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Does the law of one price hold in 82 Indonesian cities? Evidence from club convergence approach

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Abstract

This study re-examines regional price convergence across 82 cities in Indonesia. We implement club convergence analysis developed by Phillips and Sul (2007, 2009) on monthly aggregate consumer price data and its components from January 2014 to December 2019. We do not find evidence of overall convergence in aggregate consumer price data. Instead, we identify four club convergence. Using disaggregated data, four new outcomes arise; first, none of the consumer price components show overall convergence but multiple club convergence do exist, second, there is variability in the number and composition of clubs among consumer price components, third, the price of foodstuffs and education-related commodities in most cities converge to the higher level, and fourth, the formation of club convergence in aggregate price is attributed largely by housing, processed foods, transport, and health components. Policy insights include improving market efficiency and controlling the inflation rate in targeted consumer price components and locations.

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1. Introduction

The recent development in economic literature has shown a growing interest in convergence analysis. Started with economic growth issues, further progress of convergence literature has broadened the focus to other economic subjects, including monetary economics (De Grauwe, 1996; Evans and Karras, 1996; Rogers, 2007). In its simplest form, convergence behavior is seen when cross-sectional units' variation diminishes over time (Hotelling, 1933). For example, one may see convergence as a gradually decreasing variance in income per capita across various countries. However, some scholars have shown evidence of another form of convergence, where the declining variation is observed not in the entire units but within some sub-groups (Azariadis and Drazen, 1990; Galor, 1996). Usually sharing similar characteristics, the units within those sub-groups assemble a relatively similar evolution path over time. In convergence literature, this is called the club convergence hypothesis.

Why do we need to study price convergence? To answer this question, one should refer to the root of price convergence analysis; the law of one price (LOOP). LOOP is defined as the condition where the price of identical goods in separate places is uniform in a common currency unit (Rogoff, 1996). Within a country where trade restrictions are minimal, LOOP implies a similar price level across regions in the long-run (controlling logistics and transportation costs). In a very efficient market, any deviation from the LOOP will be adjusted by the market mechanism. Nevertheless, due to some market rigidities and complexities – including rigidities in the factor market and different exposure to international trade that raise uncertainty from exchange rate volatility – regional price does not adjust, at least in the short-run.[1]

Using the concept of LOOP, the analysis of price convergence within a country produces meaningful policy implications. For example, in the scope of monetary policies, regional price convergence analysis can be useful in forecasting monetary policy impacts on regional inflation (Cecchetti, Mark, and Sonora, 2000). In the context of broader economic policies, the analysis is often used to understand some structural features such as the degree of market integration among regions, the regional structure of input factors, and productivity differentials (Tirtosuharto and Adiwilaga, 2014). Understanding these structural features are essential for regional economic development strategies.

These multiple benefits have attracted many studies to focus their analysis on price convergence within a country. Most of them attempt to validate the presence of convergence by using classical models such as sigma and beta convergence (see Bernard and Durlauf, 1995; Hobijn and Franses, 2000; Phillips and Sul, 2007). However, despite widely used in convergence literature, the classical models have a drawback in the sense that they mainly consider a single common steady state. This limitation restricts the models to fully capture the possible real case of convergence given the heterogeneity in the observation (Jangam, Akram, and Sahoo, 2020). In the context of income convergence, for instance, many researchers conclude that the dispersion of income per capita across economies systematically shows clustering patterns rather than follows the direction of commons growth path (Basile, 2009; Phillips and Sul, 2009; Quah, 1996).

Unlike the classical models, a novel approach to convergence analysis developed by Phillips and Sul (2007) allows a wide range of transitional dynamics and individual

[1] Among others, the potential solutions to address the problems of market rigidities and complexities include improving factor market efficiency and integration, eliminating implicit local protectionism, and minimizing short-run exchange rate volatility (Tirtosuharto and Adiwilaga, 2014; Isard, 1977; Zax and He, 2016).

heterogeneity to capture convergence beyond single steady state outcomes. A substantive number of price convergence studies have applied this new approach and documented new empirical results; price converges in multiple club convergence.

The method is notably superior to capture price convergence in largely diversified countries like Indonesia, where substantial price differential across regions is persistent. The most recent study analyzing regional price convergence in Indonesia is conducted by Jangam and Akram (2019). Applying the convergence approach of Phillips and Sul (2007) on monthly aggregate Consumer Price Index (CPI) data in 82 cities, they do not find evidence of overall price convergence. Instead, they show evidence that regional price assembles four club convergence. However, a more in-depth examination is needed to complement this general conclusion. By construction, CPI represents the aggregate price of various commodities consumed in a society. Thus, the convergence patterns seen in aggregate CPI are the reflection of CPI components' dynamics. To understand the sources of observed convergence patterns in aggregate CPI, further convergence analysis using disaggregated data is required.

Moreover, Indonesian regions are highly interdependent, given the uneven supply capacity (Jangam and Akram, 2019). More often than not, in such a situation, disruptions in supply distribution risk country's inflation rate and volatility (Tirtosuharto and Adiwilaga, 2014). The risk can be mitigated by improving the quality of supply distribution of a selected important group of commodities in selected regions. This can be done if the underlying relationship of price dynamics among regions is fully understood. Identifying club convergence in the disaggregated price level would help policymakers to acquire a correct picture of regional price interconnection.

Against such a background, our study fills this research gap by examining regional price convergence across 82 Indonesian cities with disaggregated CPI data. To the best of our knowledge, this is the first paper that analyzes price convergence across Indonesian cities with disaggregated CPI data. The multiple outcomes discussed in this paper demonstrate the benefits of club convergence analysis using disaggregated CPI data over the aggregated one.

The rest of this paper is organized as follows; Section 2 describes the econometric methodology, Section 3 presents data description and discussion on the results, and finally, Section 4 concludes the paper.

2. Econometric methodology

2.1. The framework of convergence

Following Jangam and Akram (2019), in this paper we apply the club convergence test by Phillips and Sul (2007). To begin with, we decomposed a panel-data variable of interest, y_{it}, as follow:

$$y_{it} = \left(\frac{r_{it} + s_{it}}{\mu_t}\right)\mu_t = \Upsilon_{it}\mu_t \tag{1}$$

where r_{it} and s_{it} represent a systematic and transitory component, respectively. Υ_{it} is an idiosyncratic element and contains the error term, while μ_t is a common component. Thus, μ_t refers to a common equilibrium to all economies, while Υ_{it} explains an individual's transition path towards its equilibrium.

Under equation (1), the convergence is defined as the common movements of all individual economies towards the same transition path:

$$\lim_{t\to\infty} \Upsilon_{it} = \Upsilon \tag{2}$$

Then, Phillips and Sul (2007) define relative transition parameter, h_{it}, to estimate the transition coefficient of Υ_{it}, where a common component, μ_t, in equation (1) is eliminated by rescaling y_{it} with panel average:

$$h_{it} = \frac{y_{it}}{\frac{1}{N}\sum_{i=1}^{N} y_{it}} = \frac{\Upsilon_{it}}{\frac{1}{N}\sum_{i=1}^{N} \Upsilon_{it}} \tag{3}$$

Thus, h_{it} corresponds to the relative transition path of economy *i* with respect to the level of cross-sectional average. In this setup, convergence occurs when h_{it} converges to unity, that is $h_{it} \rightarrow 1$ for all *i* and $t \rightarrow \infty$. The null hypothesis of convergence defined in equation (3) can be translated into an equation that describes the cross-sectional variance of h_{it},

$$H_t = \frac{1}{N}\sum_{i=1}^{N} (h_{it} - 1)^2 \rightarrow 0 \tag{4}$$

where the cross-sectional variance converges to zero, $H_t \rightarrow 0$. Finally, Phillips and Sul (2007) evaluate this null hypothesis by using the following log t regression model:

$$\begin{gathered} \log\left(\frac{H_1}{H_t}\right) - 2\log\{\log(t)\} = \hat{a} + \hat{b}\log(t) + \varepsilon_t \\ \text{for } t = [rT],\ [rT]+1, \ldots, T \text{ with } r > 0 \end{gathered} \tag{5}$$

where rT is the first fraction of the data used in the regression, that is, r fraction of the data is discarded. For sample size $T \leq 50$, Phillips and Sul (2007) suggest $r = 0.3$. Under equation (5), a one-sided t test is used to prove convergence, where the null hypothesis of convergence is rejected when $t_{\hat{b}} < -1.65$.

2.2. *Identifying club convergence*

One advantage of the model of equation (5) is its ability to define multiple club convergence in the sub-sample when overall convergence in the entire sample is absent. Thus, we use this appealing feature to identify multiple club convergence by implementing an innovative data-driven algorithm. The summary of steps in the club convergence identification process is provided in Section 1 of the Appendix.

3. Data and results

3.1. *Data*

This paper uses the monthly CPI of 82 Indonesian cities from January 2014 to December 2019, published by the Indonesian Central Bureau of Statistics (2012=100). The Indonesian regional CPI data consist of one aggregate price index that can be disaggregated into seven components; 1) *foodstuffs*, 2) *processed foods*, 3) *housing and utilities,* 4) *clothing*, 5) *health*, 6) *education, leisure and sports*, and 7) *transportation, communication, and financial services*. The summary statistics of aggregate CPI in all 82 Indonesian cities presented in Table 1 of the Appendix suggest the heterogeneity of price dynamics across cities. For the disaggregated data, summary statistics of CPI components in Table 2 of the Appendix report that foodstuffs and clothing components have the highest and the lowest mean. Meanwhile, processed foods and housing components show the highest and the lowest standard deviation, respectively. Given this prevalent variability across cities and across CPI components, we implement convergence analysis in two steps; firstly, we identify club convergence using an aggregate price index, and secondly, we re-apply the first step using seven components of CPI (we follow Akram, Sahoo, and Rath, 2020; Jangam, Akram, and Sahoo, 2020; Mendez and Kataoka, 2020). By doing so, we can pinpoint the sources of club convergence in aggregate price.

3.2. Results and discussion: The identification of multiple club convergence

As discussed in the previous section, we applied a log t test to aggregate price index in the first step.[2] The result suggests rejecting the null hypothesis of overall price convergence at the 5% significant level ($\hat{b}$ is significant < 0 with t-statistic -106.97). Then, we proceeded to the steps of club convergence identification discussed in section 2.2. Table 1 presents the results.

As shown in Panel A of Table 1, we found six significant initial club convergence and one diverging city. Then, we continued to test whether some of these clubs can be merged. The merging test result show that club 2, club 3 and club 4 can be merged into one club, reducing the number of club convergence from six to four, as shown in Panel B of Table 1. Hence, our final finding of club convergence test using aggregate CPI data confirms these four subgroups as the final club convergence, while one city (Tual) is diverging. In summary, this result implies that four common trends characterize price movements in 82 Indonesian cities. Our finding is very similar to the result of Jangam and Akram (2019).

[2] We applied the test in STATA by using the club convergence package by Du (2017).

Table 1. Club convergence in aggregate CPI

Club	Number and name of cities	$\hat{b}$ coeff	t-stats
Panel A: Club convergence test result			
Full sample	All 82 cities	-1.02	-106.97
Club 1	[9 cities]	0.47	10.60
Club 2	[17 cities]	0.48	15.75
Club 3	[6 cities]	0.41	5.72
Club 4	[11 cities]	0.03	3.14
Club 5	[30 cities]	0.06	-1.35
Club 6	[8 cities]	0.08	1.46
No convergence	[1 city]		
Panel B: Club merging result			
Club 1 + 2		-0.08	-2.72
Club 2 + 3		0.27	5.23
Club 3 + 4		0.31	5.22
Club 4 + 5		-0.59	-90.11
Club 5 + 6		-0.66	-119.49
No convergence		-1.34	-97.32
Panel C: Final clubs			
Club 1	[9 cities]: Bengkulu, Cilegon, Palu, Pangkal Pinang, Pontianak, Serang, Sibolga, Tanjung Pandan, Tarakan	0.47	10.61
Club 2 (Merging from Club 2 + Club 3 + Club 4)	[34 cities]: Balikpapan, Bandar Lampung, Bandung, Banjarmasin, Batam, Bekasi, Bima, Bogor, Bulukumba, Bungo, Cilacap, Jakarta, Dumai, Jayapura, Kudus, Makassar, Manokwari, Medan, Merauke, Metro, Meulaboh, Padang, Pakanbaru, Palopo, Pematang Siantar, Samarinda, Sampit, Singaraja, Singkawang, Surabaya, Tangerang, Tembilahan, Ternate, Watampone	0.14	2.81
Club 3	[30 cities]: Bau-bau, Bukit Tinggi, Cirebon, Denpasar, Depok, Gorontalo, Jambi, Jember, Kendari, Kupang, Lhokseumawe, Lubuk Linggau, Madiun, Malang, Mamuju, Manado, Mataram, Padang Sidempuan, Palangkaraya, Palembang, Purwokerto, Semarang, Sorong, Sukabumi, Sumenep, Tanjung, Tanjung Pinang, Tasikmalaya, Tegal, Yogyakarta	-0.08	-1.35
Club 4	[8 cities]: Ambon, Banda Aceh, Banyuwangi, Kediri, Maumere, Pare-pare, Probolinggo, Surakarta	0.12	1.46
No convergence	[1 city]: Tual		

Note: Results show the evidence of club convergence. **t-stats** > -1.65 denotes that the null hypothesis of convergence is not rejected. *Source:* Authors' calculation.

Each club's relative transition path is shown in Figure 1, where the average CPI in each club (in log form) is evaluated against the cross-sectional average of samples. It is clear that all four clubs exhibit different convergence behaviors and transition paths starting from their initial conditions in 2014 until 2019. Since the transition path of clubs is diverging over time, one may conclude that the dynamics of all variables that affect price movements in each club are heterogeneous. In other words, the distinctive transition path reflects regional heterogeneity in price dynamics across Indonesia.

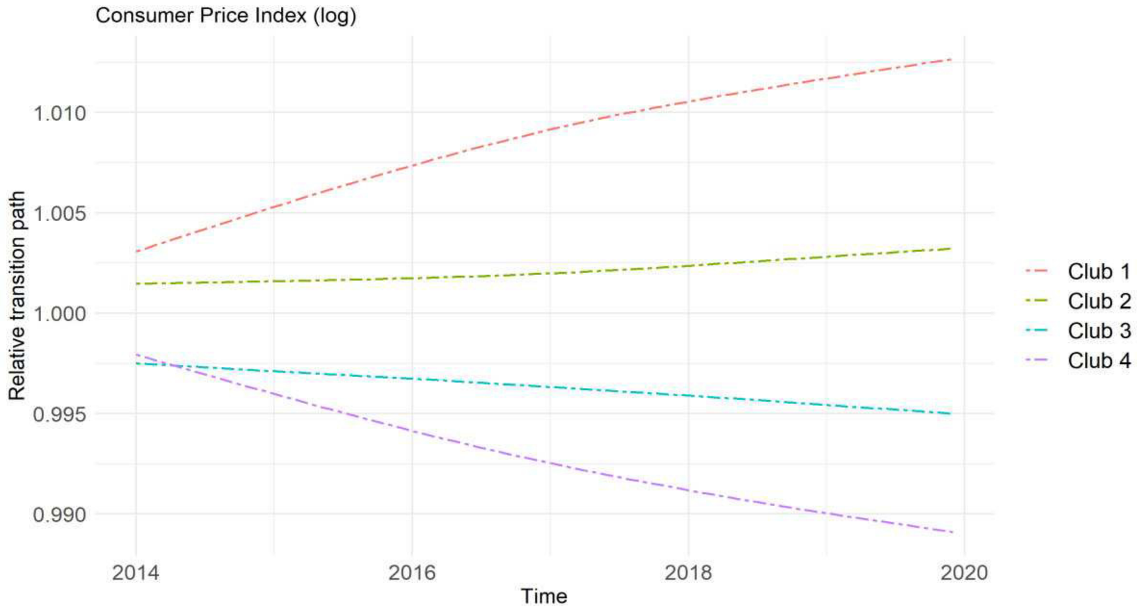

Figure 1. Transition path of clubs

Source: Authors' calculation.

Finally, we conducted a beta convergence test to confirm the robustness of the club convergence formation. To save space, we show the result of beta convergence test in Table A3 of the Appendix. The beta coefficient for all clubs is negative and statistically significant, suggesting the evidence of convergence in all clubs. In other words, the finding of club convergence formation is consistent with the result of the classical convergence framework.

Next, we continued to investigate convergence patterns in CPI components that drive the formation of four club convergence observed in aggregate CPI. Therefore, we re-applied the club convergence test to seven components of CPI repeatedly. It is important to note that similar to testing the club convergence on aggregate CPI, the algorithm generates the initial number of club convergence. Then, we proceeded with the club merging process to obtain final club convergence in each CPI component. Table 2 presents the results of final clubs generated from these procedures that are comparable to Panel C of Table 1. We also display the mean of CPI in each club to show the clubs' order from the highest CPI (club 1) to the lowest CPI (club 4). Given this order, we classify club 1, club 2, club 3 and club 4 as "high CPI", "middle-high CPI", "middle-low-CPI", and "low CPI", respectively.

Table 2. Club convergence in aggregate CPI and components

Clubs merging results				*Clubs merging results*			
Club	$\hat{b}$ coeff	t-stats	CPI[a]	Clubs	$\hat{b}$ coeff	t-stats	CPI[a]
Aggregate CPI				*Clothing*			
Full sample	-1.02	-106.97		Full sample	-0.92	-31.22	
Club 1	0.47	10.61	132.08	Club 1	-0.09	-1.57	127.69
Club 2	0.14	2.81	127.89	Club 2	0.29	5.99	118.97
Club 3	-0.08	-1.35	124.26	Club 3	-0.05	-1.04	116.78
Club 4	0.12	1.46	122.17	Club 4	-0.08	-1.10	109.18
Foodstuffs				*Health*			
Full sample	-1.15	-138.35		Full sample	-0.98	-432.94	
Club 1	-0.48	-1.27	140.15	Club 1	0.04	2.81	132.89
Club 2	0.01	0.23	132.73	Club 2	0.31	3.90	122.71
Club 3	0.84	14.10	123.98	Club 3	0.54	7.03	118.59
Club 4	0.49	9.72	118.42	Club 4	0.09	1.60	114.70
Housing				*Education*			
Full sample	-1.01	-619.70		Full sample	-1.08	-130.72	
Club 1	0.01	0.08	130.90	Club 1	0.10	0.65	129.52
Club 2	0.03	0.55	124.42	Club 2	-0.04	-0.60	118.53
Club 3	-0.06	-0.82	119.47	Club 3	0.31	2.28	112.76
Processed foods				*Transport*			
Full sample	-0.91	-40.50		Full sample	-1.21	-66.91	
Club 1	0.61	5.88	143.44	Club 1	0.36	2.77	135.61
Club 2	0.12	1.73	135.61	Club 2	0.06	1.41	128.16
Club 3	0.06	1.08	126.97	Club 3	-0.03	-0.64	121.95
Club 4	-0.02	-0.94	121.34	Club 4	0.35	6.53	116.66

Note: **t-stats** > -1.65 denotes that the null hypothesis of convergence is not rejected.
[a] indicates the mean of CPI in each club from January 2014 to December 2019. *Source:* Authors' calculation.

From the analysis using disaggregated CPI data, we found four appealing findings. First, similar to the results on aggregate CPI data, we were also able to reject the null hypothesis of overall convergence in all CPI components at the 5% significant level ($\hat{b}$ is significant < 0 with *t*-statistic < -1.65). This evidence supports the validity of our finding previously and reflects the presence of significant price divergence across Indonesian regions that prevails not only in aggregate price but also in sub-group of commodities.[3] From theory, we understand that the causes of price differentials across regions could be sourced from both countrywide and regional factors. While countrywide factors mainly related to the asymmetrical regional effects of common monetary regime and exchange rate movements, region-specific factors are more likely related to non-monetary terms such as the structure of labor market that shape the prices of input factor, different regional economic structure and business cycle position (for further discussion, see Beck, Hubrich, and Marcellino, 2014).

Second, we found variability in the number and composition of clubs across CPI components. By carefully looking at Table 2, one might notice the variability in the number of clubs across components where housing and education components have different number of clubs compared to the aggregate price and other components. A similar finding is also observed by Christou, Cunado, and Gupta (2018), where they obtain a smaller number of club convergence in housing price (7 clubs) compared to aggregate price (11 clubs) across 50 U.S. states for the period 1960-2007. This variability is more observable in terms of clubs' composition, represented by the number of cities in each club,

[3] We also plot the relative transition path of all clubs in each CPI component in Figure A1 of the Appendix. Like that in aggregate CPI, the transition path of clubs in CPI components is diverging over time.

as shown in Figure 2. None of the CPI components show identical clubs' composition, but some have a similar pattern. For example, in aggregate CPI, processed foods, health, transport, and housing components, most of the cities are in club 2 and club 3 (middle-high and middle-low CPI). Differently, clubs' composition in the clothing component is dominated by club 3 and club 4 (middle-low and low CPI). In contrast, most cities in foodstuffs and education components are in club 1 and club 2 (high and middle-high CPI).

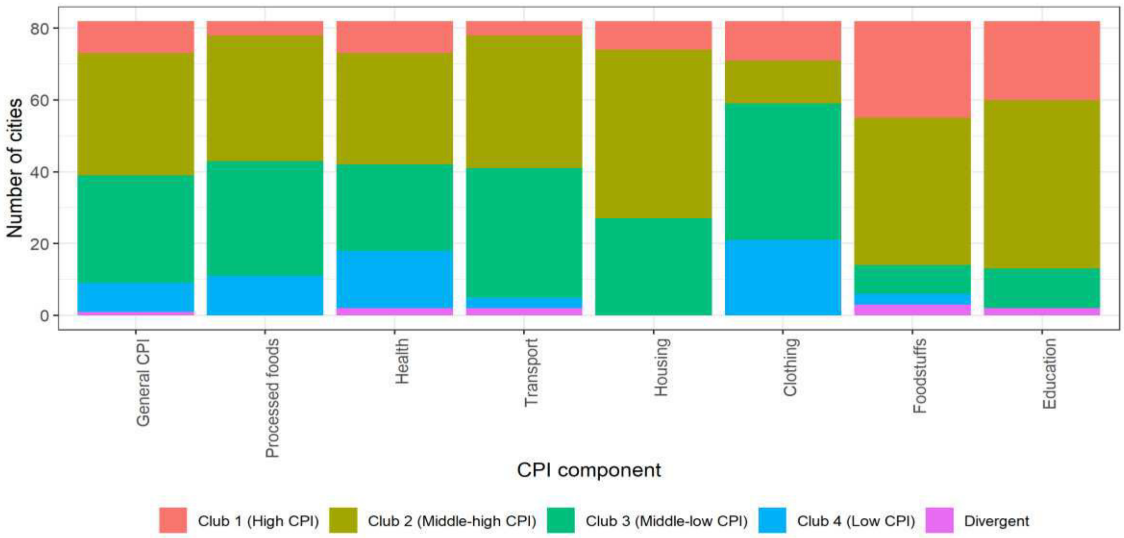

Figure 2. Club's composition in CPI components

Source: Authors' calculation.

Third, related to the second finding, clubs' composition in foodstuffs and education components implies an alarming message. As shown in Table 3, cities in club 1 have the highest inflation rate in all CPI components, followed by club 2, club 3 and, club 4 (lowest inflation rate). This means that number of cities with the highest inflation rate is much larger in foodstuffs and education components. On the other hand, although the average inflation rate of club 1 in the processed foods component is the highest among others, the number of cities in club 1 is minimal. The tendency of the foodstuffs component converging to higher price level reflects the underlying problems of food price inflation in Indonesia. A number of discussions around policies on controlling food inflation in Indonesia advocate that supply shocks (e.g., crop failure, frequent disturbance in shipment), lack of agriculture-related infrastructure, productivity stagnation in agriculture due to climate change, and seasonal religious events are the major factors that increase food price inflation. Meanwhile, the similar club's composition pattern in the education component is largely influenced by seasonal factors. More precisely, education-related expenses (e.g., school tuition fees, expenses for books and other school equipment) tend to increase around July and August, where the new academic year begins. As a whole, this third finding re-emphasizes the role of non-monetary factors in affecting the Indonesian inflation rate (Affandi, 2011; Alamsyah et al. 2001; Tirtosuharto and Adiwilaga, 2014).

To further understand the geographical pattern of clubs in all components, we show the details of the clubs' composition based on regions in Table A4 of the Appendix. Regarding the foodstuffs component, the highest percentage of cities in club 1 is observed in the Sumatra region, which is 43% (10 out of 23 cities), followed by the Java region, which is 36% (10 out of 28 cities). This geographical representation of club convergence in disaggregated price will help policymakers to prioritize regional inflation management policies. For example, if the goal is to control foodstuffs commodities' inflation rate, the policy could focus more on cities in Sumatra and Java regions. A similar analysis implies that policy should aim for cities in the Kalimantan region for the education component.

Table 3. Average inflation rate in each club

Club	Inflation[a]	Club	Inflation[a]	Club	Inflation[a]	Club	Inflation[a]
Aggregate CPI		Foodstuffs		Processed foods		Housing	
Club 1	4.76%	Club 1	5.37%	Club 1	7.14%	Club 1	4.92%
Club 2	4.05%	Club 2	4.26%	Club 2	5.46%	Club 2	3.80%
Club 3	3.66%	Club 3	3.00%	Club 3	4.47%	Club 3	3.05%
Club 4	3.14%	Club 4	0.96%	Club 4	3.25%		
Clothing		Health		Transport		Education	
Club 1	5.38%	Club 1	5.73%	Club 1	5.73%	Club 1	5.11%
Club 2	4.28%	Club 2	4.37%	Club 2	3.51%	Club 2	3.45%
Club 3	3.42%	Club 3	3.43%	Club 3	2.24%	Club 3	2.39%
Club 4	2.28%	Club 4	2.65%	Club 4	1.68%		

Note: [a] Mean of inflation in each club from January 2015 to December 2019. *Source:* Authors' calculation.

We further analyzed the relative contribution of CPI components towards the club convergence in aggregate CPI by comparing the number of common cities in aggregate CPI and each component. From the results presented in Table 4, we show that there are 17 cities in the foodstuffs component which follow the same transition path of cities belong to the aggregate CPI club convergence, 35 cities in processed foods, 41 cities in housing, 23 cities in clothing, 33 cities in health, 17 cities in education and 36 cities in transport component. We justified our evaluation by computing each component's relative contribution by dividing the total common cities in each component with the average number of common cities across all components. As the final finding from the disaggregated CPI data analysis, we reveal that housing, processed foods, transport, and health components make relatively larger (above average) contribution to the club convergence formation in the aggregate CPI, while foodstuffs, clothing, and education components constitute smaller contribution (below average). The result of this evaluation suggests the policymakers focus more on reducing regional price variability in housing, processed foods, transport, and health components to achieve a higher degree of convergence in regional price.

Table 4. Relative contribution to aggregate CPI club convergence

Club	Aggr. CPI	Foodstuffs vs Aggr. CPI	Processed foods vs Aggr. CPI	Housing vs Aggr. CPI	Clothing vs Aggr. CPI	Health vs Aggr. CPI	Education vs Aggr. CPI	Transport vs Aggr. CPI
Club 1	9	9	1	2	0	2	9	1
Club 2	34	4	19	23	5	14	6	17
Club 3	30	2	13	16	17	14	2	17
Club 4	8	2	2	-	1	3	-	1
Total	82	17	35	41	23	33	17	36
Contr.		0.59	1.21	1.42	0.80	1.14	0.59	1.25

Note: vs stands for versus. Aggr. CPI and Contr. refers aggregate CPI and to relative contribution. - denotes the absence of club 4 for the housing and education component. The relative contribution is computed as total cities in each CPI component that follow the same transition path in aggregate CPI club convergence divided by the average of total cities across CPI components that follow the same transition path in aggregate CPI club convergence. The relative contribution shows that processed foods, housing, health, and transport components contribute relatively higher (above average) to the aggregate CPI club convergence. Non-convergence cities for aggregate CPI, health, education, and transport components are Tual, Tanjung Pandan and Ternate, Jakarta and Sorong, Tual, and Bengkulu, respectively. In general, the format of the table follows Akram, Sahoo, and Rath (2020). *Source:* Authors' calculation.

4. Conclusions

The purpose of this study is to examine price convergence across 82 cities in Indonesia by using aggregate CPI and its components. We implement recent convergence frameworks and clustering techniques developed by Phillips and Sul (2007, 2009) in two steps; first, we identify club convergence using aggregate CPI, and second, we identify club convergence using seven components of CPI. The data used in this study is monthly CPI from January 2014 to December 2019.

Using aggregate CPI data, we do not find evidence of overall price convergence. Instead, we identify four club convergence. This result is consistent with the finding in previous study by Jangam and Akram (2019). Next, further examination using CPI components produces appealing outcomes. First, overall price convergence does not exist in any of CPI components, supporting the result from aggregate CPI. Second, there is variability in the number and composition of clubs across CPI components. Third, the price of foodstuffs and education-related commodities in most cities converges to a higher level, reflecting the role of non-monetary factors in affecting Indonesia's inflation dynamics. Fourth, housing, processed foods, transport, and health components constitute a relatively larger contribution to the club convergence formation in the aggregate CPI.

Overall, our study demonstrates that club convergence identification using disaggregated consumer price data would reveal some important details which are not observed in aggregate price. In the context of Indonesian cities, the details are rich with policy implications. First, the rejection of price convergence suggests price rigidities that attribute to persistent regional price variability. In order to reduce the degree of variability in aggregate price, policies should target improving market efficiency in housing, processed foods, transport, and health-related sectors. Second, when the goal is to control the inflation rate, region-based price management policies can be implemented to control the price of foodstuffs and education commodities or services, particularly in cities of Sumatra, Java and Kalimantan regions. As for future research, our findings open the opportunities to investigate the conditioning factors of club convergence formation in Indonesian regional price, particularly by integrating the role of spatial spillovers as emphasized by recent convergence studies.

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Appendix

1. Four steps in identifying club convergence:
   i. CPI of 82 cities are arranged in decreasing order according to their value in the last period, that is December 2019.
   ii. A core group of sample cities is identified based on the maximum t_k obtained from a series of sequential estimations of equation (5) for the k largest group ($2 \leq$ kN).
   iii. Cities not belonging to the core group are re-evaluated one at a time with log t regression. A new group is formed when t-statistic > -1.65.
   iv. Steps 1 to 3 are performed again for remining cities. If no core group is found, remining cities are labeled as divergent, and the algorithm stops.

Table A1. Summary statistics of aggregate CPI in 82 Indonesian cities

No.	City	Mean	Std Dev	Min.	Max.	No.	City	Mean	Std Dev	Min.	Max.
1	Ambon	123.87	6.95	108.58	134.47	42	Medan	129.69	9.84	111.57	146.7
2	Balikpapan	129.64	9.14	111.85	142.36	43	Merauke	130.14	8.5	111.84	141.02
3	Banda Aceh	120.08	6.9	107.26	130.34	44	Metro	133.14	6.64	120.34	143.58
4	Bandar Lampung	126.57	8.81	109.89	139.92	45	Meulaboh	126.04	7.55	112.05	139.73
5	Bandung	125.14	8.31	109.87	138.22	46	Padang	130.79	8.94	113.48	144.55
6	Banjarmasin	125.61	9.23	108.22	140.15	47	Padang Sidempuan	124.5	7.94	110.39	136.97
7	Banyuwangi	122.72	6.04	111.04	131.95	48	Pakanbaru	127.05	8.99	110.92	141.09
8	Batam	126.16	9.43	109.24	140.33	49	Palangkaraya	123.47	7.31	109.63	135.43
9	Bau-bau	128.14	7.9	109.84	139.31	50	Palembang	123.52	8.03	108.41	134.81
10	Bekasi	123.82	7.85	110.15	137.79	51	Palopo	124.4	8.52	108.84	136.62
11	Bengkulu	133.25	10.52	112.57	147.98	52	Palu	128.31	9.71	110.78	144.4
12	Bima	128.9	8.3	113.35	141.86	53	Pangkal Pinang	130.15	10.96	110.52	146.22
13	Bogor	126.76	8.85	111.73	140.86	54	Pare-pare	122.01	6.97	108.21	132.6
14	Bukit Tinggi	123.71	7.32	109.55	135.18	55	Pematang Siantar	129.84	8.88	113.32	143.12
15	Bulukumba	132.03	8.55	116.06	144.75	56	Pontianak	134.38	10.77	111.78	149.42
16	Bungo	124.59	8.06	109.75	137.75	57	Probolinggo	123.4	5.81	112.23	132.35
17	Cilacap	128.59	8.28	112.9	140.75	58	Purwokerto	123.75	7.23	110.49	134.88
18	Cilegon	130.85	10.49	111.46	146.63	59	Samarinda	128.7	8.38	113.78	140.25
19	Cirebon	122.47	6.56	110.11	132.58	60	Sampit	127.16	9.58	109.94	141.87
20	Denpasar	123.15	7.49	109.14	134.62	61	Semarang	124.81	7.5	110.39	136.59
21	Depok	125.06	7.64	111.53	137.36	62	Serang	133.35	11.13	111.98	149.63
22	Dumai	127.3	8.52	110.67	139.49	63	Sibolga	129.41	10.65	110.37	148.33
23	Gorontalo	122.03	7.61	107.91	133.53	64	Singaraja	133.38	9.23	114.67	146.5
24	Jakarta	126.55	8.21	110.75	139.62	65	Singkawang	126.72	9.18	109.14	139.61
25	Jambi	125.43	7.67	111.26	137.3	66	Sorong	125.75	8.32	108.43	137.06
26	Jayapura	127.87	9.23	111.64	142.49	67	Sukabumi	125.71	7.61	111.29	137.19
27	Jember	122.96	6.76	110.65	133.28	68	Sumenep	122.98	6.96	109.42	133.45
28	Kediri	122.99	5.76	111.91	131.63	69	Surabaya	125.94	8.34	110.47	138.23
29	Kendari	121.93	7.63	107.34	135.35	70	Surakarta	122.46	6.79	109.5	133.1
30	Kudus	131.81	8.55	116.25	145.17	71	Tangerang	133.13	9.31	114.82	147.82
31	Kupang	126.78	7.5	111.39	136.64	72	Tanjung	125.71	8.19	109.57	136.8
32	Lhokseumawe	121.81	7.77	107.19	132.73	73	Tanjung Pandan	133.46	9.54	114.68	147.92
33	Lubuk Linggau	123.23	8.4	106.76	134.66	74	Tanjung Pinang	125.64	7.1	111.87	136.54
34	Madiun	123.79	7.69	109.71	135	75	Tarakan	135.56	10.22	113.64	150.66
35	Makassar	126.41	9.66	108.65	140.02	76	Tasikmalaya	124.32	7.7	109.2	134.58
36	Malang	126.34	7.96	111.03	137.6	77	Tegal	122.65	8.03	107.62	134.71
37	Mamuju	124.42	7.86	108.75	134.52	78	Tembilahan	130.78	7.99	115.63	144.3
38	Manado	125.4	8.33	109.05	140.99	79	Ternate	129.49	8.41	111.57	141.42
39	Manokwari	121.15	9.09	106.28	138.31	80	Tual	141	14.32	112.53	160.83
40	Mataram	124.41	7.44	110.53	135.15	81	Watampone	122.98	7.97	108.28	135.06
41	Maumere	119.81	5.9	108.76	128.73	82	Yogyakarta	123.8	7.32	110.77	135.46

Note: The format of the table follows Jangam and Akram (2019). *Source:* Authors' calculation.

Table A2. Summary statistics of aggregate CPI and components

CPI component	Mean	Std. Dev.	Minimum	Maximum
Aggregate	126.44	9.04	106.28	150.66
Foodstuffs	133.84	12.91	101.02	189.76
Processed foods	130.70	13.32	103.06	172.10
Housing	123.42	9.24	102.84	157.31
Clothing	116.61	10.59	97.05	171.16
Health	121.02	10.75	100.93	166.64
Education	120.40	11.23	97.78	162.72
Transport	125.93	10.07	103.04	191.42

Note: The Indonesian regional CPI data consist of one aggregate price index that can be disaggregated into seven components; 1) foodstuffs, 2) processed foods, 3) housing and utilities, 4) clothing, 5) health, 6) education, leisure and sports, and 7) transportation, communication and financial services. Source: Authors' calculation.

Table A3. Result of beta convergence test for each club

Club	Beta coefficient	Standard error	R-square
Club 1	-0.54***	0.09	0.84
Club 2	-0.42***	0.07	0.53
Club 3	-0.41***	0.09	0.42
Club 4	-0.49**	0.16	0.61

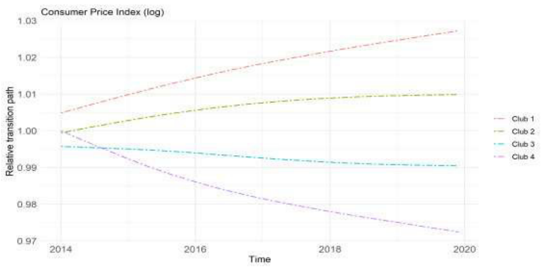
Note: ***, ** denote statistical significance at 1% and 5% levels respectively.
Source: Authors' calculation.

Table A4. Number of cities in each club of CPI components by regions

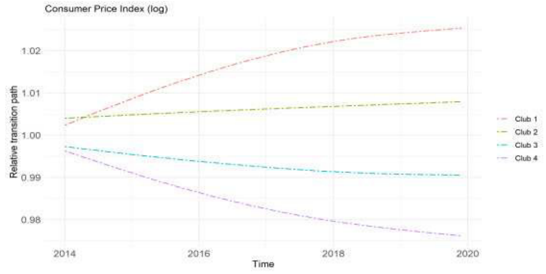
CPI component	Club	Number of cities	Region			
			Sumatra	Java-Bali	Kalimantan	Eastern
Aggregate CPI	Club 1	9	4	2	2	1
	Club 2	34	11	9	5	9
	Club 3	30	7	13	2	8
	Club 4	8	4	4	-	3
	No convergence	1	-	-	-	1
	Total	82	23	28	9	22
Foodstuffs	Club 1	27	10	10	2	5
	Club 2	41	10	13	6	12
	Club 3	8	2	2	1	3
	Club 4	3	-	2	-	1
	No convergence	3	1	1	-	1
	Total	82	23	28	9	22
Processed foods	Club 1	4	-	1	-	3
	Club 2	35	10	13	4	8
	Club 3	32	9	8	5	10
	Club 4	11	4	6	-	1
	No convergence	-	-	-	-	-
	Total	82	23	28	9	22
Housing	Club 1	8	2	2	2	2
	Club 2	47	17	17	5	8
	Club 3	27	4	9	2	12
	No convergence	-	-	-	-	-
	Total	82	23	28	9	22
Clothing	Club 1	11	3	3	1	4
	Club 2	12	4	2	2	4
	Club 3	38	11	14	5	8
	Club 4	21	5	9	1	6
	No convergence	-	-	-	-	-
	Total	82	23	28	9	22
Health	Club 1	9	-	4	3	2
	Club 2	31	12	8	5	6
	Club 3	24	4	11	1	8
	Club 4	16	6	5	-	5
	No convergence	2	1	-	-	1
	Total	82	23	28	9	22
Education	Club 1	22	8	5	4	5
	Club 2	47	12	20	4	11
	Club 3	11	3	2	1	5
	No convergence	2	-	-	-	1
	Total	82	23	28	9	22
Transport	Club 1	4	1	-	2	1
	Club 2	37	9	13	3	12
	Club 3	36	12	14	4	6
	Club 4	3	1	1	-	2
	No convergence	2	-	-	-	1
	Total	82	23	28	9	22

Source: Authors' calculation.

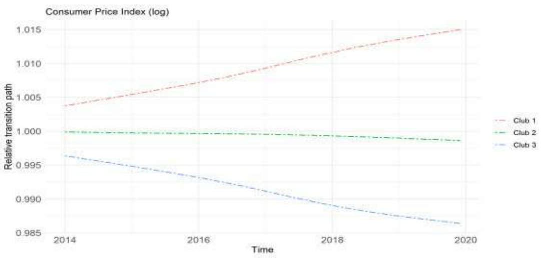
Figure A1. Transition path of clubs for all CPI components



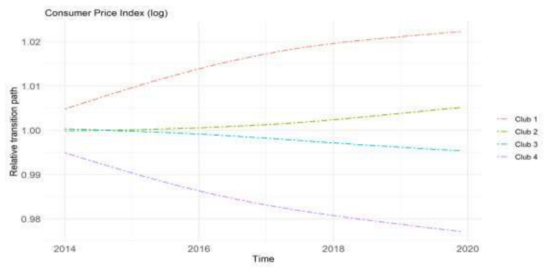
Foodstuffs



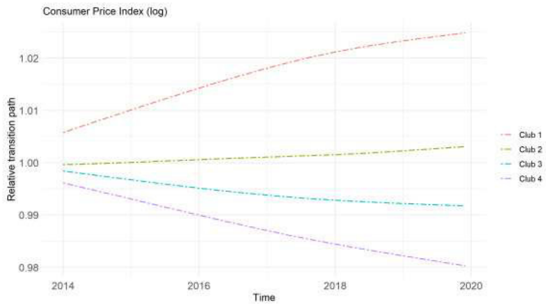
Processed foods



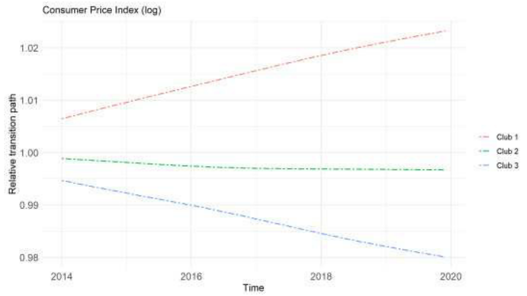
Housing



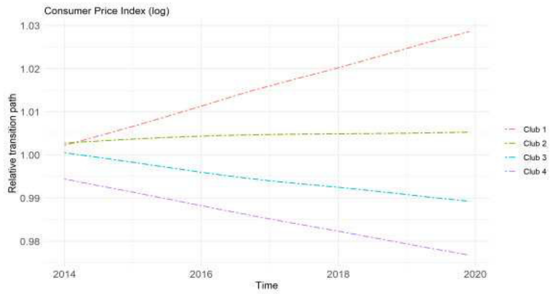
Clothing



Health



Education



Transport

Source: Authors' calculation.