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# UNDERSTANDING INDONESIA'S CITY-LEVEL CONSUMER PRICE FORMATION: IMPLICATIONS FOR PRICE STABILITY

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## ABSTRACT

Using the Consumer Price Index (CPI) data of 82 Indonesian cities, we propose the hypothesis of heterogeneity in the cities' contribution to the aggregate Indonesian CPI. Using a price discovery model fitted to monthly data, we discover that (1) of the 23 cities in the province of Sumatera, five contribute 44% and nine contribute 66.7% to price changes, and (2) of the 26 cities in Java, four alone contribute 41.6% to price changes. Even in smaller provinces, such as Bali and Nusa Tenggara, one city alone dominates the change in aggregate CPI. From these results, we draw implications for maintaining price stability.

*Keywords: Consumer Price Index; Cities; Price discovery; Bank Indonesia.*
**JEL Classifications: E31; E37.**

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## I. INTRODUCTION

Inflation is an important subject that dictates policymaking. Both monetary and fiscal policies are inflation dependent. Therefore, an understanding of the determinants of inflation and its relations with other macroeconomic variables has formed the basis for multiple theories and hypotheses in economics, including those of Alba and Papell (1998), Hendry (2001), Ciccarelli and Mojon (2010), Narayan, Narayan, and Mishra (2011), and Sharma (2019). In this paper, we do not engage in either of these areas of analysis; rather, we propose a question that has not been previously addressed by the literature: among multiple cities, which city (or group of cities) dominates the formation of Consumer Price Index (CPI) inflation? The intuition is the following. In a large region/province/state, there are multiple cities. Given many cities, we argue—and it is natural, too—that some cities will be price takers and some price setters. This will result from the fact that some cities are small while others are large. Size dictates the level of economic activity, which, in turn, influences price changes and their evolution. In such a situation, the question is not only which city contributes most to price changes, but how much, precisely, do they contribute to price changes?

This paper addresses these two questions using quarterly CPI data for 82 cities from Indonesia's six provinces. We employ a recent price discovery methodology proposed by Westerlund, Reese, and Narayan (2017; WRN hereafter). This method has several advantages. The one that motivates our hypothesis proposal and test is that, unlike other econometric methods (e.g., a vector autoregressive or vector error correction model), WRN's method does not restrict the number of price variables that can be simultaneously modeled. This ensures that we can avoid the price variable selection bias that characterizes many empirical papers on price discovery.

Our empirical analysis leads to the following conclusions. Of Sumatera's 23 cities, nine alone contribute 66.7% to price changes and five contribute 44%. Similarly, of the 26 cities in Java, nine contribute 65% to all price changes, with four contributing 41.6%. Even in smaller provinces, such as Bali and Nusa Tenggara, where there are only five cities, one city alone contributes around 43% to all price changes. Across all six provinces, we identify leader cities (that is, those cities that drive the bulk of the price changes). The implication of our results is that each province in Indonesia has between six and 26 cities, for a total of 82 cities. In controlling prices, given that the objective of Bank Indonesia, the central bank, is to maintain price stability, pricing-related policy should pay more attention to the cities we identify as leaders in moving aggregate (national) CPI.

Our contributions to the literature are threefold. First, our proposal, a hypothesis that aims to test the heterogeneity in the cities' contribution to the aggregate CPI (which in other words identifies leader cities') is original. This type of analysis on a search for leading cities (or a leader city) in price changes (from an inflation perspective) has not been previously considered. Our idea can therefore be tested in other countries to see if groups of cities can be identified that drive price changes. This information is important for price stability-based policies in countries and/or regions with many cities. In this regard, the novelty of our research question and approach contributes broadly to the literature on the evolution of price changes; see, for instance, Zozicki and Tinsley (2012) and Kilian (2008).

Second, our work is connected to the literature (see, *inter alia*, Basher and Westerlund, 2008; Culver and Papell, 1997; Westelius, 2005) that tests for persistency of inflation. The idea inherent in this literature is policy based, in that, if shocks to inflation are temporary (short term), then the persistency test (typically conducted using unit root tests) will imply a stationary inflation rate. By comparison, if the inflation rate appears to be nonstationary, then shocks are likely to have a long-term effect. Finding evidence of temporary or long-term effects of shocks on inflation has implications for price stability, particularly about policies that can support price stability. The unit root literature's limitation in informing policy in this way is that it considers one city (or country) at a time; that is, the cities or countries are not all modeled simultaneously. This is wasteful, because there is a loss of information from cities ignored by the analysis. Therefore, one could argue that a unit root test is always associated with a model misspecification problem when the hypothesis test is of the type we examine in this paper. This is not to say that unit root tests should not be used. They are powerful tools which should be employed by researchers; however, our argument is that when one wants to search for leader cities amongst a large group of cities, the unit root test is unlikely to be the most suitable tool. It follows that the type of price discovery model we employ circumvents this model misspecification concern by considering all cities in a single model. We argue that, by employing the WRN framework, we have a relatively complete model for understanding the joint (among cities, as in our example) evolution of prices.

Our final contribution is to the Indonesia-specific literature on inflation. In a recent paper that inspired our proposed hypothesis test, Jangam and Akram (2019) show that city-level prices in Indonesia weakly converge. Their analysis points to four convergence clubs among a large group of Indonesian cities. Their policy recommendation is rather complex, because they suggest targeting those four groups of cities to achieve price convergence. Our results support theirs, in that the bulk of Indonesian cities do not contribute to price changes in a statistically significant manner. Where we differ, however, is in our identification of leader cities. A key advantage of our approach and finding is the recommendation to target those cities that are price drivers (or leaders). Our policy recommendation is thus less complex, tractable, and easy to implement.

The remainder of the paper is organized as follows. Section II explains the methodology. Section III describes the data and the results. Section IV highlights our key findings and implications.

## II. METHODOLOGY

To test our hypothesis that certain cities in Indonesia contribute more to the Consumer Price Index (CPI) than others, we employ the discovery model of WRN. WRN's model is a common factor model, of the following form:

$$P_{i,t} = \alpha_i CF_t + Z_{i,t} \tag{1}$$

where $CPI_{i,t}$ is the CPI of city $i$, $i$=1,…,82, in period $t$=2014$M$01,…,2018$M$04, where M01 denotes the month of January and M04 the month of April. The monthly data frequency ensures that each city has 52 data points.

The common factor, $CF_t$, is the aggregate (country) Indonesian CPI. The construction of Equation (1) implies that the common factor (the CPI of Indonesia) is thus applicable (or is common) to each Indonesian city. Each city's relation to the common factor is represented by $\alpha_i$. Finally, $Z_{i,t}$ is an idiosyncratic error term. According to price discovery theory, the fundamental price ($CF_t$) should follow a random walk and be common across cities, while the noise component ($Z_{i,t}$) should be stationary and idiosyncratic. It therefore follows that $\alpha_1$=...= $\alpha_{82}$=1 . The idea behind Equation (1) is to discover (hence the term *price discovery*) which city contributes, and how much, to the movement of the aggregate CPI.

To extract the share (or contribution) of each city's CPI to the aggregate CPI, we employ Hasbrouck's (1995) information share (*Contribution*), which has been extended by WRN to a panel version (to accommodate the panel of 82 cities in our example) in the spirit of Narayan, Sharma, and Thuraisamy (2014) as follows:

$$Contribution_i = \frac{\alpha_i^2 \sigma_{cf}^2 \sigma_{Z,i}^{-2}}{\sum_{n=1}^{82} \alpha_n^2 \sigma_{cf}^2 \sigma_{Z,n}^{-2}} \qquad (2)$$

where $\sigma_{Z,i}^2$ is the variance of $Z_{i,t}$ and $\sigma_{cf}^2$ is the variance of $cf_t = CF_t - CF_{t-1}$, the shock to the fundamental price. This equation states that (a) the lower the amount of noise ($\sigma_Z^2$) in the CPI of city *i*, the higher that city's contribution to the aggregate CPI, and (b) as the covariance between the CPI of city *i* and the aggregate CPI ($\alpha_i$) increases, that city's contribution to the aggregate CPI rises. Further details on the methodology are provided by Narayan, Phan, Thuraisamy, and Westerlund (2016) and Narayan, Sharma, Thuraisamy, and Westerlund (2018). We refer readers to these papers.

## III. DATA AND RESULTS

The data for this paper are taken from an earlier paper published in this journal (Jangam and Akram, 2019). The data set is monthly and spans the period from January (M01) 2014 to April (M04) 2018. It should be noted that, while Jangam and Akram (2019) use data up to August 2019, we had to truncate the sample to a common end date to remain consistent with the econometric methodology. Further details on the data are given by Jangam and Akram (2019).

Before we examine our main hypothesis, a descriptive story of the data set is in order. Table 1 reports common descriptive statistics organized by city and categorized into the six provinces. A key feature of the data is that not only do the mean and the variance of *CPI* inflation vary by city and by province, but also, as noted in the last column, the sample growth rate and average annual growth rate of the *CPI* vary vastly both among cities in a province and across provinces. Some discussion on this is warranted. In Sumatera, for instance, the annual average price growth is recorded at 4.64%, with 13 of 23 cities experiencing annual price growth in excess of 4.64%. Java has an annual average price growth rate of 4.27%, with 13 of 26 cities experiencing a rate in excess of 4.27%. In other, smaller provinces, the story is similar: in Bali, Kalimantan, and Sulawesi, three of six, five of nine, and six of 11 cities, respectively, have growth rates in excess of their province's annual average growth rate. When comparing *CPI* growth rates across cities, we also see differences: Maluku-Papua has the highest annual average price growth rate (5%), followed by Kalimantan (4.94%), Sumatera (4.64%), Sulawesi (4.54%), Java (4.27%), and Bali (4.21%). There is almost a 20% difference in price growth between the high–price growth rate provinces (e.g., Maluku-Papua and Kalimantan) and the low–price growth rate provinces (e.g., Java and Bali).[1]

**Table 1.**
**Descriptive Statistics**

This table reports some commonly used descriptive statistics (mean, standard deviation, skewness and kurtosis) of each city's *CPI* return. The final two columns report the average annual growth rate and full sample growth rate of each city's *CPI*.

| Region | City | *CPI* returns | | | | *CPI* | |
|---|---|---|---|---|---|---|---|
| | | Mean | S.D. | Skewness | Kurtosis | Average annual growth rate | Full sample growth rate |
| Sumatera | Meulaboh | 0.310 | 0.697 | 0.834 | 5.432 | 3.746 | 17.465 |
| | Banda Aceh | 0.306 | 0.635 | 0.469 | 3.592 | 3.843 | 17.249 |
| | Lhokseumawe | 0.346 | 0.859 | -0.005 | 3.669 | 4.353 | 19.697 |
| | Sibolga | 0.431 | 1.132 | -0.384 | 3.383 | 5.481 | 25.102 |
| | Pematang Siantar | 0.372 | 0.710 | 0.563 | 4.481 | 4.817 | 21.327 |
| | Medan | 0.405 | 0.723 | -0.160 | 3.723 | 5.319 | 23.453 |
| | Padang Sidempuan | 0.336 | 0.712 | 0.217 | 3.478 | 4.238 | 19.105 |
| | Padang | 0.379 | 0.935 | 0.372 | 5.192 | 4.798 | 21.815 |
| | Bukit Tinggi | 0.341 | 0.825 | -0.421 | 4.437 | 4.077 | 19.396 |
| | Tembilahan | 0.389 | 0.633 | 1.160 | 5.255 | 4.015 | 22.410 |
| | Pekanbaru | 0.385 | 0.602 | 0.116 | 4.027 | 4.859 | 22.195 |
| | Dumai | 0.379 | 0.506 | 0.623 | 4.013 | 4.891 | 21.815 |
| | Bungo | 0.341 | 0.707 | 0.461 | 3.544 | 4.316 | 19.407 |
| | Jambi | 0.341 | 0.836 | -0.059 | 3.657 | 4.087 | 19.382 |
| | Palembang | 0.359 | 0.613 | 1.191 | 6.756 | 4.669 | 20.552 |
| | Lubuk Linggau | 0.391 | 0.762 | 0.765 | 4.680 | 4.976 | 22.569 |
| | Bengkulu | 0.446 | 0.838 | 0.916 | 4.696 | 5.803 | 26.104 |
| | Bandar Lampung | 0.384 | 0.578 | 1.049 | 6.303 | 4.963 | 22.074 |
| | Metro | 0.285 | 1.713 | -1.037 | 19.759 | 3.758 | 15.971 |
| | Tanjung Pandan | 0.418 | 1.248 | 0.183 | 2.820 | 4.945 | 24.304 |
| | Pangkal Pinang | 0.442 | 1.193 | 0.310 | 3.150 | 5.754 | 25.822 |
| | Batam | 0.392 | 0.677 | 0.667 | 4.156 | 5.182 | 22.641 |
| | Tanjung Pinang | 0.308 | 0.664 | 0.514 | 5.798 | 3.942 | 17.359 |

[1] We do not conduct the Narayan and Popp (2010, 2013) endogenous structural break test because it was unlikely to change the hypothesis we are proposing to test. However, we believe that doing a persistency test of CPI using the dataset we have here will constitute a separate paper. In such an endeavor, the half-life can be computed to understand the heterogeneity of city-based inflation to shocks.

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**Table 1.**
**Descriptive Statistics (Continued)**

This table reports some commonly used descriptive statistics (mean, standard deviation, skewness and kurtosis) of each city's *CPI* return. The final two columns report the average annual growth rate and full sample growth rate of each city's *CPI*.

| Region | City | *CPI* returns | | | | *CPI* | |
|---|---|---|---|---|---|---|---|
| | | Mean | S.D. | Skewness | Kurtosis | Average annual growth rate | Full sample growth rate |
| Java | Jakarta | 0.361 | 0.480 | 2.538 | 12.479 | 4.452 | 20.639 |
| | Bogor | 0.360 | 0.483 | -0.088 | 5.881 | 4.513 | 20.584 |
| | Sukabumi | 0.345 | 0.479 | 1.712 | 8.335 | 4.172 | 19.644 |
| | Bandung | 0.368 | 0.459 | 1.464 | 7.678 | 4.480 | 21.069 |
| | Cirebon | 0.303 | 0.431 | 0.720 | 4.003 | 3.605 | 17.043 |
| | Bekasi | 0.324 | 0.543 | 0.856 | 4.515 | 3.897 | 18.321 |
| | Depok | 0.316 | 0.528 | 0.871 | 4.845 | 4.024 | 17.889 |
| | Tasikmalaya | 0.365 | 0.458 | 1.620 | 8.883 | 4.484 | 20.893 |
| | Cilacap | 0.365 | 0.534 | 0.817 | 2.921 | 4.433 | 20.898 |
| | Purwokerto | 0.318 | 0.520 | 0.612 | 3.774 | 3.942 | 17.958 |
| | Kudus | 0.374 | 0.568 | 1.041 | 5.057 | 4.496 | 21.489 |
| | Surakarta | 0.319 | 0.545 | 0.680 | 5.492 | 3.812 | 18.072 |
| | Semarang | 0.343 | 0.518 | 1.038 | 6.136 | 4.166 | 19.495 |
| | Tegal | 0.357 | 0.499 | 0.371 | 2.746 | 4.512 | 20.399 |
| | Yogyakarta | 0.318 | 0.416 | 1.095 | 4.586 | 3.946 | 18.008 |
| | Jember | 0.307 | 0.542 | 2.089 | 8.889 | 3.800 | 17.330 |
| | Banyuwangi | 0.280 | 0.492 | 1.412 | 9.597 | 3.397 | 15.654 |
| | Sumenep | 0.318 | 0.513 | 1.456 | 8.384 | 3.995 | 17.979 |
| | Kediri | 0.274 | 0.526 | 1.633 | 8.250 | 3.403 | 15.289 |
| | Malang | 0.356 | 0.513 | 1.912 | 10.009 | 4.538 | 20.310 |
| | Probolinggo | 0.269 | 0.457 | 1.601 | 6.908 | 3.322 | 15.013 |
| | Madiun | 0.343 | 0.465 | 1.413 | 6.819 | 4.318 | 19.533 |
| | Surabaya | 0.374 | 0.470 | 1.650 | 7.024 | 4.657 | 21.460 |
| | Serang | 0.432 | 0.730 | -0.751 | 6.270 | 5.553 | 25.168 |
| | Tangerang | 0.461 | 0.901 | 0.835 | 8.141 | 5.452 | 27.070 |
| | Cilegon | 0.439 | 0.672 | 0.837 | 6.422 | 5.576 | 25.618 |
| Bali & Nusa Tenggara | Singaraja | 0.418 | 0.763 | 0.525 | 3.797 | 5.130 | 24.303 |
| | Denpasar | 0.353 | 0.488 | 1.161 | 4.659 | 4.134 | 20.143 |
| | Mataram | 0.331 | 0.584 | 0.679 | 3.999 | 4.101 | 18.786 |
| | Bima | 0.363 | 0.718 | 0.262 | 2.371 | 4.255 | 20.782 |
| | Maumere | 0.262 | 0.614 | 0.831 | 4.040 | 3.354 | 14.598 |
| | Kupang | 0.337 | 0.906 | 1.020 | 4.990 | 4.306 | 19.127 |
| Kalimantan | Pontianak | 0.459 | 0.833 | 0.920 | 4.000 | 5.851 | 26.982 |
| | Singkawang | 0.432 | 0.683 | 0.624 | 2.829 | 5.040 | 25.170 |
| | Sampit | 0.396 | 0.577 | -0.110 | 3.509 | 4.857 | 22.881 |
| | Palangkaraya | 0.317 | 0.552 | 0.141 | 2.367 | 3.934 | 17.936 |
| | Tanjung | 0.406 | 0.744 | 0.438 | 3.267 | 4.731 | 23.504 |
| | Banjarmasin | 0.379 | 0.461 | 0.639 | 3.037 | 5.046 | 21.807 |

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**Table 1.**
**Descriptive Statistics (Continued)**

This table reports some commonly used descriptive statistics (mean, standard deviation, skewness and kurtosis) of each city's *CPI* return. The final two columns report the average annual growth rate and full sample growth rate of each city's *CPI*.

| Region | City | *CPI* returns | | | | *CPI* | |
|---|---|---|---|---|---|---|---|
| | | Mean | S.D. | Skewness | Kurtosis | Average annual growth rate | Full sample growth rate |
| | Balikpapan | 0.396 | 0.716 | 0.681 | 2.773 | 5.062 | 22.836 |
| | Samarinda | 0.346 | 0.509 | 1.691 | 7.399 | 4.534 | 19.725 |
| | Tarakan | 0.431 | 0.678 | 1.176 | 4.763 | 5.419 | 25.108 |
| Sulawesi | Manado | 0.378 | 0.948 | 0.940 | 5.169 | 4.733 | 21.729 |
| | Palu | 0.372 | 0.876 | 0.223 | 3.616 | 4.584 | 21.315 |
| | Bulukumba | 0.372 | 0.674 | 0.534 | 4.691 | 4.269 | 21.349 |
| | Watampone | 0.335 | 0.643 | 0.617 | 4.497 | 3.981 | 19.052 |
| | Makassar | 0.420 | 0.580 | 1.186 | 5.510 | 5.371 | 24.395 |
| | Pare-pare | 0.310 | 0.804 | 1.373 | 7.34 | 4.109 | 17.487 |
| | Palopo | 0.394 | 0.665 | 1.288 | 4.889 | 4.584 | 22.726 |
| | Kendari | 0.29 | 0.897 | 1.415 | 6.619 | 4.296 | 16.291 |
| | Bau-bau | 0.364 | 1.079 | 0.269 | 2.897 | 4.765 | 20.822 |
| | Gorontalo | 0.303 | 0.836 | 1.641 | 9.163 | 4.395 | 17.083 |
| | Mamuju | 0.364 | 0.608 | 0.553 | 4.667 | 4.827 | 20.838 |
| Maluku-Papua | Ambon | 0.31 | 0.891 | -0.03 | 4.394 | 4.131 | 17.510 |
| | Tual | 0.517 | 1.509 | -0.166 | 3.045 | 8.317 | 30.837 |
| | Ternate | 0.374 | 0.878 | 0.264 | 4.209 | 4.554 | 21.448 |
| | Manokwari | 0.308 | 0.803 | 0.050 | 2.893 | 4.206 | 17.341 |
| | Sorong | 0.365 | 0.748 | 0.382 | 2.927 | 4.519 | 20.891 |
| | Merauke | 0.431 | 1.154 | 0.40 | 5.515 | 4.902 | 25.154 |
| | Jayapura | 0.362 | 0.996 | 1.039 | 5.831 | 4.405 | 20.688 |

When we note the volatility of the inflation rate, as depicted by the standard deviation of the price change, we again see that, within provinces, some cities experience higher volatility in price changes. The results in Table 2 show evidence of serial correlation in price changes and their persistence. We observe that the majority of the cities have price changes that are best characterized as serially correlated, suggesting that current price changes are related to future price changes. Although this is true for most cities, what is different is the magnitude of serial correlation as measured by the first-order autoregressive coefficient reported in the last column. Kalimantan, Java, and Bali, and Nusa Tenggara have a price persistency of 0.22, 0.20, and 0.19, respectively, while, for Java, Sulawesi, and Maluku-Papua, the persistency in prices is much lower, at 0.12, 0.07, and 0.05, respectively.

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**Table 2.**
**Persistence of Cities' *CPI* Returns**

This table reports the persistency of *CPI* returns by way of the estimated first-order autoregressive, or AR(1), coefficient and the Ljung-Box *Q*-stat for serial correlation at lag 1–12.

| Province/ Region | City | Ljung-Box test | | AR(1) | |
|---|---|---|---|---|---|
| | | *Q*-stat | *p*-value | Coef. | *p*-value |
| Sumatera | Meulaboh | 13.545 | 0.331 | 0.127 | 0.321 |
| | Banda Aceh | 53.562 | 0.000 | 0.196 | 0.144 |
| | Lhokseumawe | 39.303 | 0.000 | 0.199 | 0.140 |
| | Sibolga | 29.139 | 0.004 | 0.135 | 0.320 |
| | Pematang Siantar | 29.049 | 0.004 | 0.031 | 0.830 |
| | Medan | 16.613 | 0.165 | 0.257 | 0.068 |
| | Padang Sidempuan | 24.569 | 0.017 | 0.065 | 0.644 |
| | Padang | 19.654 | 0.074 | 0.304 | 0.026 |
| | Bukit Tinggi | 23.472 | 0.024 | 0.178 | 0.194 |
| | Tembilahan | 15.878 | 0.197 | 0.011 | 0.930 |
| | Pekanbaru | 10.975 | 0.531 | 0.099 | 0.488 |
| | Dumai | 14.992 | 0.242 | 0.284 | 0.044 |
| | Bungo | 24.505 | 0.017 | 0.306 | 0.027 |
| | Jambi | 29.688 | 0.003 | 0.135 | 0.336 |
| | Palembang | 25.416 | 0.013 | 0.187 | 0.183 |
| | Lubuk Linggau | 15.579 | 0.211 | 0.140 | 0.319 |
| | Bengkulu | 20.129 | 0.065 | 0.237 | 0.093 |
| | Bandar Lampung | 12.188 | 0.431 | 0.114 | 0.427 |
| | Metro | 23.688 | 0.022 | -0.602 | 0.000 |
| | Tanjung Pandan | 38.956 | 0.000 | 0.219 | 0.099 |
| | Pangkal Pinang | 23.991 | 0.020 | -0.107 | 0.418 |
| | Batam | 28.299 | 0.005 | 0.175 | 0.223 |
| | Tanjung Pinang | 26.493 | 0.009 | 0.167 | 0.234 |
| Java | Jakarta | 13.427 | 0.339 | 0.173 | 0.217 |
| | Bogor | 16.274 | 0.179 | 0.033 | 0.819 |
| | Sukabumi | 16.387 | 0.174 | 0.190 | 0.172 |
| | Bandung | 20.477 | 0.059 | 0.169 | 0.225 |
| | Cirebon | 23.456 | 0.024 | 0.256 | 0.070 |
| | Bekasi | 19.696 | 0.073 | 0.266 | 0.057 |
| | Depok | 22.656 | 0.031 | 0.219 | 0.123 |
| | Tasikmalaya | 21.434 | 0.044 | 0.125 | 0.379 |
| | Cilacap | 38.837 | 0.000 | 0.235 | 0.097 |
| | Purwokerto | 39.571 | 0.000 | 0.218 | 0.121 |
| | Kudus | 16.963 | 0.151 | 0.123 | 0.364 |
| | Surakarta | 26.828 | 0.008 | 0.245 | 0.076 |
| | Semarang | 23.584 | 0.023 | 0.163 | 0.248 |
| | Tegal | 31.764 | 0.002 | 0.174 | 0.221 |
| | Yogyakarta | 38.833 | 0.000 | 0.206 | 0.135 |
| | Jember | 18.906 | 0.091 | 0.252 | 0.065 |
| | Banyuwangi | 26.382 | 0.01 | 0.307 | 0.028 |
| | Sumenep | 28.445 | 0.005 | 0.261 | 0.063 |

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**Table 2.**
**Persistence of Cities' *CPI* Returns (Continued)**

This table reports the persistency of *CPI* returns by way of the estimated first-order autoregressive, or AR(1), coefficient and the Ljung-Box *Q*-stat for serial correlation at lag 1–12.

| Province/ Region | City | Ljung-Box test | | AR(1) | |
|---|---|---|---|---|---|
| | | *Q*-stat | *p*-value | Coef. | *p*-value |
| | Kediri | 13.430 | 0.339 | 0.189 | 0.168 |
| | Malang | 21.849 | 0.039 | 0.267 | 0.057 |
| | Probolinggo | 30.623 | 0.002 | 0.221 | 0.111 |
| | Madiun | 18.236 | 0.109 | 0.266 | 0.056 |
| | Surabaya | 26.950 | 0.008 | 0.263 | 0.055 |
| | Serang | 17.815 | 0.121 | 0.248 | 0.076 |
| | Tangerang | 13.110 | 0.361 | -0.098 | 0.491 |
| | Cilegon | 16.035 | 0.190 | 0.304 | 0.028 |
| Bali & Nusa Tenggara | Singaraja | 10.506 | 0.572 | 0.137 | 0.339 |
| | Denpasar | 27.476 | 0.007 | 0.365 | 0.006 |
| | Mataram | 46.085 | 0.000 | 0.269 | 0.047 |
| | Bima | 33.367 | 0.001 | 0.015 | 0.916 |
| | Maumere | 9.4810 | 0.661 | 0.063 | 0.663 |
| | Kupang | 63.387 | 0.000 | 0.296 | 0.035 |
| Kalimantan | Pontianak | 34.502 | 0.001 | 0.032 | 0.824 |
| | Singkawang | 45.872 | 0.000 | 0.225 | 0.101 |
| | Sampit | 52.395 | 0.000 | 0.329 | 0.016 |
| | Palangkaraya | 80.801 | 0.000 | 0.246 | 0.073 |
| | Tanjung | 27.618 | 0.006 | 0.172 | 0.194 |
| | Banjarmasin | 87.189 | 0.000 | 0.321 | 0.022 |
| | Balikpapan | 36.693 | 0.000 | 0.158 | 0.260 |
| | Samarinda | 51.588 | 0.000 | 0.258 | 0.057 |
| | Tarakan | 24.010 | 0.020 | 0.264 | 0.061 |
| Sulawesi | Manado | 6.487 | 0.890 | -0.079 | 0.580 |
| | Palu | 41.871 | 0.000 | 0.004 | 0.977 |
| | Bulukumba | 22.071 | 0.037 | 0.184 | 0.190 |
| | Watampone | 14.167 | 0.290 | 0.036 | 0.802 |
| | Makassar | 15.815 | 0.200 | 0.119 | 0.398 |
| | Pare-pare | 53.812 | 0.000 | 0.272 | 0.055 |
| | Palopo | 27.943 | 0.006 | 0.032 | 0.813 |
| | Kendari | 21.780 | 0.04 | 0.205 | 0.150 |
| | Bau-bau | 30.515 | 0.002 | 0.025 | 0.856 |
| | Gorontalo | 24.767 | 0.016 | -0.131 | 0.361 |
| | Mamuju | 54.407 | 0.000 | 0.141 | 0.325 |
| Maluku-Papua | Ambon | 6.136 | 0.909 | 0.107 | 0.457 |
| | Tual | 15.262 | 0.227 | 0.067 | 0.654 |
| | Ternate | 12.735 | 0.389 | -0.159 | 0.267 |
| | Manokwari | 29.911 | 0.003 | -0.038 | 0.791 |
| | Sorong | 48.474 | 0.000 | 0.257 | 0.068 |
| | Merauke | 23.209 | 0.026 | 0.288 | 0.037 |
| | Jayapura | 19.478 | 0.078 | -0.194 | 0.166 |

The persistence of the *CPI* is also confirmed by the panel unit root test results reported in Table 3. The results show that the idiosyncratic component (from Equation (1)) turns out to be stationary. These unit root tests are consistent with the theoretical expectations of Equation (1) (WRN, 2017). These statistical features suggest the following: (1) city-level prices are different, so, when considered within a province, the most and least influential cities in shaping the aggregate *CPI* should become clear from our price discovery model. (2) City-based prices differ across provinces and, hence, provinces differ; therefore, we expect heterogeneity in terms of the number of cities that move prices the most within a province.

**Table 3.**
**Unit Root Test**

In this table we report the ADF and IPS unit root test results for the estimated common and idiosyncratic components, respectively. Both tests allow for a constant and a liner trend in the estimated model.

| Province/Region | Component | Test | Value | p-value |
|---|---|---|---|---|
| Sumatera | Common | DF | -1.090 | >0.10 |
| | Idiosyncratic | IPS | -2.068 | 0.019 |
| Java | Common | DF | -1.331 | >0.10 |
| | Idiosyncratic | IPS | -1.620 | 0.053 |
| Bali & Nusa Tenggara | Common | DF | -1.306 | >0.10 |
| | Idiosyncratic | IPS | -2.087 | 0.018 |
| Kalimantan | Common | DF | -1.753 | >0.10 |
| | Idiosyncratic | IPS | -2.101 | 0.018 |
| Sulawesi | Common | DF | -1.316 | >0.10 |
| | Idiosyncratic | IPS | -1.773 | 0.038 |
| Maluku-Papua | Common | DF | -1.759 | >0.10 |
| | Idiosyncratic | IPS | -2.459 | 0.007 |
| 31 top cities | Common | DF | -1.475 | >0.10 |
| | Idiosyncratic | IPS | -2.297 | 0.011 |

**Table 4.**
**Price Discovery – By province/region**

This table reports results from the price discovery test by province/region. The Information share is reported in column 2 and the factor loading is reported in column 3. The next three columns test the null hypothesis that the information share (price discovery) is equal to zero: the standard error (SE) of the test, its resulting *t*-statistic and *p*-values occupy these columns. The cities highlighted in red colours have the highest information shares in each province/region and their total PIS contribute more than 65% to each province/region *CPI*.

| City | PIS | $\pi$ | S.E | *t*-statistic | *p*-value |
|---|---|---|---|---|---|
| | | | **Panel A: Sumatera** | | |
| Lubuk Linggau | 11.83% | 1.046 | 0.063 | 16.690 | 0.000 |
| Bungo | 10.54% | 0.867 | 0.086 | 10.122 | 0.000 |
| Padang Sidempuan | 8.58% | 0.975 | 0.062 | 15.781 | 0.000 |
| Tanjung Pinang | 7.01% | 0.779 | 0.088 | 8.898 | 0.000 |
| Banda Aceh | 6.12% | 0.783 | 0.067 | 11.606 | 0.000 |
| Lhokseumawe | 6.09% | 0.936 | 0.111 | 8.440 | 0.000 |
| Bengkulu | 5.97% | 1.167 | 0.092 | 12.698 | 0.000 |
| Tembilahan | 5.36% | 0.855 | 0.083 | 10.248 | 0.000 |

**Table 4.**
**Price Discovery – By province/region (Continued)**

This table reports results from the price discovery test by province/region. The Information share is reported in column 2 and the factor loading is reported in column 3. The next three columns test the null hypothesis that the information share (price discovery) is equal to zero: the standard error (SE) of the test, its resulting *t*-statistic and *p*-values occupy these columns. The cities highlighted in red colours have the highest information shares in each province/region and their total PIS contribute more than 65% to each province/region *CPI*.

| City | PIS | π | S.E | *t*-statistic | *p*-value |
|---|---|---|---|---|---|
| Meulaboh | 5.18% | 0.808 | 0.089 | 9.114 | 0.000 |
| Padang | 3.80% | 1.213 | 0.100 | 12.077 | 0.000 |
| Pangkal Pinang | 3.67% | 1.202 | 0.174 | 6.896 | 0.000 |
| Palembang | 3.22% | 0.837 | 0.063 | 13.289 | 0.000 |
| Sibolga | 3.10% | 1.359 | 0.133 | 10.239 | 0.000 |
| Batam | 2.96% | 0.930 | 0.075 | 12.378 | 0.000 |
| Bukit Tinggi | 2.82% | 1.030 | 0.086 | 11.991 | 0.000 |
| Medan | 2.69% | 1.002 | 0.084 | 11.871 | 0.000 |
| Pematang Siantar | 2.58% | 0.898 | 0.092 | 9.783 | 0.000 |
| Jambi | 2.09% | 1.087 | 0.083 | 13.109 | 0.000 |
| Tanjung Pandan | 1.88% | 1.247 | 0.193 | 6.449 | 0.000 |
| Pekanbaru | 1.84% | 0.850 | 0.071 | 11.893 | 0.000 |
| Metro | 1.13% | 0.951 | 0.332 | 2.868 | 0.004 |
| Bandar Lampung | 1.05% | 0.805 | 0.072 | 11.181 | 0.000 |
| Dumai | 0.50% | 0.722 | 0.071 | 10.105 | 0.000 |
| | | | **Panel B: Java** | | |
| Malang | 16.17% | 1.054 | 0.041 | 25.433 | 0.000 |
| Sukabumi | 12.14% | 0.975 | 0.046 | 21.280 | 0.000 |
| Cilacap | 7.05% | 1.072 | 0.063 | 17.137 | 0.000 |
| Madiun | 6.22% | 0.958 | 0.038 | 25.526 | 0.000 |
| Yogyakarta | 5.04% | 0.857 | 0.042 | 20.541 | 0.000 |
| Semarang | 4.83% | 1.046 | 0.037 | 28.009 | 0.000 |
| Kudus | 4.82% | 1.180 | 0.054 | 21.848 | 0.000 |
| Sumenep | 4.62% | 0.978 | 0.044 | 22.043 | 0.000 |
| Jakarta | 4.19% | 0.985 | 0.046 | 21.195 | 0.000 |
| Bandung | 3.39% | 0.965 | 0.045 | 21.395 | 0.000 |
| Depok | 3.39% | 1.016 | 0.046 | 21.925 | 0.000 |
| Bekasi | 3.21% | 0.960 | 0.068 | 14.016 | 0.000 |
| Cilegon | 3.20% | 1.253 | 0.091 | 13.762 | 0.000 |
| Purwokerto | 2.83% | 0.999 | 0.050 | 20.096 | 0.000 |
| Tegal | 2.56% | 0.952 | 0.061 | 15.510 | 0.000 |
| Surabaya | 2.21% | 0.981 | 0.052 | 18.874 | 0.000 |
| Tasikmalaya | 2.20% | 0.940 | 0.050 | 18.707 | 0.000 |
| Cirebon | 2.19% | 0.793 | 0.062 | 12.852 | 0.000 |
| Jember | 1.77% | 0.978 | 0.057 | 17.037 | 0.000 |
| Probolinggo | 1.76% | 0.865 | 0.042 | 20.651 | 0.000 |
| Banyuwangi | 1.59% | 0.893 | 0.052 | 17.290 | 0.000 |
| Surakarta | 1.43% | 1.016 | 0.052 | 19.536 | 0.000 |
| Serang | 1.12% | 1.170 | 0.131 | 8.906 | 0.000 |
| Bogor | 1.03% | 0.927 | 0.069 | 13.362 | 0.000 |

**Table 4.**
**Price Discovery – By province/region (Continued)**

This table reports results from the price discovery test by province/region. The Information share is reported in column 2 and the factor loading is reported in column 3. The next three columns test the null hypothesis that the information share (price discovery) is equal to zero: the standard error (SE) of the test, its resulting *t*-statistic and *p*-values occupy these columns. The cities highlighted in red colours have the highest information shares in each province/region and their total PIS contribute more than 65% to each province/region *CPI*.

| City | PIS | π | S.E | *t*-statistic | *p*-value |
|---|---|---|---|---|---|
| Kediri | 0.76% | 0.951 | 0.050 | 19.151 | 0.000 |
| Tangerang | 0.27% | 0.993 | 0.202 | 4.929 | 0.000 |
| **Panel C: Bali & Nusa Tenggara** | | | | | |
| Mataram | 43.46% | 0.867 | 0.076 | 11.377 | 0.000 |
| Singaraja | 17.43% | 1.073 | 0.125 | 8.576 | 0.000 |
| Bima | 16.73% | 0.925 | 0.117 | 7.892 | 0.000 |
| Denpasar | 10.97% | 0.805 | 0.062 | 13.031 | 0.000 |
| Maumere | 6.02% | 0.646 | 0.103 | 6.246 | 0.000 |
| Kupang | 5.39% | 1.180 | 0.122 | 9.648 | 0.000 |
| **Panel D: Kalimantan** | | | | | |
| Sampit | 23.97% | 0.918 | 0.072 | 12.722 | 0.000 |
| Pontianak | 18.06% | 1.197 | 0.119 | 10.033 | 0.000 |
| Palangkaraya | 11.75% | 0.784 | 0.072 | 10.919 | 0.000 |
| Balikpapan | 11.39% | 1.063 | 0.092 | 11.571 | 0.000 |
| Samarinda | 11.18% | 0.842 | 0.058 | 14.506 | 0.000 |
| Tarakan | 8.50% | 1.074 | 0.093 | 11.527 | 0.000 |
| Singkawang | 7.13% | 0.960 | 0.097 | 9.908 | 0.000 |
| Tanjung | 6.19% | 0.993 | 0.107 | 9.263 | 0.000 |
| Banjarmasin | 1.82% | 0.799 | 0.055 | 14.654 | 0.000 |
| **Panel E: Sulawesi** | | | | | |
| Palu | 19.58% | 0.970 | 0.118 | 8.199 | 0.000 |
| Palopo | 17.01% | 0.910 | 0.066 | 13.748 | 0.000 |
| Gorontalo | 16.07% | 0.968 | 0.090 | 10.719 | 0.000 |
| Manado | 9.62% | 1.016 | 0.132 | 7.710 | 0.000 |
| Bulukumba | 9.08% | 0.963 | 0.073 | 13.205 | 0.000 |
| Pare-pare | 7.19% | 1.022 | 0.073 | 13.981 | 0.000 |
| Kendari | 6.56% | 1.051 | 0.097 | 10.816 | 0.000 |
| Watampone | 5.62% | 0.826 | 0.071 | 11.672 | 0.000 |
| Bau-bau | 4.70% | 1.152 | 0.146 | 7.879 | 0.000 |
| Mamuju | 2.85% | 0.818 | 0.069 | 11.804 | 0.000 |
| Makassar | 1.71% | 0.866 | 0.061 | 14.152 | 0.000 |
| **Panel F: Maluku-Papua** | | | | | |
| Ternate | 30.96% | 0.826 | 0.141 | 5.875 | 0.000 |
| Jayapura | 19.28% | 0.730 | 0.176 | 4.140 | 0.000 |
| Ambon | 13.44% | 0.742 | 0.144 | 5.142 | 0.000 |
| Tual | 11.81% | 1.236 | 0.280 | 4.420 | 0.000 |
| Manokwari | 11.52% | 0.715 | 0.117 | 6.106 | 0.000 |
| Merauke | 10.01% | 0.893 | 0.205 | 4.348 | 0.000 |
| Sorong | 2.98% | 0.583 | 0.132 | 4.432 | 0.000 |

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**Figure 1.**
**Time Series *CPI* Index Returns**

This figure plots the equally weight *CPI* returns for the top cities and non-top cities by province/ region over the sample period of January 2014 to April 2018.

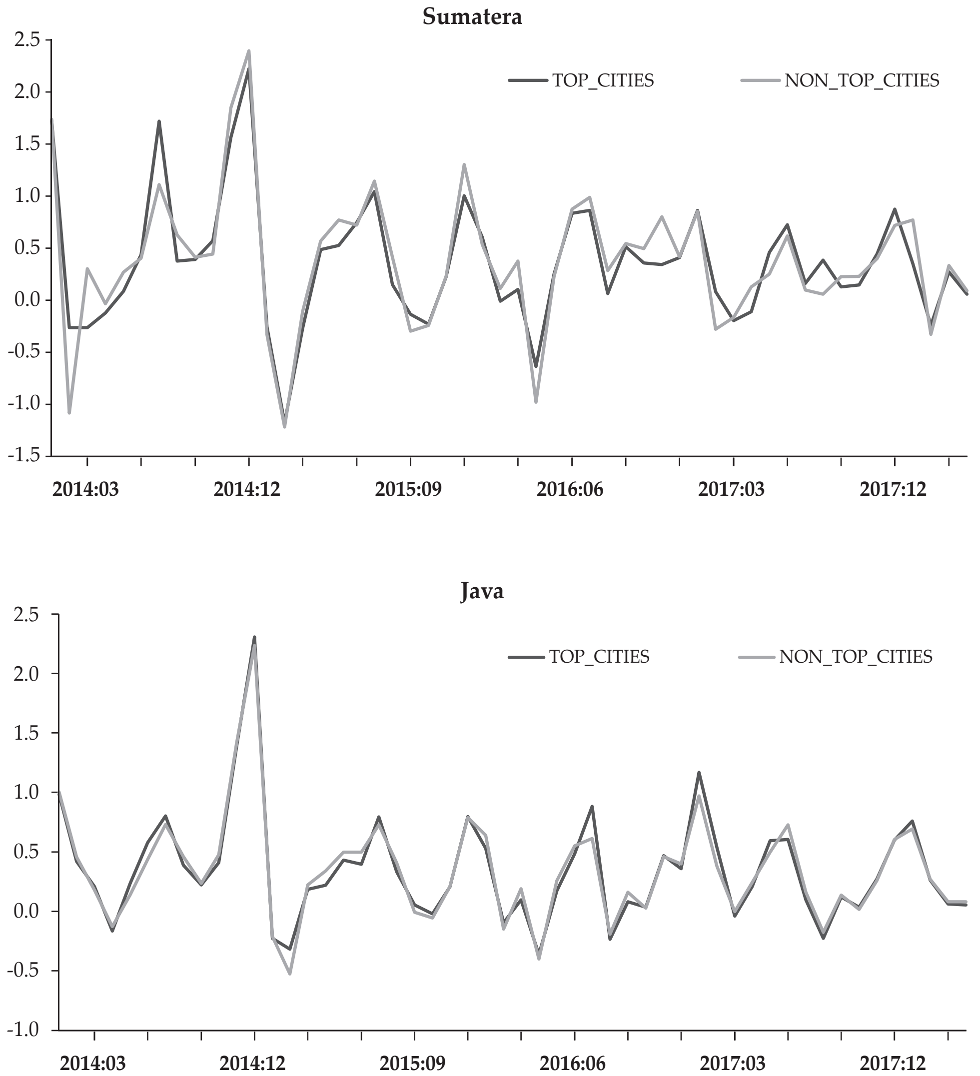
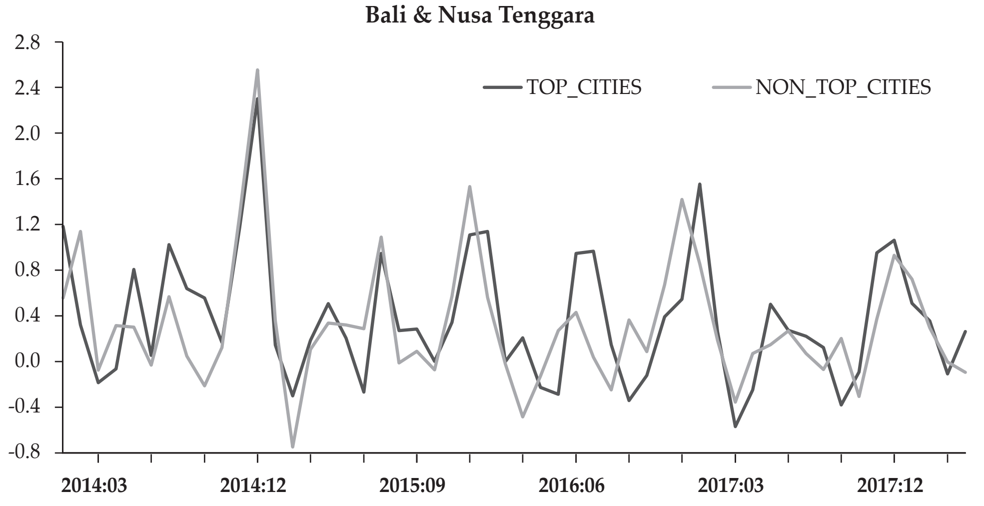


**Figure 1.**
**Time Series *CPI* Index Returns (Continued)**



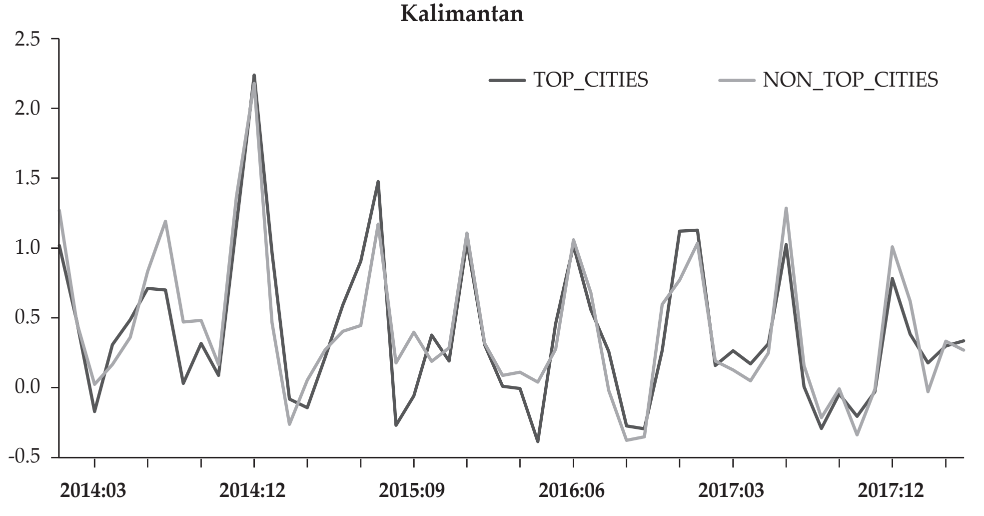
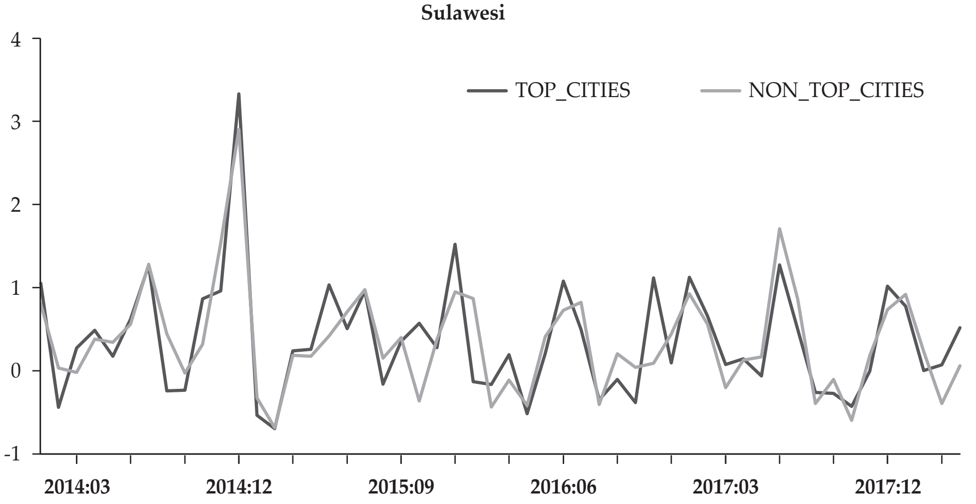
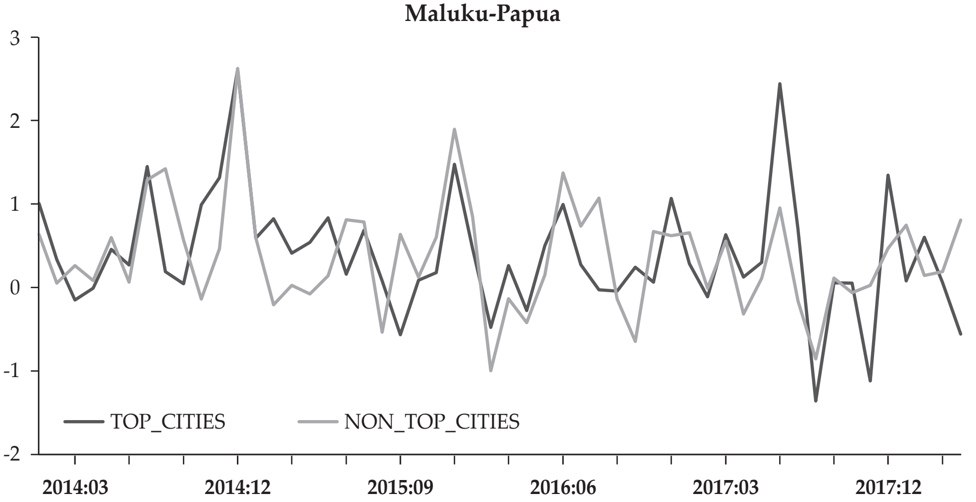



**Figure 1.**
**Time Series *CPI* Index Returns (Continued)**



We conclude with evidence of price discovery, that is, the relative importance of cities in the movement of prices in each of the six provinces. Of Sumatera's 23 cities, nine alone contribute 66.7% to the price changes, and five cities contribute 44% to all price changes. Similarly, among Java's 26 cities, nine contribute 65% to all price changes, with four contributing 41.6%. Even in smaller provinces, such as Bali and Nusa Tenggara, which have only five cities, one city alone contributes around 43% to all price changes. Across all six provinces, therefore, we identify a leader city and a group of cities that dominate the price changes. Our results imply that each province in Indonesia has between six and 26 cities, for a total of 82 cities. In controlling prices, given that the objective of Bank Indonesia, the central bank, is to maintain price stability, pricing-related policy should pay greater attention to the cities we identify as movers and shakers, or leaders.

To demonstrate their impact, we plot an equal-weighted price index for the leader cities against the other cities (Figure 1). The distinction between these two groups of cities in each province is obvious. This simple graphical analysis gives credence to our approach of searching for cities that contribute to price changes in a meaningful manner. The cost of not doing so is huge, because, from a policy point of view, the policy uncertainty resulting from not knowing which cities to target to control prices is not trivial. Our effort goes toward providing a guide to city selection when it comes to policymaking.

## IV. CONCLUSIONS AND IMPLICATIONS

This paper aims to understand the CPI dynamics across Indonesian cities and provinces. A total of 82 cities belonging to six Indonesian provinces were analyzed to determine the leader cities, that is, those cities that contribute the most to the aggregate price changes for each province. Monthly time series data (2014M01 to 2018M04) were employed and the data fitted to a price discovery model that associates price changes with a common factor (i.e., the aggregate price change) and an idiosyncratic component of city price changes. A model based on the work of WRN paves the way for our empirical analysis. Simple characteristics of the CPI data for the sample of 82 cities indicate that city-based prices are heterogeneous across a range of statistical tests. This heterogeneity is reflected across provinces, suggesting that some cities move aggregate prices more than others. In formal price discovery tests, we observe precisely this: that each province contains cities that contribute more to prices changes and cities that contribute less. This finding has important implications for inflation policy.

The main takeaway from our paper is that it determines which cities to target if the objective is to control prices (or achieve price stability) in each province. Better price control in these leader cities will allow for faster convergence to price stability.

As a natural extension of our paper, future research can investigate why those cities appear as price leaders and why the other cities in each province do not contribute much to the aggregate price change. While answers to these questions will offer insights on the characteristics of cities about which we do not commentate in this paper, these answers though are independent of our policy recommendation.

**REFERENCES**

Alba, J.D., and Papell, D.H., (1998) Exchange Rate Determination and Inflation in Southeast Asian Countries, *Journal of Development Economics*, 55, 421-437.

Basher, S.A., and Westerlund, J., (2008) Is There Really a Unit Root in the Inflation Rate? More Evidence from Panel Data Models, *Applied Economic Letters*, 15, 161-164.

Ciccarelli, M., and Mojon, B., (2010) Global Inflation, *Review of Economics and Statistics*, 92, 524-535.

Culver, S.E., and Papell, D.H., (1997) Is There a Unit Root in Inflation Rate? Evidence from Sequential Break and Panel Data Models, *Journal of Applied Econometrics*, 12, 435-444.

Hasbrouck, J., (1995) One Security, Many Markets: Determining the Contributions to Price Discovery, *Journal of Finance 50*, 1175-1199.

Hendry, D.F., (2001) Modelling UK Inflation, 1875-1991, *Journal of Applied Econometrics*, 16, 255-275.

Jangam, B.P., and Akram, V., (2019) Do Prices Converge Among Indonesian Cities? an Empirical Analysis, *Bulletin of Monetary Economics and Banking*, 22, 239 – 262.

Kilian, L., (2008) A Comparison of The Effects Of Exogenous Oil Supply Shocks on Output and Inflation in G7 Countries, *Journal of the European Economic Association*, 6, 78-121.

Narayan, P.K., Sharma, S.S., Thuraisamy, K.S., and Westerlund, J., (2018) Some Preliminary Evidence of Price Discovery in Islamic Banks, *Pacific-Basin Finance Journal*, 52, 107-122.

Narayan, P.K., Sharma, S., and Thuraisamy, K., (2014) An Analysis of Price Discovery from Panel Data Models of CDS and Equity Returns, *Journal of Banking and Finance*, 41, 167-177.

Narayan, P.K., Phan, D.H.B., Thuraisamy, K. Westerlund, J., (2016) Price Discovery and Asset Pricing, *Pacific-Basin Finance Journal*, 40, 224-235.

Narayan, P.K., Narayan, S., and Mishra, S., (2011) Do Remittances Induce Inflation? Fresh Evidence from Developing Countries, *Southern Economic Journal*, 77, 914-933.

Narayan, P. K., & Popp, S. (2010). A New Unit Root Test with Two Structural Breaks in Level and Slope at Unknown Time. *Journal of Applied Statistics*, 37, 1425-1438.

Narayan, P. K., & Popp, S. (2013). Size and Power Properties of Structural Break Unit Root Tests. *Applied Economics*, 45, 721-728.

Sharma, S.S., (2019) Which Variables Predict Indonesia's Inflation? *Bulletin of Monetary Economics and Banking*, 22, 87-102.

Westelius, N.J., (2005) Discretionary Monetary Policy and Inflation Persistence, *Journal of Monetary Economics*, 52, 477-496.

Westerlund, J., Reese, S., and Narayan, P.K., (2017) A Factor Analytical Approach to Price Discovery, *Oxford Bulletin of Economics and Statistics*, 79, 366-394.

Zozicki, S., and Tinsley, P.A., (2012) Effective Use of Money Information in Estimating The Evolution of Expected Inflation, *Journal of Money Credit and Banking*, 44, 145-169.

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