where $\Gamma_t = N^{-1} \sum_{i-1}^{N} (\hbar_{it} - 1)^2$ is cross-sectional variance of relative transition coefficient, $\hbar_{it} = p_{it} / (N^{-1} \sum_{i=1}^{N} p_{it})$.[32] This regression model is motivated by the intuition that under the null of convergence cross-sectional dispersion relative to initial level, Γ_1, must shrink over time. Accordingly, (13) and (14) are now transformed into

$$H_0 : b \geq 0 \quad \text{and} \quad H_A : b < 0, \tag{16}$$

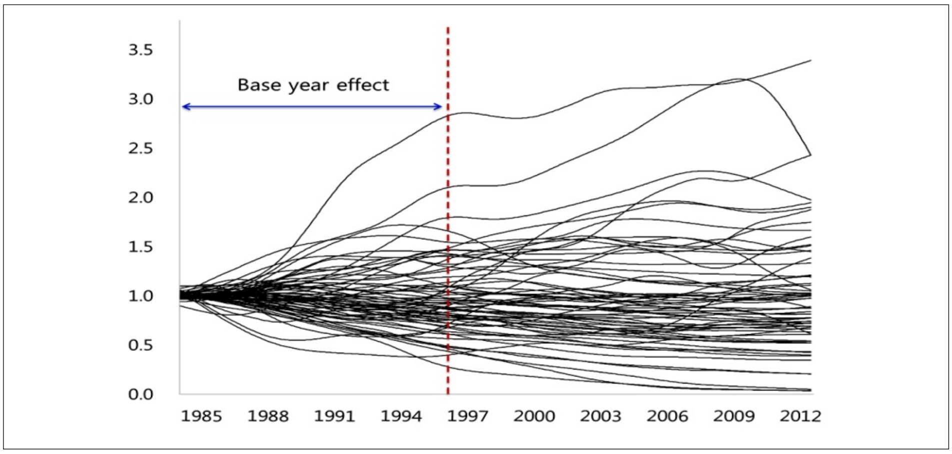
where b is the slope coefficient of log- t regression model. Thus, one-sided t - test of $b \geq 0$ is used to determine if all individual prices have a tendency toward a common stochastic trend.[33]

---

[32] Note that Phillips and Sul (2007) suggest r value in the interval [0.2, 0.3] to use $(1-r)$ fraction of sample for the regression analysis. In addition, to construct relative transition coefficient, $\hbar_{it}$, we use the Hodrick-Prescott trend of log price index of CPI component i at time t, p_{it}, to filter out business cycle component.

[33] The heteroskedasticity and autocorrelation consistent (HAC) estimator for the covariance of b is used due to serially correlated regression errors.

[Figure 3] Relative Transition Curves and Base Year Effect



Before reporting empirical results, it is worth noting that a price index, designed to reflect change in price of an item between different time periods, is subject to base year problem. For example, if the base year is 2010, then by construction all price indices are identical in that year suggesting convergence. To avoid this spurious result, we take the initial period, 1985:M1, as the base year. However, by construction, all prices initially diverge from the base year. In order to avoid this base year effect, it is necessary to discard some initial observations until the initialization effect disappear. Figure 3 plots relative transition curves ($\hbar_{it}$) shows initial dispersion appears to be reduced around year 1997 and thus we discard the first 144 observations.

As shown in Figure 3, there is little evidence of convergence among 67 disaggregate prices. We now apply a formal statistical method, the log- t , convergence test described above. Log- t convergence test results for the panels of 67 disaggregate CPI components are presented in Table 5. There is strong evidence against overall convergence as the slope coefficient is significantly less than zero, regardless of the value of r . This empirical finding points out that the extant core measures relying on single-component model are not suitable to measure the trend of underlying inflation, and thus the use of a multiple-component model that is compatible with the apparent features of the data is inevitable.

[Table 5] Log- t Regression Results

	First Observation in the Log-t Regression					
	2000:M3 ($r = 0.20$)	2000:M7 ($r = 0.22$)	2000:M11 ($r = 0.24$)	2001:M3 ($r = 0.26$)	2001:M7 ($r = 0.28$)	2001:M11 ($r = 0.30$)
$\hat{b}$	-1.160	-1.167	-1.171	-1.173	-1.173	-1.171
$t_{\hat{b}}$	-465.9	-956.7	-299.7	-191.6	-177.6	-209.1

IV. Clustering Common Trends in Disaggregate Prices

In this section, we analytically show that multiple-component model is compatible with the stylized facts of core inflation estimators regarding volatility and disparities among the measures. Next, by utilizing clustering procedure due to Phillips and Sul (2007), the number of common stochastic trends will be estimated. We also discuss characteristics of convergence clubs and diverging CPI components.

4.1. Multiple-Component Model

From the analysis of overall convergence among disaggregate prices in the previous section, we confirm that persistent discrepancy between any pair of extant core inflation is not consistent with single-component model. Accordingly, there is another possibility that all prices are diverging over time. In the case of divergence, $\delta_{it} \to \delta_i$ or $\alpha_i < 0$ for some i in Eq. (11), we have

$$\pi_{it} = \delta_i \Delta\theta_t + \psi_{it} t^{-\alpha_i^*} \Delta\theta_t + [\psi_{it} t^{-\alpha_i^*} - \psi_{it-1}(t-1)^{-\alpha_i^*}]\theta_{t-1}, \tag{17}$$

and cross-sectional mean becomes

$$\bar{\pi}_t = \pi_t^c + O_p(N^{-1/2}) + O_p(t^{\tau-\alpha^*} N^{-1/2}) \to \pi_t^c \text{ and } N, T \to \infty, \tag{18}$$

where $\pi_t^c = \delta\Delta\theta_t$.

To examine this case more explicitly, we consider the example used in Eq. (12) so that $p_{it} = (\delta_i + p_{it}^o t^{-\tau}) = \delta_{it}\theta_t$. As a consequence,

$$\pi_{it} = \delta_i [t^\tau - (t-1)^\tau] + \Delta p_{it}^o = \pi_t^c + (\delta_i - \delta)\Delta\theta_t + \pi_{it}^o, \tag{19}$$

and, as long as $\tau \le 0$, cross-sectional mean can be a consistent estimator of core inflation as $N \to \infty$,

$$\bar{\pi}_t = \pi_t^c + O_p(N^{-1/2}) + O_p(N^{-1/2} t^{\tau-1}). \tag{20}$$

Therefore this implies that any conventional core estimator has no ability to generate a lower volatility of inflation under price divergence since the maximum order in probability is the same as cross-sectional mean. In addition, all three measures of core inflation considered should exhibit the same long-run pattern and thus this case is not consistent with the observed disparities.[34]

[34] When $\delta_{it} \to \delta_i$ and $\alpha_i < 0$, simple cross-sectional mean is no longer be a consistent estimator

Now we consider a more general case where there exist more than one common trends and, possibly, a small number of items that do not converge to any of those trends. This is motivated by the fact that the null of overall convergence is strictly rejected, but the alternative hypothesis of (16) include the possibility of club convergence. Without loss of generality, we assume that there is a finite number of common trends. That is, $\delta_{j,it} \to 0$, if $i \notin S_j$,

$$p_{it} = \begin{cases} \delta_{1,it}\lambda_{it} & \text{for} \quad \delta_{1,it} \to b_1 \qquad i \in S_1 \\ \vdots & \qquad\qquad\qquad\quad \vdots \\ \delta_{M,it}\lambda_{it} & \text{for} \quad \delta_{M,it} \to b_M \quad i \in S_M \end{cases}. \tag{21}$$

Let N_m be the number of CPI components in club S_m. Since individual prices asymptotically converge to M different common trends, $\theta^*_{mt} = \delta_m \theta_{mt}$, core CPI can be defined as $\theta^c_t = \delta\theta_t$, and thus $\theta^*_{mt} = \theta^c_t + \delta_m(\theta_{mt} - \theta_t) + (\delta_m - \delta)\theta_t$. We now revisit the example of a quasi-trend stationary process by considering

$$\pi_{it} = \begin{cases} c_1\Delta\theta_t + \pi^o_{it}, & i \in S_1 \\ \quad\vdots & \quad\vdots \\ c_M\Delta\theta_t + \pi^o_{it}, & i \in S_M \end{cases}. \tag{22}$$

Then measure of core inflation is defined as $\pi^c_t = c\Delta\theta_t$, so that

$$\pi_t = c\Delta\theta_t + \pi^o_{it}, \tag{23}$$

where $c = \text{plim}_{N^+ \to \infty} N^{-1} \sum_{m=1}^{M} N_m c_m$ for $N^+ = \min[N_m]$. It is important to point out that the median estimator for each club becomes a consistent estimator for $c_m\Delta\theta_t$ as $N_m \to \infty$ and it has ability to produce a lower volatility as discussed in Eq. (12).[35]

Finally, we consider a more realistic case where a few prices are permitted to diverge from any common trend while there are some convergence clubs. Using the example we considered in Eq. (12), let's assume that $\sum_{m=1}^{M} N_m = N - 1$. In addition, we assume that $c_1 \neq c_m$ but $\tau_i = 1$ for $i > 1$ so that

---

and the extant core measures can explain why headline CPI inflation is more volatile. Still, it is not possible to account for why the measures are not converging over time.

[35] However, the conventional median is not a consistent estimator in this case. To see this, let $M = 2$ and $N_1 < N_2$. Then the probability limit of median estimator becomes, $c_2\Delta\theta_t$ even $N_1, N_2 \to \infty$.

$$\pi_{it} = \begin{cases} c_1[t^{\tau_1} - (t-1)^{\tau_1}] + \pi_{1t}^o, & i = 1 \\ c + (c_m - c)\pi_{it}^o, & i > 1 \end{cases}. \tag{24}$$

This implies that neither cross-sectional mean nor median becomes inconsistent as in Eq. (23).[36] As a consequence, this case may be consistent with the observed divergence among the extant core measures.

4.2. Clustering Analysis

By utilizing the log-t regression model discussed, we now estimate the number of common trends underlying disaggregate prices. In addition, a group of diverging CPI components will be identified.[37] As Phillips and Sul (2007) suggested, we employ a stepwise application of log-t tests.[38] Empirical application from a panel of 67 disaggregate prices confirms that there are four distinct common stochastic trends and a few diverging components as shown in Table 6. For each convergence club, none of slope coefficient estimate, $\hat{b}$, is significantly less than zero and club members tend to converge toward their own common trend. Figure 4 illustrates relative transition curves, $\hbar_{it}$ for club 1 members, and there is a marked reduction in cross-sectional dispersion over time, which implies convergence among the member CPI components.[39] In particular, the relative transition paths present substantial heterogeneity. For example, 'domestic services and household services' and 'personal effects n.e.c.' differ in terms of initial state. Interestingly, 'water and sewage disposal charge' starts off relatively low price but displays a sustained increase in the relative transition coefficient becoming one of the highest price component.

Club 1, highest price group, consists of mostly food and energy items and some service component such as educational services. There is another large group of 22 CPI components, club 2, involving food- and energy-related items and services, for example housing, health, transportation, and education. It is important to point out that a majority of food and energy items are included in clubs 1 and 2. Thus, the exclusion of those items in measuring the trend of underlying inflation may cause a

---

[36] Note that a trimmed mean estimator or an excluded-item measure can be consistent because CPI components removed may act like outliers as $N \to \infty$.

[37] It is worth noting that clustering analysis allows researchers to find fundamental factors driving price divergence and club convergence, for example Kim and Rous (2012) and Choi, Greenaway-McGrevy, Kim, and Sul (2014). However, we leave this analysis for future research direction as this well beyond the scope of the current paper.

[38] For a detailed instruction on clustering algorithm and club-merging test, see Phillips and Sul (2009).

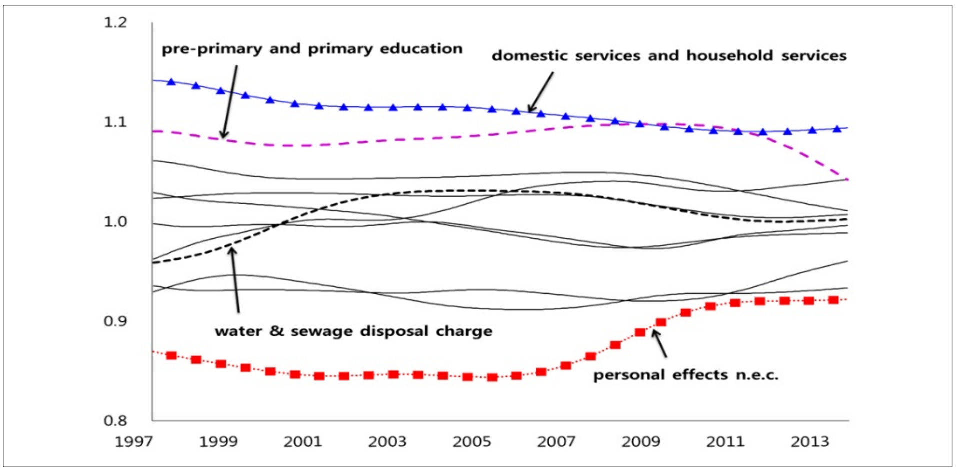
[39] To conserve on space, relative transition curves for other clubs are not presented. They are available from the authors upon request.

[Table 6] Club Membership of CPI Components

Club	$\hat{b}(t_{\hat{b}})$	CPI components
Club 1 [11]	0.06 (1.20)	fish and seafood; vegetables & seaweeds; sugar, jam, honey, chocolate and confectionery; food products n.e.c.; water & sewage disposal charge; other fuels and energy; domestic services and household services; passenger transport by road; pre-primary and primary education; tertiary education; personal effects n.e.c.
Club 2 [22]	-0.01 (-0.12)	meat; milk, cheese and eggs; oils and fats; fruit; coffee, tea and cocoa; mineral waters, soft drinks, fruit and vegetable juices; garment for children & infants; actual rentals for housing; maintenance and repair of the dwelling; gas; outpatient services; hospital services; fuels and lubricants for personal transport equipment; passenger transport by railway; passenger transport by air & sea and inland waterway; other recreational items and equipment, gardens and pets; newspapers and periodicals; stationery; private institutions and supplementary education; private institutions for adults & other education; catering services; hairdressing salons and personal grooming establishments
Club 3 [20]	0.01 (0.19)	bread and cereals; alcoholic beverages; tobacco; garment for men; garment for women; casual wear; cleaning, repair and hire of clothing; footwear; other services relating to the dwelling n.e.c; furniture and furnishings, carpets and other floor coverings; household textiles; glassware, tableware and household utensils; non-durable household goods; other services in respect of personal transport equipment; postal services; other major durables for recreation and culture; books; secondary education; accommodation services; other services
Club 4 [7]	0.01 (0.25)	other articles of clothing and clothing accessories; tools and equipment for house and garden; pharmaceutical products; medical products and therapeutic appliances; recreational and sporting services; cultural services; electric appliances & other appliances, articles and products for personal care
Diverging components [7]	-2.20 (-196.6)	electricity; household electronic appliance & household appliances; purchase of vehicles; telephone and telefax equipment; telephone and telefax services; audio-visual equipment; equipment & spare parts and accessories for information processing

Note: Entries in square brackets represent the number of CPI components in a subgroup. $\hat{b}$ and $t_{\hat{b}}$ denotes estimated slope coefficient and its corresponding t -statistic, respectively.

[Figure 4] Relative Transition Curves for CPI Components: Club 1



serious problem as we discussed earlier in this paper.[40] Next, club 3 encompasses a variety of nondurables and services and a majority of durable goods are included in club 4. Finally, a group of 7 diverging components that does not belong any convergence club is found and they are all durable goods, except electricity.

In sum, empirical findings of clustering analysis suggest that there are four distinct common stochastic trends and multiple-component model is a proper way of measuring core inflation. The characteristics of each convergence club is generally determined by major product category. Prices of nondurable goods and services tend to exhibit long-run upward trends while the prices of durable goods appears to be relatively stable. In addition, some CPI components are diverging from a common trend, and hence they are not quite useful to understand the mid- and long-term behavior of headline inflation.

V. A New Measure of Core Inflation

Motivated by the observation that none of conventional core inflation measures is a consistent estimator, we suggest a new measure of core inflation based on estimated common trends in the previous section. We will examine whether the new measure dominate the extant measures in its ability to account for forecasting the underlying trend of inflation and for generating low volatility.

---

[40] With regard to convergence club classification, there is a striking difference between US and Korea. Despite the fact that some services are included in club 1, nondurable goods are attributable for long-term increase in aggregate inflation. On the other hand, using US PCE data, Greenaway-McGrevy, Kim, and Sul (2014) document that a majority of services are includes in the highest price club, while the common trend for nondurables is relatively low.

5.1. Limited Influence Estimators under Price Divergence

To construct a better measure of core inflation when there are a finite number of multiple common stochastic trends underlying disaggregate prices, we utilize limited influence estimators. However, it is not obvious which limited influence estimator must be used for each club.[41] In this paper, following Greenaway-McGrevy, Kim, and Sul (2014), we suggest a general framework for measuring core inflation that nests a variety of limited influence estimators such as median and symmetric and asymmetric trimmed mean. This is because the choice of limited influence estimator is based on its ability to forecast future inflation and thus which estimator is being selected depends on sample period and the extent of disaggregation.

As shown in Bryan, Cecchetti, and Wiggins (1997) and Dolmas (2005), a trimmed mean estimator truncating some components in the tails of the distribution appears to minimize mean squared distance from ex-post trend inflation. Accordingly, we employ an asymmetric weighted trimmed mean estimator, which is relatively less influenced by skewness of the distribution, together with four common trends from our clustering analysis. That is, a new core inflation is given by

$$\pi_t^c = \sum_{m=1}^{M} \vartheta_m \pi_{m,t}^c , \tag{25}$$

where $\pi_{m,t}^c$ is common stochastic trend for club m and $\vartheta_m \in (0,1)$ is the share of club m.

To provide a complete description of the new core measure of inflation, we first assign values to the parameters of the estimator, π_t^c. Let $\tilde{\pi}_{i,t}$ be reordered inflation rate for CPI component i at time t in the increasing order so that $\tilde{\pi}_{i,t} \geq \tilde{\pi}_{k,t}$ for $i \geq k$. The new measure is now constructed by finding optimal truncation points $\{\alpha_m, \beta_m\}_{m=1}^M$ and optimal weights for each convergence club $\{\vartheta_m\}_{m=1}^M$ in Eq. (25) in the sense that the new core measure has minimum distance with ex-post underlying trend of inflation.

$$\{\alpha_m, \beta_m, \vartheta_m\}_{m=1}^M = \arg\min \frac{1}{T} \sum_{t=1}^{T} \left[\left(\sum_{m=1}^{M} \vartheta_m \sum_{i=\iota(\alpha_m)}^{\iota(\beta_m)} \frac{1}{1-\alpha_i-\beta_i} \tilde{\omega}_{i,m} \tilde{\pi}_{i,m,t} \right) - \pi_t^{trend} \right]^2 , \tag{26}$$

[41] For discussion about how the limited influence estimators are used in practice, see Greenaway-McGrevy, Kim, and Sul (2014).

where π_t^{trend} is trend inflation, which is measured by 3-year centered moving average as Bryan, Cecchetti, and Wiggins (1997) suggested. In addition, the truncation point for each tail is given by

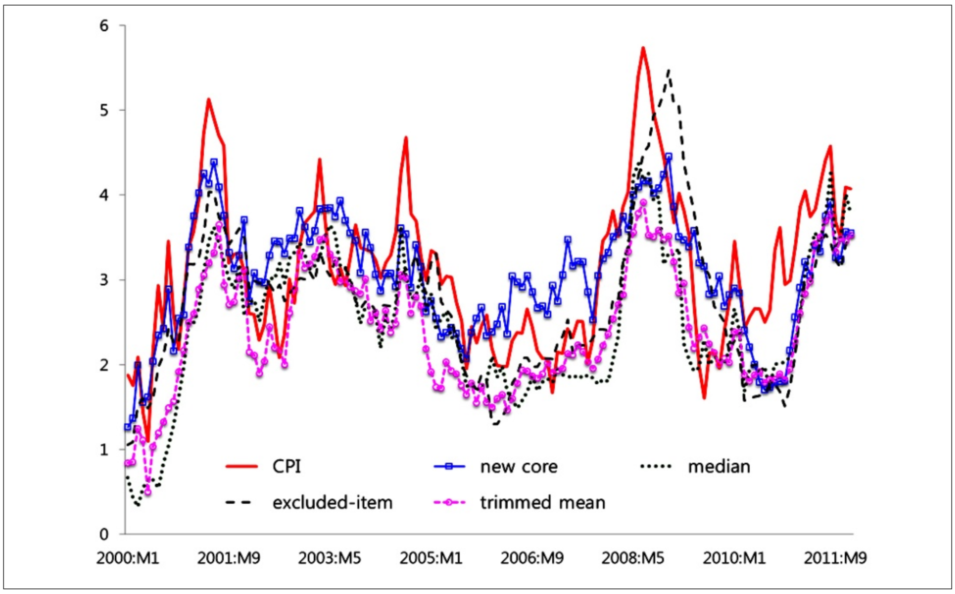
$$\iota(\alpha_m) = \min\left\{ I_m \left| \sum_{i=1}^{I_m} \tilde{\omega}_{i,m} \geq \alpha_m \right. \right\} \text{ and } \iota(\beta_m) = \min\left\{ I_m \left| \sum_{i=0}^{I_m - 1} \tilde{\omega}_{N_m - i,m} \geq \beta_m \right. \right\}, \quad (27)$$

where $\alpha_m \in [0, 0.5]$ is the smallest index I_m for convergence club m such that the sum of the weights $\tilde{\omega}_{i,m}$ over $i = 1$ to $i = I_m$ is greater than α_m, and β_m is defined in the same manner. Table 7 presents calibrated optimal upper and lower tail truncation points, α_m and β_m, respectively, and club weights for the new core measure of inflation. Finally, our new core measure based on the calibrated parameters together with headline inflation and some extant core measures are shown in Figure 5.

[Table 7] Calibrated Parameters for the New Core Inflation

	α_m	β_m	ϑ_m
Club 1	0.346	0.221	0.146
Club 2	0.318	0.197	0.240
Club 3	0.213	0.257	0.464
Club 4	0.250	0.250	0.151

[Figure 5] 12-month CPI and Core Inflation Rates



5.2. Evaluation of the New Core Inflation

In addition to its central tendency, a good measure of core inflation must display less volatility than headline inflation and have ability to predict the underlying trend of the inflation. We now examine whether the new core inflation dominates conventional core inflation measures in its ability to generate low volatility and predictability with special emphasis on central tendency.

[Table 8] In-sample Performance of Core Inflation Measures

	π^{CPI}	π^{new}	π^{med}	π^{excl}	π^{s_trim}	π^{a_trim}
mean	4.39	4.23	3.68	3.97	3.57	3.88
variance	4.28	3.23	4.55	4.00	4.06	3.86
MSE	1.65	0.77	1.73	1.30	1.63	1.38

Note: π^{s-trim} and π^{a-trim} refers the 10% symmetric trimmed mean and asymmetric trimmed mean, respectively.

As apparent in Figure 5 and Table 8, during the sample period, 1986-2011, the new core measure performs better than the extant core measures.[42] First, as we documented earlier, one of serious shortcomings of conventional core measures is to underestimate the trend inflation, which is measure by 3-year centered moving average. On the other hand, time-series mean of the new core is relatively much closer to CPI inflation than other core measures. This may be due to the fact that the new core based on convergence club, by construction, removes diverging CPI components that exhibits downward long-term trend. In addition to its central tendency, the new core measure performs better than other indicators in its ability to smooth volatile movements of price changes as the new core has the lowest time-series variance amongst the core measures. Next, not surprisingly, it also exhibits the lowest mean squared error (MSE) when compared to the other indicators.[43]

[42] To evaluate the new core measure, we scrutinize 12-month inflation rates. The results for month-to-month inflation rates are quite similar to 12-month case. In addition to symmetric trimmed mean (π^{s-trim}), we also consider asymmetric trimmed mean (π^{a-trim}) and calibrated parameter values for right-tail and left-tail truncation points are $\alpha = 0.103$ and $\beta = 0.141$, respectively.

[43] The MSE measures how much each core inflation measure is deviated from underlying trend of inflation. That is, $MSE^j = \frac{1}{T}\sum_{t=1}^{T}(\pi_t^j - \pi_t^{trend})^2$, where π_t^{trend} is denotes ex-post underlying trend of inflation and π_t^j is a measure of (core) inflation rate.

[Table 9] Out-of-sample Predictability of Core Inflation Measures

horizon (h)	π^{CPI}	π^{new}	π^{med}	π^{excl}	π^{s_trim}	π^{a_trim}
Panel I: h -month inflation ($h=k$)						
6	2.13	**0.67**	2.16	1.56	2.02	0.74
12	2.47	**0.81**	2.21	1.74	2.09	0.85
18	2.74	**0.96**	2.28	1.95	2.18	0.99
24	2.93	**1.08**	2.37	2.06	2.28	1.11
36	3.01	**1.22**	2.54	2.08	2.47	1.24
48	3.18	1.34	2.59	2.19	2.50	**1.32**
60	3.31	1.35	2.51	2.15	2.45	**1.27**
Panel II: 12-month inflation ($k=12$)						
6	1.99	**0.63**	2.22	1.49	2.08	0.73
12	2.47	**0.81**	2.21	1.74	2.09	0.85
18	3.08	**1.13**	2.37	2.21	2.28	1.14
24	3.39	**1.38**	2.55	2.42	2.47	1.42
36	3.23	**1.55**	2.79	2.32	2.66	1.63
48	3.14	**1.47**	2.76	2.28	2.62	1.48
60	3.11	1.20	2.42	2.00	2.35	**1.13**

Note: The minimum MSFE for each forecasting horizon is shown in boldface.

We now turn to examine relative performance of core inflation measures in terms of out-of-sample forecastability. Following Stock and Watson (2007), pseudo out-of-sample forecasts of inflation over k interval at h forecast horizon is given by

$$\pi_{t+h,k} = 1/k \sum_{i=0}^{k-1} \pi_{t+h-i} \,. \tag{28}$$

Out-of-sample predictability of core inflation measures can be assessed in terms of random walk forecast since the random walk forecast of Atkeson and Ohanian (2001), $\hat{\pi}^{j}_{t,12} = \frac{1}{12}\sum_{i=0}^{11} \pi^{j}_{t-i}$ performs better than a variety of forecasts at horizons in excess of one year. Accordingly, mean squared forecasting error (MSFE) for each core indicator can be computed as

$$MSFE^{j} = \frac{1}{T}\sum_{t=1}^{T}\left(\pi_{t+h,k} - \hat{\pi}^{j}_{t,12}\right)^{2} . \tag{29}$$

Table 9 presents the MSFE of various core inflation measures for forecast horizons $h \in \{6,12,18,24,36,48,60\}$. With regard to the interval over which inflation rate is measured, we consider the following two cases. First, we set $h=k$ implying the forecasting horizon of h is the same as the inflation interval k . As shown in Panel I of the table, all core measures tend to predict the trend inflation reasonably well and performs better than headline CPI inflation in terms of out-of-sample predictability. In particular, except for long horizons, $h=48$ and $h=60$, the new core dominates all other core measures in accounting for future development of price changes as it produces the lowest MSFE. It is worth noting that asymmetric trimmed mean estimator works well particularly for long-horizon forecasting, while median generally performs poorly across all considered horizons. Next, as presented in Panel II of Table 9, we fix $k=12$ and forecasting power of 12-month inflation rates for a variety of forecast horizons is evaluated.[44] Overall, similar to h-month inflation results, the new core measure works best. In addition, the median estimator and symmetric trimmed mean exhibit a relatively lower out-of-sample forcastability, but asymmetric trimmed mean performs nearly as good as the new core inflation.

In sum, although all extant measures appear to be less volatile than headline CPI inflation and have ability to account for the underlying trend of inflation, the new measure of core inflation based on multiple-component model performs best in every respect. Albeit its empirical performance reflecting better the underlying trend of inflation, it is worth noting that the increased complexity when calculating the new core measure limits communicability with the public in setting monetary policy.

VI. Conclusion

To decide on proper actions given the objective of maintaining overall price stability, monetary policymakers must understand the current inflation rate and where it is headed. However, there is a longstanding issue whether central banks use the headline or the core measure of inflation to track medium-term inflationary pressures, particularly in inflation targeting regime. One of main sources of the debate is due to the fact that economists disagree about how best define core inflation and thus extant measures exhibit substantial disparities even in the long run. Nonetheless, in practice, monetary policymakers often focus on core inflation to prevent themselves from being too hawkish to transitory changes in prices.

In this paper, we document some important facts of conventional core inflation measures, such as excluded-item, median, and trimmed mean estimators. From disaggregate CPI data for Korea spanning from 1985 to 2013, we found that the extant measures of core inflation tend to underestimate headline CPI inflation. In addition, persistent disparities among the core inflation measures are apparent in the data, which is not compatible with traditional models for disaggregate prices.

[44] Since the forecast is given by $\pi_{t+h,12}=\pi_{t,12}$, the MSFE for $h=12$ in Panel I is the same as that stated in Panel I for $h=12$. For a detailed forecasting experiment of 12-month inflation rates, see Clark (2001).

Accordingly, we employ the time-varying common factor representation based on Phillips and Sul (2007), and show that individual prices are better explained by multiple common stochastic trends with some diverging prices. We utilize a new measure of core inflation that is consistent with the stylized facts documented in this paper. Our empirical analysis suggests that the new core inflation based on our clustering analysis dominates the extant core indicators in its ability to account for central tendency of price distribution and for generating low variance of price changes. In particular, it provides a relatively more accurate forecast of the underlying trend of headline CPI inflation.

References

Atkeson, A., and L. E. Ohanion (2001), "Are Phillips Curves Useful for Forecasting Inflation?" *Quarterly Review*, 2-11, Federal Reserve Bank of Minneapolis.

Bai, J. (2003), " Inferential Theory for Factor Models of Large Dimensions," *Econometrica*, 71(1), 153-172.

Bai, J., and S. Ng (2006), "Evaluating Latent and Observed Factors in Macroeconomics and Finance," *Journal of Econometrics*, 131, 507-537.

Ball, L., and N. G. Mankiw (1995), "Relative Price Changes as Aggregate Supply Shocks," *Quarterly Journal of Economics*, 110(1), 161-193.

Blinder, A. S. (1982), "The Anatomy of Double-Digit Inflation," in *Inflation: Causes and Effects*, ed. by R. E. Hall, 261-282. Chicago: University of Chicago Press.

____________ (1997), "Commentary on Measuring Short-Run Inflation for Central Bankers," *Review*, Federal Reserve Bank of St. Louis (May/June 1997), 157-160.

Bryan, M. F., and C. Pike (1991), "Median Price Changes: An Alternative Approach to Measuring Current Monetary Inflation," *Economic Commentary*, Federal Reserve Bank of Cleveland, 1 December.

Bryan, M. F., and S. G. Cecchetti (1994), "Measuring Core Inflation," in *Monetary Policy*, ed. by. N.G. Mankiw, 195-215. The University of Chicago Press.

Bryan, M. F., S. G. Cecchetti, and R. L. Wiggins (1997), "Efficient Inflation Estimator," Working Paper 6183, National Bureau of Economic Research.

Bullard, J. (2011), "Measuring Inflation: The Core is Rotten," *Review*, Federal Reserve Bank of St. Louis, 93(July/August), 223-234.

Choi, H., R. Greenaway-McGrevy, Y. S. Kim, and D. Sul (2014), "The Role of Labor Share in Relative Price Divergence," mimeo, Sungkyunkwan University.

Clark, T. E. (2001), "Comparing Measures of Core Inflation," *Economic Review*, Federal Reserve Bank of Kansas City, 86(2), 5-31.

Cogley, T. (2002), "A Simple Adaptive Measure of Core Inflation," *Journal of Money, Credit and Banking*, 34(1), 94-113.

Dolmas, J. (2005), "A Fitter, Trimmer Core Inflation Measure," *Southwest Economy*, Issue 3, May/June 2005, 4-9, Federal Reserve Bank of Dallas.

Eckstein, O. (1981), *Core Inflation*, Prentice Hall, Englewood Cliffs, NJ.

Gordon, R. J. (1975), "Alternative Responses of Policy to External Supply Shocks," *Brookings Papers on Economic Activity*, 6(1), 183-206.

Greenaway-McGrevy, Y. S. Kim, and D. Sul (2014), "Measuring Core Inflation under Price Divergence," mimeo, Sungkyunkwan University.

Kim, Y. S., and J. J. Rous (2012), "House Price Convergence: Evidence from US State and Metropolitan Area Panels," *Journal of Housing Economics*, 21(2), 169-186.

Mishikin, F. S. (2007), "Headline versus Core Inflation in the Conduct of Monetary Policy," Speech at the Business Cycles, International Transmission and Macroeconomic Policies Conference, HEC Montreal, Montreal, Canada.

Phillips, P. C., and D. Sul (2007), "Transition Modeling and Econometric Convergence

Tests," *Econometrica*, 75(6), 1771-1855.

__________ (2009), "Economic Transition and Growth," *Journal of Applied Econometrics*, 24(7), 1153-1185.

Quah, D., and S. P. Vahey (1995), "Measuring Core Inflation," *Economic Journal*, 105(432), 1130-1144.

Smith, J. K. (2004), "Weighted Median Inflation: Is This Core Inflation?" *Journal of Money, Credit and Banking*, 36(2), 253-263.

__________ (2005), "Inflation Targeting and Core Inflation," *Canadian Journal of Economics*, 38(3), 1018-1036.

Stock, J. H., and M. W. Watson (2002), "Forecasting Using Principal Components from a Large Number of Predictors," *Journal of the American Statistical Association*, 97, 1167-1179.

__________ (2007), "Why Has U.S Inflation Become Harder to Forecast?" *Journal of Money, Credit and Banking*, 39(1), 3-33.

Svensson, L. E. (1997), "Inflation Forecast Targeting: Implementing and Monitoring Inflation Targets," *European Economic Review*, 41(6), 1111-1146.

Wynne, M. A. (2008), "Core Inflation: A Review of Some Conceptual Issues," *Review*, Federal Reserve Bank of St. Louis, Issue May, 205-228.