Food Price Crisis in Indonesia: Alert from the Key Markets

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Abstract

Food price variations can be very costly when they abrupt and unanticipated. In the current new era of market uncertainty, monitoring food prices become highly important to foresee any potential crisis. This study proposes an alternative approach in monitoring food price movements in many different markets within a country by focusing only on the key markets. Using monthly retail rice prices from the 25 major markets in Indonesia, we identify the key markets whose price movements can help to forecast price movements in all other markets. The key markets are identified using granger causality tests conducted in the vector error correction model framework. The relevance of monitoring the key markets in detecting price crisis is tested using Probit and Poisson models. We found that albeit not all of alert phases lead to crises, monitoring the key markets can help to forecast price movements in all markets across the country.

Keywords: *volatility, crisis, transmission, early warning system, Indonesia*.
JEL Classification: C22, F1, F47, Q1

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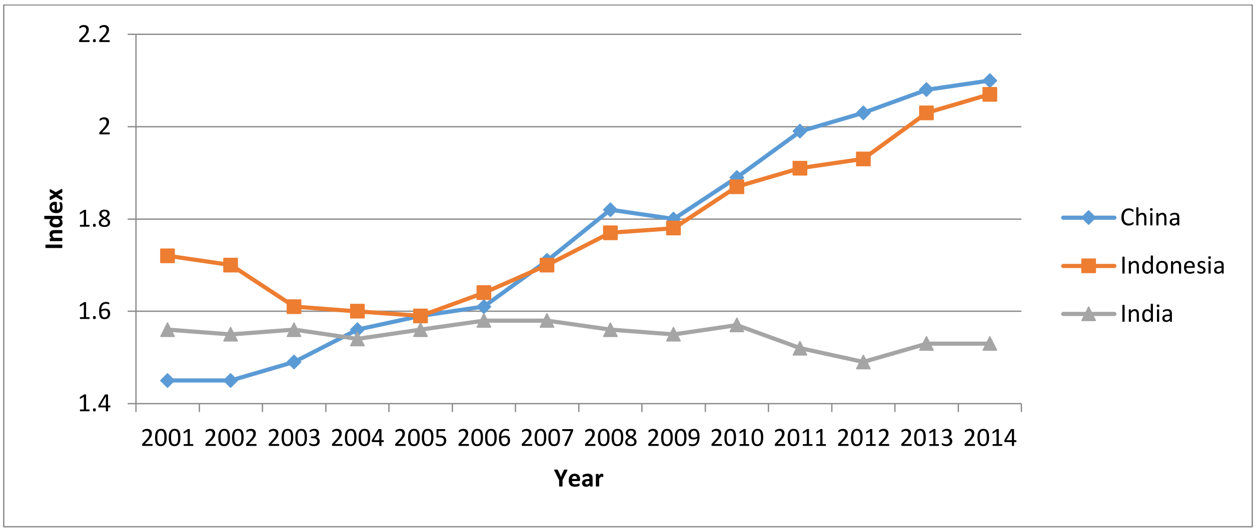
Introduction

Indonesia is the largest economy in Southeast Asia and the fourth most populous country in the world[2] (UN DESA, 2013). The country consists of more than 13 thousand islands; with around 6 thousand of them are inhabitants[3]. Notwithstanding the high economic growth in the past decade, Indonesia is still home for 30 million people living under poverty line and an additional 65 million people vulnerable to poverty (World Bank, 2012). These poor households, who are like many others in the developing countries, spend more than half of their income on food (von Braun and Tadesse, 2012). Thus, soaring food prices in the recent years plays an important role in the purchasing power of a large part of Indonesian population, bringing threats to their food and nutrition security.

Figure 1. Food price index of selected countries 2001 - 2014



Source: FAOSTAT

Furthermore, in the recent years, Indonesia experiences high food price volatility accompanied by high risk of food and nutrition insecurity. Using food price index data from ILOSTAT and combined anthropometric data from WHO, UNICEF and World Bank, Mujahid and Kalkuhl (2014) show that Indonesia is among countries that experience "high" or "very high" food price volatility as well as "high" or "very high" chronic and acute malnutrition. Moreover, evidences have shown that the increase of food prices raises the rate of poverty in Indonesia (Ivanic et. al., 2012; Warr and Yusuf, 2013).

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[2] After China, India and USA

[3] *Badan Informasi Geospasial*/Geospatial Information Body http://www.bakosurtanal.go.id/ accessed December 5th, 2014.

In this context, monitoring food price movements becomes highly important for Indonesia which can help to better anticipate any potential of “abnormal” food prices in the country. Given the peculiar geographic characteristic of Indonesia, where markets are spread in its archipelago, an efficient approach in monitoring food price movement is needed. Using the concept of price transmission and market integration, we investigate whether price movements in many different markets in the country can be monitored by focusing only on the key markets. Furthermore, we analyze the relevance of monitoring the key markets in detecting potential price crisis events in Indonesia.

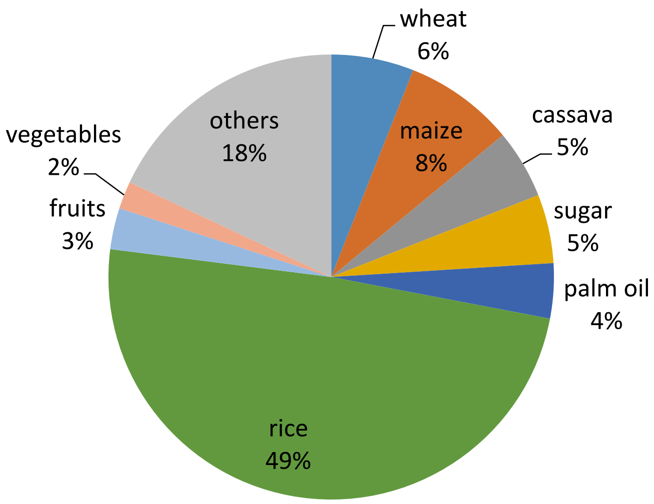
The approach is based on the information provided by market price. Market is assumed to be efficient which its prices reflect all available information not only on current food availability but also on agents’ expectations about future scarcity (Deaton and Laroque, 1992; Ravallion, 1985). Similar to this approach, Araujo et al. (2012) use price signals to detect potential price crises in Mali, Burkina Faso and Niger.

The rest of this paper is organized as follows: the next section provides context of the analysis and description of price data that will be used. Section 3 explores the prices in the 25 markets in Indonesia to further define price crisis. Section 4 aims to identify the key markets whose prices can be used to forecast price movements in all other markets. In section 5, we test the relevance of using the key markets to detect price crisis. Section 6 provides summary and conclusion.

Context and data description

Food supply in Indonesia mostly comes from own production. Rice, sugar and palm oil are the three largest quantities being produced in the country. Nevertheless, supplies of some food commodities are not met by own production, including rice, Indonesians’ main staple food which accounted for nearly half of their calorie’s intake. Indonesia is still importing around 3-6 percent of their domestic rice supplies annually to fulfill high demand in the country (FAOSTAT, 2014).

Figure 2. Indonesian's per capita calorie intake 2011

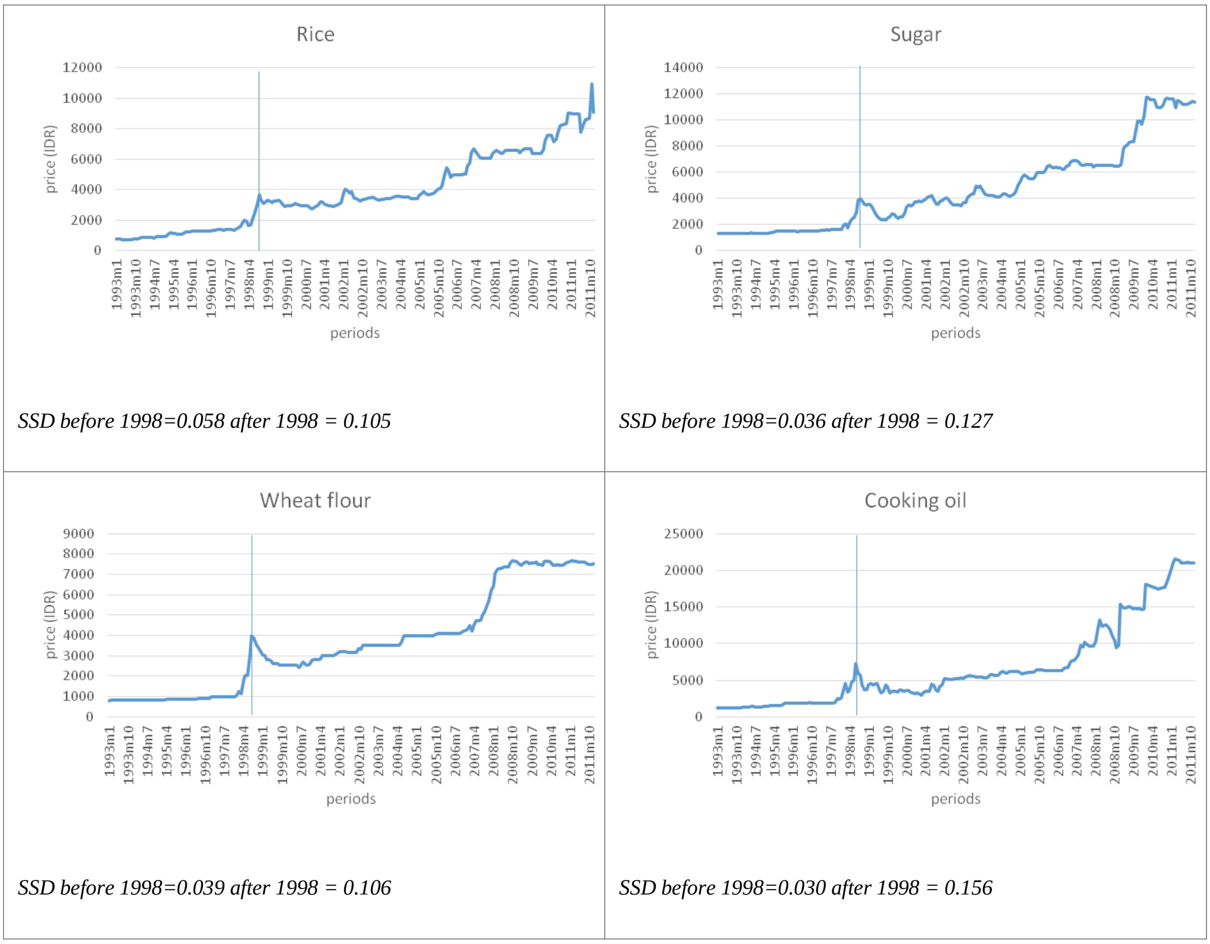


Source: own elaboration based on FAOSTAT

For many years, price stabilization in Indonesia was managed by *Badan Urusan Logistik* (BULOG), a national food reserve agency created in 1968 with a special objective to protect domestic markets from sharp fluctuations of prices on world markets. The end of New Order regime in late 1990s was the emerging era of more open trade policy in Indonesia. The country loosened its monopoly structure and created competitions within the domestic market. BULOG lost its domestic power to monopolize sugar and rice trade because Indonesia was required to comply with the IMF Letter of Intent to make market more efficient. After finishing the engagement with IMF, Indonesia decided to shift to a more managed trade policy and started to impose tariffs on sugar and rice imports.

The policy was not long lasting as Indonesia started to create more liberal economy by reducing tariffs. Since then, export oriented policies have been the picture of Indonesia's agricultural trade policy. Agricultural exports increased by 16 percent on average annually during 2004-2009 (Octaviani et al., 2010). However, in this 'Reform Era' in which the market was relatively open, food prices were relatively higher and more volatile than it was before, when BULOG has a strong power to intervene the market (figure 3). Estimations of volatility using standard deviations of log of prices in difference (SSD) for some commodities including rice, sugar, wheat flour and cooking oil show that the SSD are much higher for the periods after 1998 compare to the periods before 1998. Nevertheless, BULOG ran at high fiscal cost. A financial audit report by Arthur Anderson covering the period of April 1993 to March 1998 suggested that total inefficiency of BULOG was about 400 million USD per year (Arifin, 2008).

Figure 3. Prices of several food commodities in Indonesia before and after major reform



SSD before 1998=0.058 after 1998 = 0.105

SSD before 1998=0.036 after 1998 = 0.127

SSD before 1998=0.039 after 1998 = 0.106

SSD before 1998=0.030 after 1998 = 0.156

Note: SSD=Standard deviations of log of prices in difference
Source: Own estimations based on BPS/Statistics Indonesia data

Our focus in this study is rice, the main staple food for Indonesians. The analysis uses monthly retail rice prices from 25 major markets in Indonesia for the periods of 2000 - 2013. The sample markets in this study are among the 33 main markets of the capital city provinces in Indonesia which spread in its 5 main islands and 30 other smaller islands. The data come from *Badan Pusat Statistik* (BPS), a national bureau of statistics of Indonesia. BPS regularly publishes the weighted average of several different types of rice that are sold in all major retail markets in Indonesia.

Figure 4. Sample markets

Source: own elaboration.

Food Price Movement: Defining the Crisis

Despite a relatively well established concept of food security[4], no common definition of food price crisis can be found in the literature (Cuesta et al, 2014). In fact, without any clear concept, the term food price crisis is widely known and used for analytical and operational purposes, especially in the light of explaining the global excessive price volatility and spike events in 2008 and 2011.

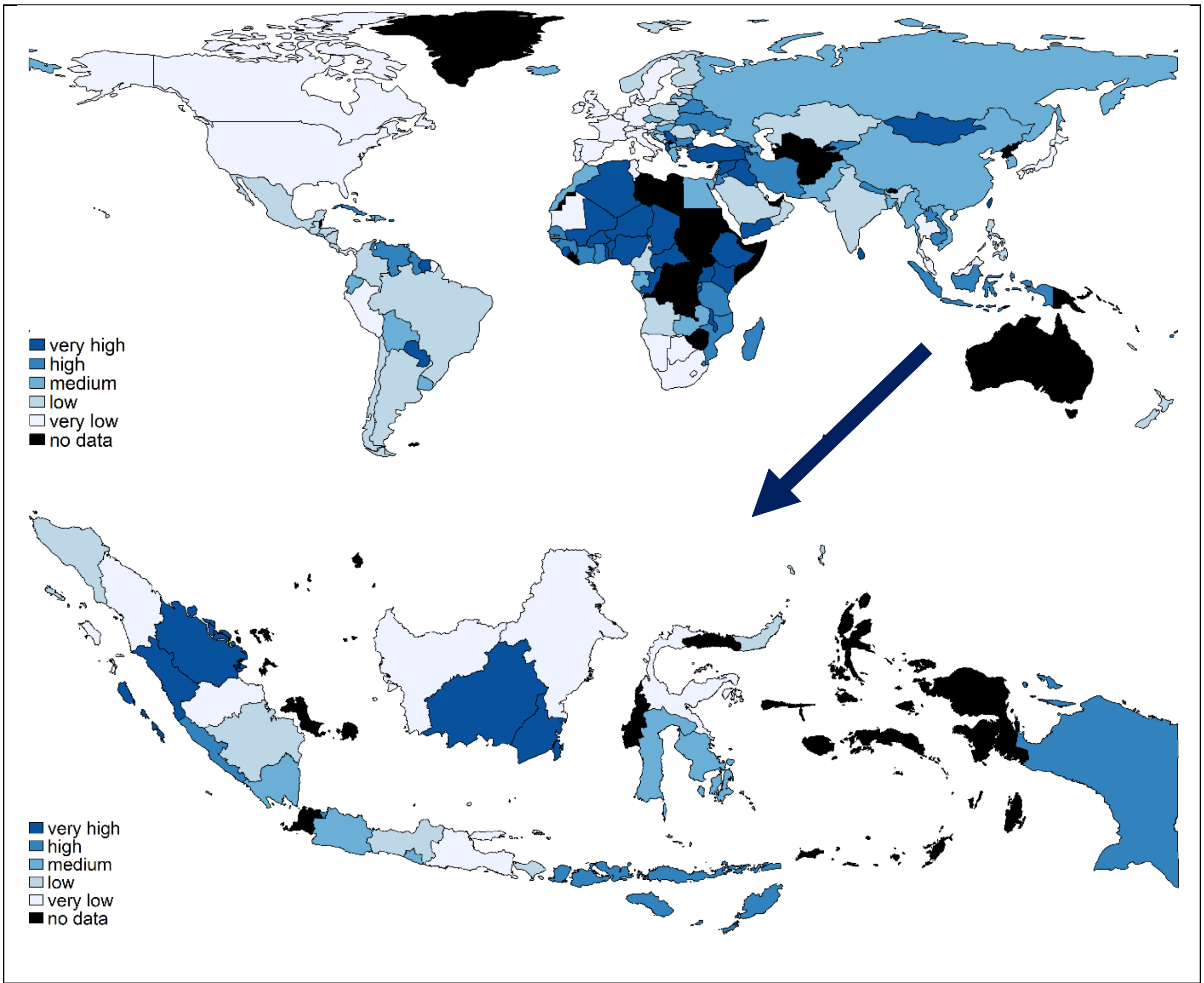
At this point, it is important to understand the different terms that are commonly used to explain price dynamics. von Braun and Tadesse (2012) observed that most studies on food price dynamics focus on high food prices. They argue, however, that price movements should be distinguished as *trend*, *volatility* and *spike*.

A price trend is the smooth, long-term average movement of prices over time that shows the general tendency of prices for a certain period of time. Price volatility refers to frequent short-term fluctuations of the prices around a rather stable long-term price or price trend. It measures the strength and frequency of the price changes. In general, both positive and negative variations affect price volatility. There are sets of methods available in the literature to analyze price volatility, the common ways include: (i) coefficient of variation from mean or trend

[4] FAO concept of food security “food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food for a healthy and active life” is considered to be widely accepted.

(Huchet-Bourdon, 2011), (ii) changes of log returns (Gilbert and Morgan, 2010) and (iii) GARCH model (Roache, 2010; Karali and Power, 2013).

Figure 5. Food price volatility in the global and Indonesia markets



Note: The global market (upper map) uses the monthly food price index for the period 2000 – 2012 taken from ILO database. The Indonesia market (lower map) uses monthly retail rice price data for the period 2000 – 2013 taken from Statistics of Indonesia.
Source: Mujahid and Kalkuhl (2014) and own elaboration.

Figure 5 presents volatility map in the global and Indonesia food market, estimated using the coefficient of variation from trend. The upper map shows the rate of food price volatility in different countries which shows that Indonesia is among the high rates of volatility compare to all other countries for the period 2000-2012. The lower map shows the rate of volatility in the different markets in Indonesia for the period 2000-2013. It divides the markets into quintiles and shows that Padang, Pekanbaru, Banjarmasin and Palangkaraya experience the highest volatility among all major markets in Indonesia. Another term is price spike which is closely related to price volatility. While volatility measures the price changes over a certain period, price spike is usually measured as a relative change of prices over two consecutive periods. The most common way to measure price spike is using percentage change as the logarithm of the rate of period-over-period prices.

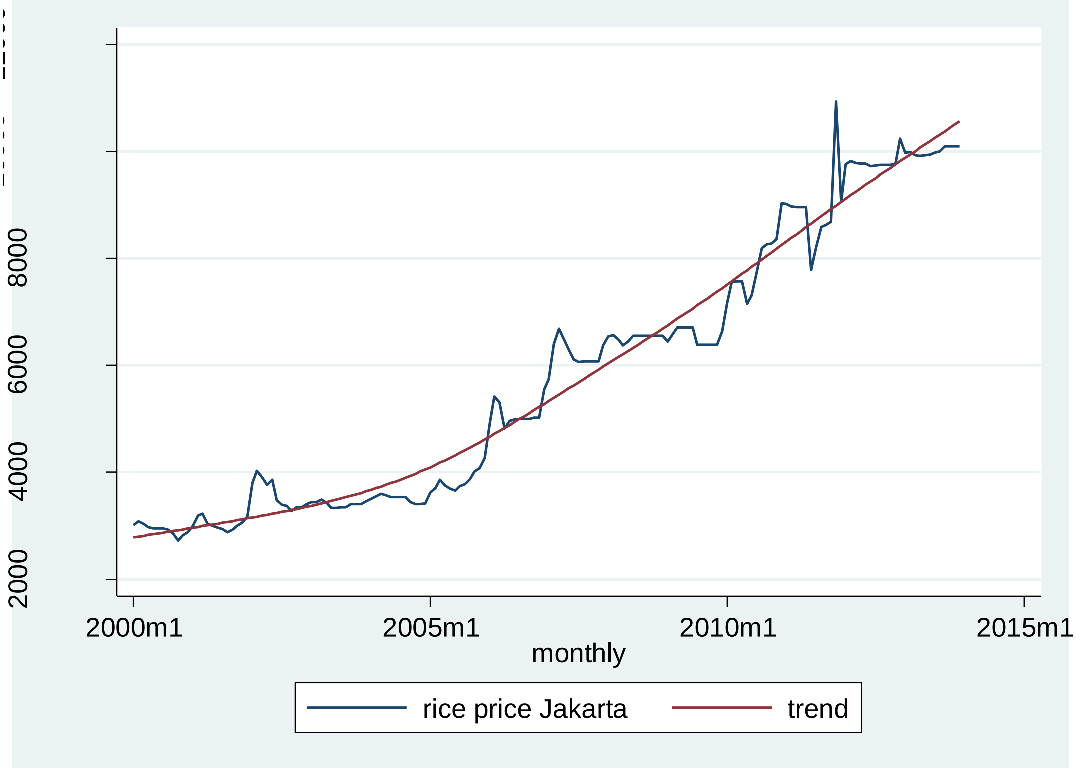
Not all price movements are troublesome. Price variations can be very costly only when they abrupt and unanticipated by the economic agents (HLPE, 2011). It is also important to note that price changes may have different impacts on the different economic agents. High food prices can be incentives for net food producers to produce more food. More income can be generated when food prices are on the upward trend relative to input prices. On the other hand, high food prices negatively impact consumers. Poor people will have to spend much more of their income on food when the prices are higher.

In the absence of a common definition of food price crisis, for the purpose of the analysis, this study will limit the definition of the crisis to only from the customer point of view. According to our definition, food price is considered as a crisis when the observed price is above a certain level of the price that can be considered as normal. We first estimate the trend for each market over the whole period using Hodrick-Prescott-filter (HP filter). The HP filter is widely used to remove cyclical component of macroeconomic time series data to obtain a smoothed-curved representation of the series which can be written as:

$$\min_{\tau}\left(\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2\right)$$

The first term of the equation is the sum of the squared deviations $d_t = y_t - \tau_t$ which penalizes the cyclical component. The second term is a multiple smoothing parameter (λ) of the sum of squares of the trend component’s second differences. This second term penalizes variation in the growth rate of the trend component. The larger the λ, the larger the penalty. As recommended for monthly data, λ is chosen to be 129600.

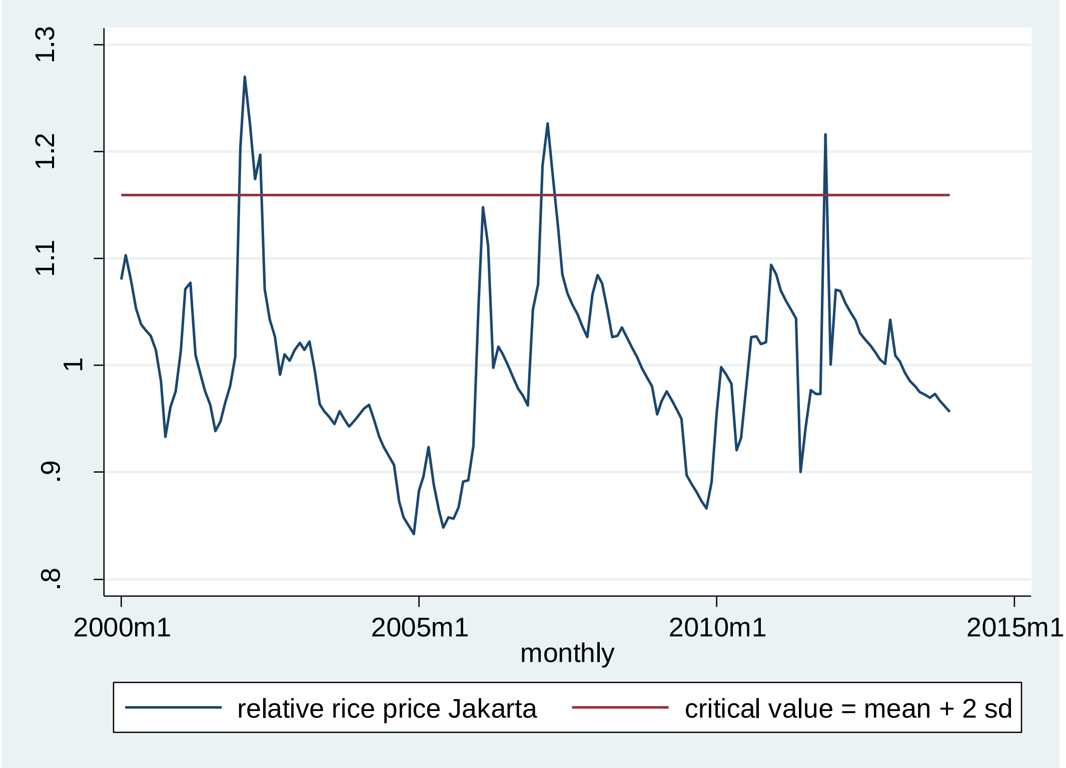
Figure 6. Rice price and trend in Jakarta



Source: own elaboration

Our definition on "abnormal" price i.e. the price above certain level of price that can be considered as normal, comes from relative spread not the absolute one because of price inflations and long-term trends increase the absolute spread in both directions (positive and negative). For instance, an increase of Rp.100/kg is large if the price is Rp.200/kg but small if the price is Rp.1000/kg. To obtain relative spread, we divide the price series by its HP-price trend which is normalized to 1 where we can observe only relative fluctuation. We further estimate the standard deviation from these relative fluctuations for the analyzed period. We consider price is in crisis when the relative spread between the relative price and its mean value is greater than two standard deviation (figure 6).

Figure 7. Food price crisis in Jakarta



Source: own elaboration

Key Markets Identification

The approach in monitoring food price movements by focusing only on the key market proposed in this study uses the concept of spatial price transmission and market integration. The key theoretical concept in spatial price transmission analysis is spatial arbitrage, which implies that the difference between prices of homogeneous goods in different markets is only subject to transaction costs. Therefore, most of empirical works in spatial price transmission analysis aim at assessing whether the *Law of One Price* holds true or not (Listorti and Esposti, 2012).

Our analysis aims to measure the degree of integration in each market and uses the information to analyze how markets are being connected each other. Two markets are defined as being integrated when shocks arising in one market are transmitted to the other market (Fackler and Goodwin, 2001). More specifically, market i for good x is said to be spatially integrated with market j for the same good if a shock in i that changes, for instance, demand in i but not in j, affects the prices in both i and j. This implies that the price series for homogenous commodity in the two markets shared a long run stochastic trend.

We perform granger causality tests that are conducted in the vector error correction (VEC) model framework to identify the key markets whose prices can help to forecast price movements in other markets. The granger causality is a statistical hypothesis test which suggests whether one time series is useful in forecasting another (Granger, 1969). In this study, we test whether there is a causal relationship between current prices on market *i* and lagged prices on market *j*.

The VEC model is appropriate to analyze short term and long term effects of one price on another when two conditions are met. First, every price series is non stationary and integrated to degree 1, which can be written as (I(1)), and second, the two or more series are co-integrated. When two I(1) are co-integrated, there is a linear combination of the two series that is stationary. In this study, we are analyzing two prices at a time, so that the co-integrating equation can be written as:

$$P_i = \alpha + \beta P_j + \varepsilon \quad \text{or} \quad \varepsilon = P_i - \alpha - \beta P_j, \quad \text{where } \varepsilon \text{ is stationary.}$$

We test the stationary of each price series using Augmented Dickey Fuller (ADF) and the results show that the price series for each market is stationary at (I(1))[5]. Each pair of the series is also found to be co-integrated, which means that there is a long run relationship between prices of two markets. We estimate the VEC model for each pair of the price series using the following formulation:

$$\Delta P_t^i = \alpha + \theta\left(P_{t-1}^i - \beta P_{t-1}^j\right) + \delta \Delta P_{t-1}^j + \rho \Delta P_{t-1}^j + \varepsilon_t$$

Where P_t^i is the price of market i and P_t^j is the price of market j. Δ is the difference operator, so $\Delta P_t = P_t - P_{t-1}$. $\alpha, \theta, \beta, \delta, \rho$ are the estimated parameters and ε is error term.

By having already concluding that each pairs of the price series are co-integrated, meaning that the two series have a long-run causal relationship, the causality being tested in the VEC model indicate a short-run granger causality. It is important to note that if *i* is said to be granger causes *j*, does not imply that *j* is the result of *i*. Granger causality measures precedence and information content, but does not by itself indicate causality in the more common term. Here, the Granger

[5] ADF test results can be found in appendix.

causality test shows whether prices in one market lead another. The results of the tests are as follows:

Table 1. Granger causality test result

Market	Granger causes… other markets	Market	Granger causes… other markets
Banda Aceh	13	Denpasar	19
Medan	18	Mataram	16
Padang	16	Kupang	18
Riau	19	Pontianak	18
Jambi	14	Palangkaraya	21
Palembang	19	Banjarmasin	18
Bengkulu	19	Samarinda	18
Bandar Lampung	17	Manado	17
Jakarta	17	Palu	15
Bandung	17	Makassar	20
Semarang	20	Kendari	12
Yogyakarta	18	Jayapura	13
Surabaya	21		

Note: Granger causality tests are conducted in the VEC model framework and performed separately for each pair of the markets at the significance level of 5percent.

We found that almost all markets granger-cause many other markets with Surabaya and Palangkaraya as the two most influential markets. This finding is not really surprising as Surabaya and Palangkaraya are two important cities in Indonesia, especially in terms of intra country trade network. Surabaya has an important port connecting Java island with many other islands, while Palangkaraya is located in central Kalimantan which may have influence to many other markets especially those in the east part of Indonesia.

We attempt to find one market that granger causes all other markets. In other words, prices in this market play significant roles in explaining prices in all other markets and can help to predict the latter. However, the results show that no single market granger-causes all other markets. Surabaya and Palangkaraya, the two most widely granger-cause other markets, each of them only granger-causes 21 markets. This means that three markets are not granger caused by each of them (table 2). The results lead us to consider more than one market to be identified as the key market. The combination of Surabaya and Palangkaraya, are found to granger-cause all markets in Indonesia. Thus, we identify these two markets as the key markets which their prices are expected to help in forecasting prices in all other markets in Indonesia.

Table 2. Granger causality test for the key markets

Key Market	Not granger causes..
Surabaya	Jakarta, Banjarmasin, Makassar
Palangkaraya	Pekanbaru, Samarinda, Palu

Detecting Price Crisis by Monitoring the Key Markets

This section is devoted to test the relevance of using the key markets to predict the price crisis in the country. As defined previously, we consider price is in crisis when the relative spread i.e. the spread between the relative price and its mean value is greater than two standard deviation. We will first determine an alert indicator that expected to predict the crisis. Further, the probability of the alert that leads to a crisis is tested econometrically using Probit and Poisson regressions.

Alert Indicator

We first distinguish the periods of "abnormal" prices based on the relative spread of the prices. The crisis phase, where the spread between the relative price and its mean value is more than two standard deviation, is usually preceded by a phase of an increasing price that moves from the level that can be considered as normal. We will consider the periods of this increasing price as an alert phase. It is the periods when the spread of the relative price is more than one standard deviation but below two standard deviation (figure 7). Our alert indicator to predict potential crisis in any market in the country will be the alert phase of the two key markets. The following Probit and Poisson models will test whether it is relevant to observe the alert indicator in the key markets to predict crisis in other markets.

Figure 7. Alert and crisis phases in the key markets

Source: Own elaboration

Probit Model

Probit model, also called probit regression, is used to model dichotomous or binary outcome variables. The inverse standard normal distribution of the probability is modeled as a linear combination of the predictors. This test aims at testing the probability of the alert in the key markets that leads to a crisis in any market of the country. The dependent variable is a binary variable taking value 1 if one or more markets are in the crisis phase at time t and 0 otherwise. The independent variable is a binary variable of the alert phase of each key market, taking value of 1 if the key market is on alert and 0 otherwise. A regression model is created by parameterizing the probability of the price crisis to depend on a regressor of the alert phase of the key market where:

$$p_{it}^{*} = \beta x_{kt} + \varepsilon_{it}$$

p_{it}^{*} is the latent dependent variable which refers to the probability of the crisis; p_{it} is the observed binary outcome variable defined as:

$$p_{it} = \begin{cases} 1 \; if \; p_{it}^{*} > 0 \\ 0 \; otherwise \end{cases}$$

x_{kt-1} is the alert phase at the lagged value of each key market and ε_{kt} is error term. We test the alert phase of Surabaya and Palangkaraya that may lead to crisis in any market of the country separately.

The results of the tests are as follows:

Table 3. Probit regression result

Key Market	Coefficient	Marginal Effect
Surabaya	0.8334*** (0.2987)	0.21
Palangkaraya	1.0597*** (0.3682)	0.28

*Note: Standard errors are in parentheses, * p<0.1, ** p<0.05, *** p<0.01*

We found that the coefficients of the key markets for the tests are positive and significant with 0.83 for Surabaya and 1.06 for Palangkaraya. The marginal effect for Surabaya is 0.21 while for Palangkaraya is 0.28. This means that when Surabaya is on alert, the probability of any other market that will be in crisis in the following month increases by 0.21 and when Palangkaraya is on alert, the probability of any other market will be in crisis in the following month increases about 0.28 percent.

Poisson Model

Another test is performed by Poisson regression that seeks to explain the extent of the crisis. The outcome is the number of markets within the country that will be in crisis if the key market is on alert. The Poisson regression is found to be appropriate when the dependent variable is a count data. In this test, the dependent variable is the number of market that is in crisis within the country, while the independent variable remains the same as in Probit regression which is a binary variable of the alert phase of each key market, taking value of 1 if the key market is on alert and 0 otherwise.

The basic Poisson probability specification can be written as:

$$f(y_t|x_t) = \frac{e^{\mu}\mu^{y_t}}{y_t!}$$

Where y_t is factorial, it is the number of markets that is experiencing a price crisis at time t. x_t is the alert phase of each key market and μ is the parameter of Poisson distribution. For $\mu > 0$, the mean and variance of this distribution can be shown to be:

$$E(y) = var(y) = \mu$$

Since the mean is equal to the variance, any factor that affects one will also affects the other, thus, the usual assumption of homoscedasticity would not be appropriate for Poisson data.

The results of the Poisson tests are as follows:

Table 4. Poisson regression result

Key Market	Coefficient	Marginal Effect
Surabaya	0.6806*** (0.2278)	0.44
Palangkaraya	1.6771*** (0.3480)	1.13

*Note: Standard errors are in parentheses, * p<0.1, ** p<0.05, *** p<0.01*

The coefficient for Surabaya and Palangkaraya both are found to be positive and significant with 0.68 for Surabaya and 1.68 for Palangkaraya and the marginal effect for Surabaya is 0.44 while for Palangkaraya is 1.13. This means that an alert in Surabaya leads to an increase of the number of other markets that will be in crisis by 0.44 and an alert in Palangkaraya leads to an increase of the number of other markets that will be in crisis by 1.13.

Summary and Conclusion

Indonesia is found to be among the countries that experience high food price volatility accompanied by high risk of food and nutrition security (Mujahid and Kalkuhl, 2014). Maintaining food prices at a sustainable level is prime important for a developing country such Indonesia, where the large part of its citizen spend more than half of their income on food. Thus, uncertainty as a result of food price volatility brings threats to their food and nutrition security. This study investigates price movements in the major markets in Indonesia, identifies the key markets and analyzes whether price movements in all markets in the country can be monitored by focusing only on the key markets.

Using monthly retail rice prices from 25 major markets in Indonesia for the periods of 2000-2013, we identify the key markets using granger causality tests that are conducted in the VEC model framework. The results show that Surabaya and Palangkaraya can be considered as the key markets whose price movements can help to explain prices in all other markets. This finding is not surprising as Surabaya and Palangkaraya are two important cities in the trade network within Indonesia. Surabaya has an important port connecting Java island with many other islands and Palangkaraya is located in central Kalimantan which may have influence to many other markets especially those in the east part of Indonesia.

We also test econometrically the relevance of using the information from the key markets to predict potential crisis in the country using Probit and Poisson models. The Probit regression results show that when Surabaya is on alert, the probability of any other market that will be in crisis increases by 0.83 and when Palangkaraya is on alert, the probability of any other market will be in crisis increases about 1.06 percent. In the Poisson regressions, the results show that an alert in Surabaya leads to an increase of the number of other markets that will be in crisis by 0.68 and an alert in Palangkaraya leads to an increase of the number of other markets that will be in crisis by 1.68 percent.

While the findings can be interpreted as not all alerts phases lead to a crisis, the positive and significant results of the regressions show the relevance of monitoring the key markets to forecast price movements in many other markets. When the key markets are on alerts, the probability of the price to move to a crisis is higher than the probability

This study shows an efficient approach in monitoring price movement using the information from the market price. In a large developing country such Indonesia, where markets are located in different islands with considerable distances, the results become important as it is possible to monitor price movement in the country with less resource. By monitoring only Surabaya and Palangkaraya, price movement in the 25 markets in Indonesia can be forecasted. Although the results indicate that not all alert phases lead to a crisis, monitoring price movement can help to better anticipate possible price crisis events. While one may argue that the cost of monitoring food prices in all markets is low in the current new era of information technology, the proposed study can serve as an alternative approach which can be useful in integrating policies between different markets.

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Appendix

Table A.1. Summary statistics

Market	Obs	Mean	Std. Dev.	Min	Max
Banda Aceh	168	5476.87	2256.13	2552.45	9745.2
Medan	168	5516.15	2130.11	2895	9387.17
Padang	168	5918.94	2759.36	2751.46	12273.25
Riau	168	5775.55	2576.28	2772.5	11310.25
Jambi	168	5138.05	2349.91	2326.56	9712.17
Palembang	168	5043.33	2257.42	2186.25	9210.83
Bengkulu	168	5018.60	2095.20	2137.81	8699
Bandar Lampung	168	5063.32	2367.07	2243.75	10037.33
Jakarta	168	5802.56	2487.06	2724.29	10935
Bandung	168	5118.59	2134.40	2311	8676
Semarang	168	4994.76	2195.93	2272	8966.67
Yogyakarta	168	4868.41	2221.75	2141.33	9026.4
Surabaya	168	5068.46	2312.94	2255.31	9623
Denpasar	168	5180.17	2202.66	2422.5	9370.75
Mataram	168	4577.74	2072.31	1954.69	9091
Kupang	168	5208.28	2180.96	2540.38	9754
Pontianak	168	5515.88	2727.67	2437.5	10480.8
Palangkaraya	168	6097.42	2892.92	2915	11465.91
Banjarmasin	168	5412.18	3040.06	2279.36	11723.75
Samarinda	168	5426.26	2379.46	2485.34	9999.25
Manado	168	5243.97	2110.03	2741.67	8985.5
Palu	168	4661.19	2053.29	2016.67	8183.8
Makassar	168	4491.90	1840.41	2193.75	7739.5
Kendari	168	4832.60	2174.21	1817.81	8538.17
Jayapura	168	6183.77	2410.93	3100	10633.67

Source: own calculation based on BPS database