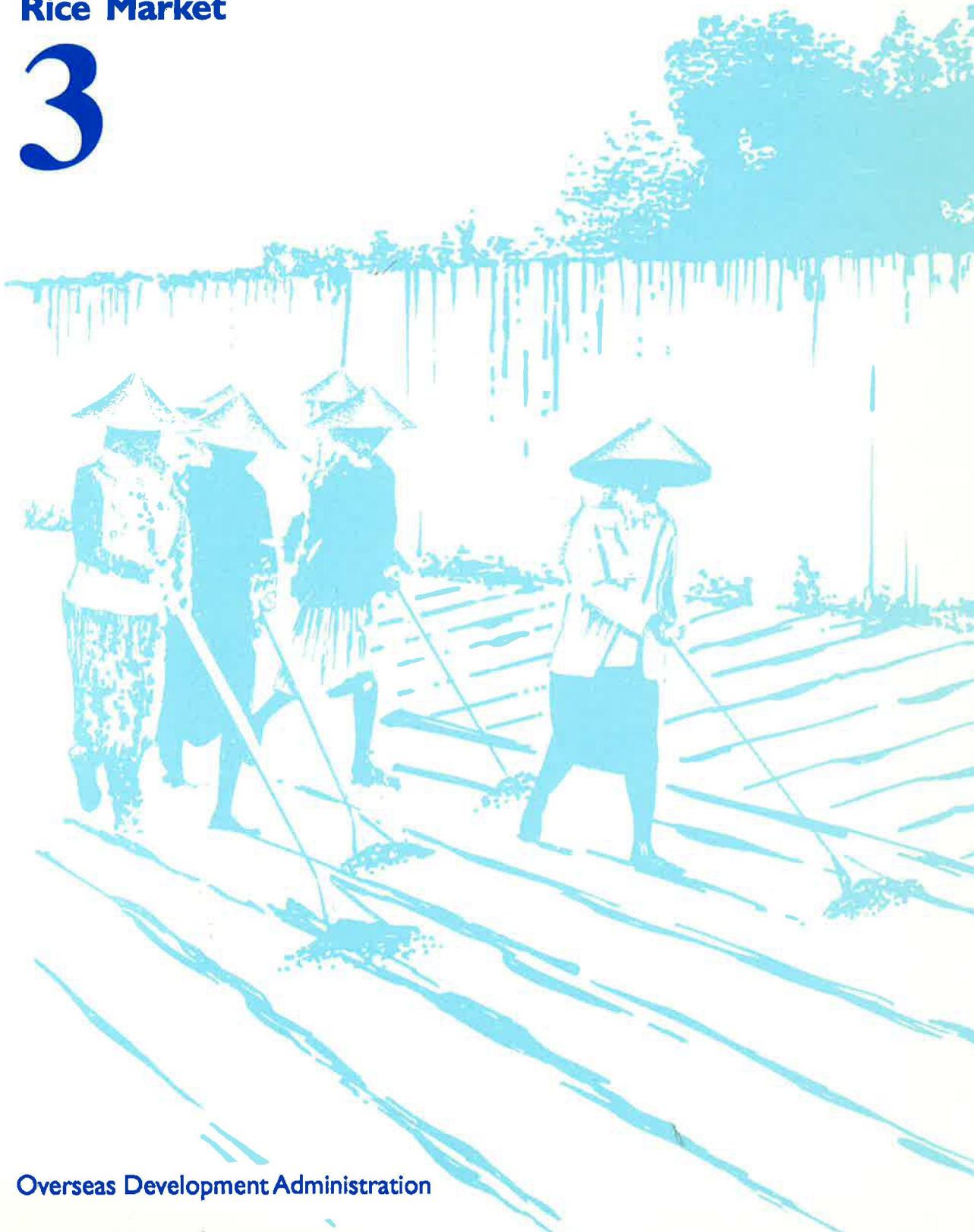


**Applying Price Analysis to
Marketing Systems: Methods and
Examples from the Indonesian
Rice Market**

3



Applying Price Analysis to Marketing Systems: Methods and Examples from the Indonesian Rice Market

B.W. Trotter

Marketing Series Volume 3



Natural Resources Institute

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CONTENTS

ACKNOWLEDGEMENTS	iv
SUMMARY	v
INTRODUCTION	1
SECTION 1 RESOURCES AND BACKGROUND TO THE INDONESIAN STUDY	3
Rice, Indonesia and BULOG	3
Data	4
Resources	5
Skill	5
SECTION 2 SEASONAL ANALYSIS: DECOMPOSING SEASONALLY VARYING TIME SERIES DATA	6
Introduction	6
Methodology	7
Application of the Methodology to Indonesian Rice Prices	10
Discussion of the Indonesian Results	14
SECTION 3 PRODUCER-CONSUMER MARGINS AND VERTICAL INTEGRATION	16
Introduction	16
Complications	16
Method and Application to Indonesian Rice Prices	20
Discussion of the Indonesian Results	24
SECTION 4 VERTICAL INTEGRATION	25
Introduction	25
Methodology(Cointegration)	26
Application of the Methodology to Indonesian Rice Prices	29
Conclusions	34
SECTION 5 SPATIAL MARKET INTEGRATION	36
Introduction	36
Methodologies	36
Application and Discussion of the Methodologies to Indonesian Rice Prices	44
Conclusions	49
REFERENCES	51
ADDITIONAL READING	53
APPENDIX 1 NEGATIVE STORAGE MARGINS IN A COMPETITIVE MARKET	54
Convenience Yield	54
Implications for the Indonesian Case and BULOG	55
APPENDIX 2 HYPOTHESIS TESTING AND CORRELATION COEFFICIENTS	58
Testing for the Absence of Correlation, $H_0: \rho=0$	58
Testing for Perfect Correlation, $H_0: \rho=+0.99$	58
Hypothesis Testing Example: Jakarta-Semarang	59
Conclusions	60

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SUMMARY

A number of techniques have evolved, some quite recently, to apply the analysis of time series price data to the questions of market integration of food staples; temporal, spatial and vertical integration.

The issue of market integration is central to addressing a range of questions: the ability of private markets to perform seasonal storage efficiently, the ability of private markets to transfer efficiently food stocks to areas of local famine, the scope for reduced operational scale and costs of parastatals. For example, if food staple markets are both spatially and vertically integrated, parastatals can intervene in central urban wholesale markets with the confidence that the price effects will be reflected in their actual target market; rural, producer markets. A complete, nationwide network of producer market buying depots is then not needed to achieve floor price stabilization.

This book is a comprehensive training manual for those wishing to apply the various methodologies relating to market integration; including seasonal indices, returns to storage, producer–consumer margins, bivariate correlation coefficients, Ravallion model of integration, Timmer’s Index of Market Connection, cointegration and Granger–causality. All the methods are applied in a step-by-step, easy-to-follow manner to Indonesian time series rice price data for the period 1980–90. Only a rudimentary knowledge of both economics and statistics is assumed.

The paper concludes that there is no best technique for spatial and vertical integration. We are still waiting for a technique that is robust enough to apply under a wide variety of assumptions and is simple to use in a field setting. For some techniques the problem is that a high level of initial market knowledge is needed in order to know if a technique can be appropriately applied. This initial knowledge level can be so stringent that the existence of this knowledge precludes the need to apply the technique in the first place.

Two major problems in applying the techniques are:

the quality of data, particularly with respect to the use of monthly rather than weekly or daily data and the use of averaged data, and

the fact that the trading relationship between any two regions cannot be categorically defined as one of exporter/importer and the relationship is not constant; either intra-seasonally or inter-annually.

The use of bivariate correlation coefficients has been much criticized. However, much of this criticism concerns poor data quality and poor application of the technique. This book concludes that bivariate correlation coefficients, if properly utilized, still offer a simple technique of assessing broad, long term integration patterns, particularly in situations where initial knowledge is low.

The Ravallion model requires more initial market knowledge, has restrictions as to its applicability and requires a high level of econometric sophistication. Assumptions of exogeneity that simplify the econometric complexity, employed in Timmer’s Index of Market Connection and in Heytens’ applications, will not be acceptable in most instances. The Ravallion model therefore remains a complicated technique for most but is more sensitive and offers the chance to assess short-run integration.

The cointegration and Granger–causality approach requires limited initial market knowledge, has wide applicability, can address questions of the causal direction of market forces but cannot address short-run integration. The econometric skill required for bivariate applications of this technique is only intermediate. However, it is unclear that the bivariate approach, as opposed to a multivariate approach, can deal with the affects of inflation in the majority of situations.

Multivariate application would then put the technique on par with the Ravallion model in terms of econometric skill required.

Although the paper is essentially one of methodology, Indonesian results are presented for the period 1980–90. The seasonal indices for the major rice production and consumption areas of Indonesian show classical patterns with low variance. Interestingly, the implied net returns to seasonal storage appear to be negative. The possibility of BULOG, the national rice parastatal, inducing this result by its own storage behaviour is discussed.

Both real producer–**rural** consumer margins and real producer–**urban** consumer margins declined steadily during the decade falling by roughly a half.

All of the techniques applied to the questions of spatial and vertical integration produce results consistent with integration. However, because of limitations with all of the techniques, the results do not allow categoric acceptance of integration, particularly short-run integration.

Introduction

The intended readership of this publication is the price analyst 'foot soldier'. Such a reader may possess only a first, or even no, degree in economics, limited statistical/econometric skills and little overseas experience, yet nonetheless faces the practical problem of assessing agricultural market performance in the developing countries using time series price data. The intention is to state clearly a practical and simple methodology, while at the same time providing the underlying economic and statistical reasons for the approach adopted. It is not meant to prescribe *the* way but merely describe *a* way adopted by a fellow 'foot soldier' in order that others might more easily find their own way.

The procedure adopted here is to follow the approach used in the author's time series price analysis of the rice market in Indonesia for the period 1980-90. However, the sections on vertical and spatial market integration, particularly, go beyond what was done for the study.

This publication concerns the practical application of methodology, not the results of a particular study. As such, the Indonesian example is used as an illustration with the hope and belief that it has general applicability. The Indonesian time series analysis was conducted as a companion piece to a 2 year sample survey of the rice market in Indonesia which focused primarily on rice marketing and storage. The time series analysis was meant to describe the overall rice market, trends within the decade 1980-90 and, if possible, provide indications of market performance. As a secondary concern, it was to address a question regarding the efficacy of using a specific aggregate rice price measure, the Medium Price, instead of actual varietal prices, in rice price analysis.

This Rice Marketing Study, comprising the sample survey and time series analysis, was carried out between 1989 and 1991. It was carried out under the auspices of the Natural Resources Institute (NRI) with funding by the Overseas Development Administration of Her Majesty's Government. It was undertaken within the umbrella of a 15 year project of technical cooperation, the NRI-BULOG Development Programme, to the Indonesian rice parastatal, BULOG. For those who are interested in the sample survey methodology, another publication in this series by Priscilla Magrath (1982) covers that issue. For those who are interested in the sample survey and time series results, a further publication by Frank Ellis deals with those subjects (Ellis *et al.*, 1992).

The background to this time series analysis makes the study slightly atypical for several reasons. First, the quality and range of data generally available in Indonesia are better than in most developing countries. Second, because of the study's connection with a long-term project, the access to the data was privileged and the general knowledge of the rice market was high. Third, the time allowed for the time series analysis was longer than NRI (or other donors) normally would permit. This allowed a more thorough investigation, particularly of methodologies and of varietal prices. However, it is not felt that these three issues substantially limit the applicability of the approaches adopted.

Finally, one would be remiss without a few words of warning to potential users of the techniques outlined here. Firstly, time series analysis can only be an aid to understanding the operation of markets and is not a substitute for field knowledge, case studies and the like. As will be highlighted throughout the publication, the results of the analysis often can have multiple interpretations. For example, a high degree of spatial integration may be due either to a competitive market, strong parastatal control, or both. Secondly, it is difficult to over-emphasize the importance of data quality. The investment of time involved with time series price analysis is only worthwhile if the underlying data can support it. If they cannot, then resources are better spent sourcing better primary (from surveys done oneself) or secondary data. Thirdly, there is a danger with this type of 'illustrative user manual' approach that readers will blindly, and hence incorrectly, attempt to apply the techniques. An attempt has been made to avoid some of this by providing the economic and statistical rationale for the use of the techniques. Nonetheless, readers are cautioned that this report is not a recipe book. The adage, 'a little bit of knowledge is a dangerous thing', applies particularly strongly to econometric time series work.

LAYOUT

Section 1 gives background information on the Indonesian rice market and BULOG's role within it. It also discusses the level of resources needed to conduct time series analysis: data, computer hardware, software and analyst skill.

Section 2 deals with seasonal analysis but more generally covers the decomposition of a price series into its respective components: trend, season, cycle and random. It focuses on deriving and interpreting gross returns to storage from price data.

Section 3 looks at producer-consumer margins. Focus is on the derivation and interpretation of gross producer-consumer margins. The analysis can, however, be applied to any margin in the vertical marketing chain.

Section 4 discusses vertical integration, the extent to which changes in retail and producer prices, in one geographic area, are connected. A newer econometric technique, cointegration, is introduced as the measure of vertical integration. This discussion and analysis has direct applicability to Section 5 on spatial integration.

Section 5 deals with spatial integration of the market. It is the most difficult and lengthy of the chapters, requiring a modest appreciation of statistics/econometrics. It first discusses the use of, and problems with, correlation coefficients as a spatial integration measure. It next discusses an alternative econometric approach, developed by Ravallion and adapted by Timmer, which attempts to overcome the shortcomings of correlation coefficients. Finally, it reintroduces cointegration, previously discussed in Section 4, as a measure of spatial integration. Conclusions are then drawn on which technique is the most appropriate.

Section 1

Resources and Background to the Indonesian Study

RICE, INDONESIA AND BULOG

Figure 1 is a map of Indonesia showing the locations used in the time series analysis of rice prices. Most of the rice production, some 60%, is on the island of Java with approximately 20% on Sumatra and 8% on Sulawesi (Wyeth, 1991).



Figure 1 Map of the Study Areas in Indonesia

Production of rice grew at a rate of 4.6% per annum, increasing from 13 to 26.5 million tonnes between 1969 and 1985. Most of that growth was due to increased yields which increased at a rate of 3.7% per year. Area increases were largely due to an increase in the cropping ratio (number of crops per year). The largest yield increases were in the latter half of the 1970s. By the middle of the 1980s more than 90% of the area was given to new high-yielding varieties of rice. This increased production was part of a government drive towards self-sufficiency. It has allowed Indonesia to turn from being a large importer of rice in the 1970s to essentially a self-sufficient producer in the 1980s.

The rice harvest pattern can be seen in Figure 2. At the national level there is essentially one large harvest, peaking March–April, with a smaller one peaking in August and finally a small one in November.

BULOG, the National Logistics Agency, was established in 1967 as a government agency with responsibility for price stabilization and maintenance of food security. It was to maintain a food reserve, intervene in markets to stabilize prices and act as the government quartermaster for physically supplying rice to government personnel. As a price stabilizer it acts in a textbook manner as a buffer stock agency, buying all rice when prices are below the floor price and re-supplying that rice to the marketplace if prices exceed a target ceiling price. BULOG is both an intra-year and inter-year price stabilizer. The floor price is essentially a pan-territorial one which is publicly announced and defended throughout the country. The ceiling price is not public knowledge and intervention is in the urban, not rural, markets. BULOG's purchases of rice are not a large portion of total annual

production, normally 6%-10%. Despite this, BULOG has been able to keep domestic rice prices much more stable than world prices. This is partly because the effect of that intervention is increased when it is more seasonally concentrated than production. As can be seen from Figure 2, approximately 80% of BULOG's purchases are in the March-June period.

DATA

The data used for the retail prices were from two sources. The Medium Price series was collected from BULOG. The various varietal prices by province by month were from the BPS, Bureau of Statistics. The two data sets, that from BULOG and that from BPS, in principle stem from the same source, a joint weekly survey of retail prices. BULOG's Medium Price, again in principle, can be viewed as the price of the modal variety in that location, i.e. the variety most often chosen by consumers in that location. The BPS does not use a modal variety price but a weighted average price. It undertakes regular provincial consumer surveys to derive varietal weights for the computation of a weighted mean rice price. However, from the BPS survey data, consumer consumption patterns appear to exhibit a large degree of both varietal diversity and flexibility. One should realize that the BULOG Medium Price is subject to variety changes at any provincial location and that at any one time, different varieties are used in different locations.

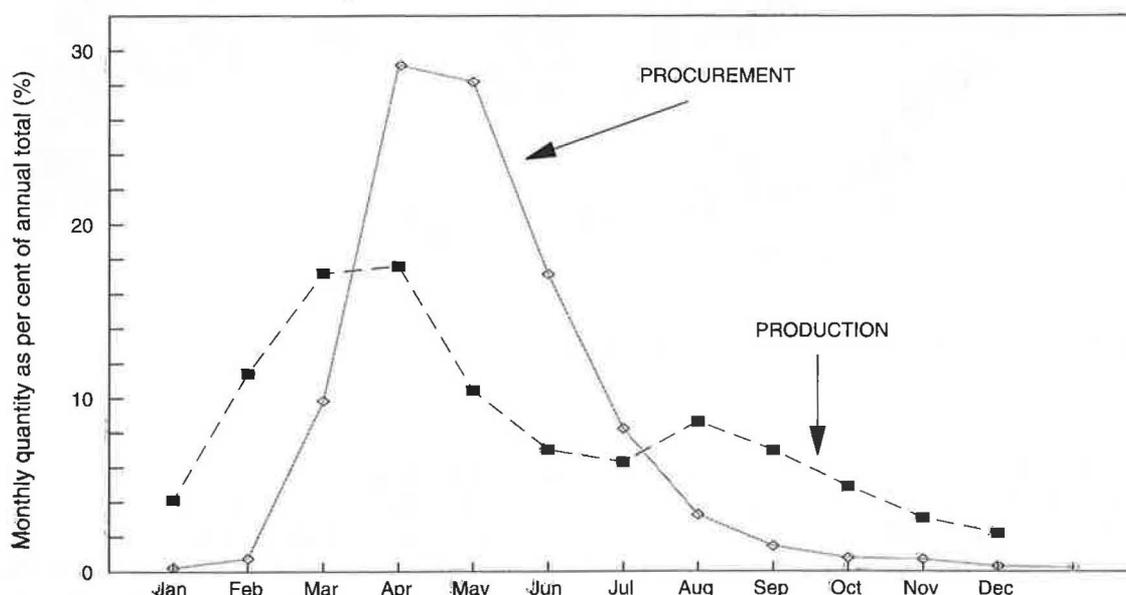


Figure 2 Comparison of Rice Production and BULOG Procurement (average 1986-90)
Source: Ellis *et al.* (1991)

The varietal price series are discontinuous, with some varietal prices disappearing and reappearing or data not being available for the whole period of study. Varietal definition is often very broad and occasionally unclear. The retail price analysis then focuses on varieties that are important in the consumption mix and for which there are sufficient data to utilize.

The data used for producer prices were from the series collected and used by BPS for computing the Farmers Terms of Trade Index. This series was for specific varieties and only covered the main Indonesian island of Java. The BULOG producer price data were not felt to be consistent enough to use. The definition of the producer price was not consistent; sometimes it represented a farm gate price and other times a wholesale price. This was unfortunate, because the BULOG producer price data covered all of Indonesia. Reliance on the BPS data necessarily restricted producer-consumer margin analysis to Java alone.

Two different consumer prices were used. One was from BPS and was a rural price series (the price paid by farmers for rice). Again this series was the basis for the BPS Farmer Terms of Trade Index series. The second was from the joint BPS/BULOG weekly survey that we have already mentioned. This was an urban consumer price series. This then allowed analysis of producer-consumer margins for both urban and rural consumers.

RESOURCES

All the analysis and presentation material was done with four different software programs. Lotus 123 was used as the spreadsheet program and for simple linear regressions, but Statgraphics was used for any other statistical analysis: correlation coefficients, multivariate regressions, model testing, etc. Freelance Graphics was used for the graphical presentation material: charts, graphs and drawings. Finally, Microsoft Word was used as the word-processing program. The names of the software programs are given as an illustration, not as an endorsement. If anyone is contemplating the analysis suggested in the following chapters they will need all four types of software programs: spreadsheet, statistics, graphic presentation and word processing. It was not found necessary to have a specifically econometrics statistics program as opposed to a general statistics package. However, an econometrics package would have saved some effort because a number of statistical procedures employed are automated within such packages.

The hardware was an IBM-compatible 286 and 386 computer. A 286 machine was sufficient to do all that was necessary.

SKILL

The question of skill level is essentially one of econometric skill. It is probably not possible to do any of the analysis in this paper without some statistical knowledge. However, one can overestimate the knowledge needed and underestimate how much one can learn by practical experience. This publication is written with the assumption that the reader will know little statistics and that it is possible 'to learn on the job'. Readers with little econometric expertise should take courage from the following comment by Kennedy (1985) about econometric forecasting

“Armstrong (1978) presents a graph reflecting his findings that a small amount of forecasting expertise dramatically improves the accuracy of forecasts but thereafter further expertise does not improve (and may even worsen) forecasts. He concludes that for forecasting the cheapest expert should be hired.”

Section 2

Seasonal Analysis: Decomposing Seasonally Varying Time Series Data

INTRODUCTION

The analysis presented here follows the work of Goetz and Weber (1986). The analysis attempts to decompose raw price data into its component parts. Our interest is with the seasonal component of a price series. The seasonal component is of major concern because, in a well-functioning market system, the rise in prices between successive harvests should reflect the costs of storage. By isolating only the seasonal component of the price series one can estimate the seasonal price rises and, hence, the gross returns to storage in the marketplace. This can then be compared to the costs of storage to obtain some idea of the net returns to, or profitability of, storage. Also one can look at the trends and at the variability of the margins. All this, in turn, will give us an indication of whether profits are excessive and if the market is not functioning well.

The lack of excessive profits to storage may be a necessary condition, but it is not a sufficient condition, for the conclusion of a well-functioning market for storage. This is because the lack of excessive profits may be due to reasons other than market competition. For example in the Indonesian case, it may be BULOG's market intervention at the floor and ceiling price which restricts seasonal price swings sufficiently to reduce what would otherwise be excessive storage profitability.

Although it is intuitively easier to understand the case of excessive profitability, one may find, as we did for Indonesia, negative net storage margins. Storage costs are greater than the gross returns to storage. One cannot necessarily conclude that the market is not functioning well in this case. At low levels of storage a well-functioning market may be compatible with negative storage margins. Appendix 1 attempts to explain why this should be so.

As pointed out in Section 1, time series analysis can only be an aid to understanding market structure. Although it can provide results about, say, returns to storage, without other information it is difficult to draw conclusions about the state of the marketplace.

The realistic problem for most analysts will be that they will have access only to time series price data but not to cost of storage data. One then can only estimate gross storage margins rather than net (after costs) storage margins. Changes in gross margins have no necessary implications for changes in net margins. Is it then worth doing the seasonal analysis?

The answer is yes. First, often there will be time series data on the largest component of the cost of storage: the cost of borrowed funds (the opportunity cost of money). Goetz and Weber (1986) suggest a technique for assessing the efficiency of storage using the interest rate series essentially as a storage cost proxy.

Second, even where no cost of storage data is available, the seasonal analysis is still worth doing. The seasonal price rises may turn out to be so high, or indeed so low, that it is obvious that net storage margins must be highly positive or highly negative. Alternatively, when the case is more ambiguous one can present the seasonal component in terms of a percentage return to storage (gross) and allow decision makers themselves to assess that, relative to their own ideas of costs of storage.

Third, seasonal analysis can also be used to determine more than just the gross return to storage. One is able to assess statistically whether seasonality is, in fact, present, the variability of seasonality and whether it is increasing or decreasing with time. Additionally, if one needs to make price forecasts using time series data, decomposing the price series into its component parts (trend,

cyclical, seasonal, random) increases the accuracy of the forecast over using a straight extrapolation of the series trend. Such a forecast would take into account the market's position within the cycle rather than assuming the cyclical component did not exist. (That said however, if one's primary focus is forecasting, there are much better approaches, such as Autoregressive Integrated Moving Average (ARIMA) models using Box-Jenkins econometric techniques.)

Another problem in practice is the length of the data series. Often it is much shorter than one would prefer. However, even monthly series of only 2 or 3 years duration may be still worth using. Essentially the short length of the series affects the quality or confidence with which one can state that there is, in fact, seasonality, what its variability is and what the trend is. This is the problem with any small-sized sample. However, because this seasonal analysis technique is a common one, you may be able partially to get around this problem by comparing your results with those of past studies to obtain a better idea of the trend. This was indeed possible with the Indonesian rice market.

METHODOLOGY

The basic idea behind decomposing a price series is that there are four components composing a price, namely, a trend, a cyclical pattern, a seasonal pattern and random or disturbance component. Intuitively one can think of the trend as reflecting general economic factors such as inflation and increased demand due to population increases. The cyclical pattern can be weather-induced or as a result of slow supply responses due to long gestation periods (tree crops, animal production). The seasonal pattern is a result of the need for relatively costly storage to match a discontinuous supply to a continuous demand for the product. Finally, the random component can be thought of as, perhaps, government policy changes or like the error term in a regression analysis. We focus here on the seasonal component, but Goetz and Weber (1986) describe how to derive the other components. A stylized example of the decomposition is given in Figure 3.

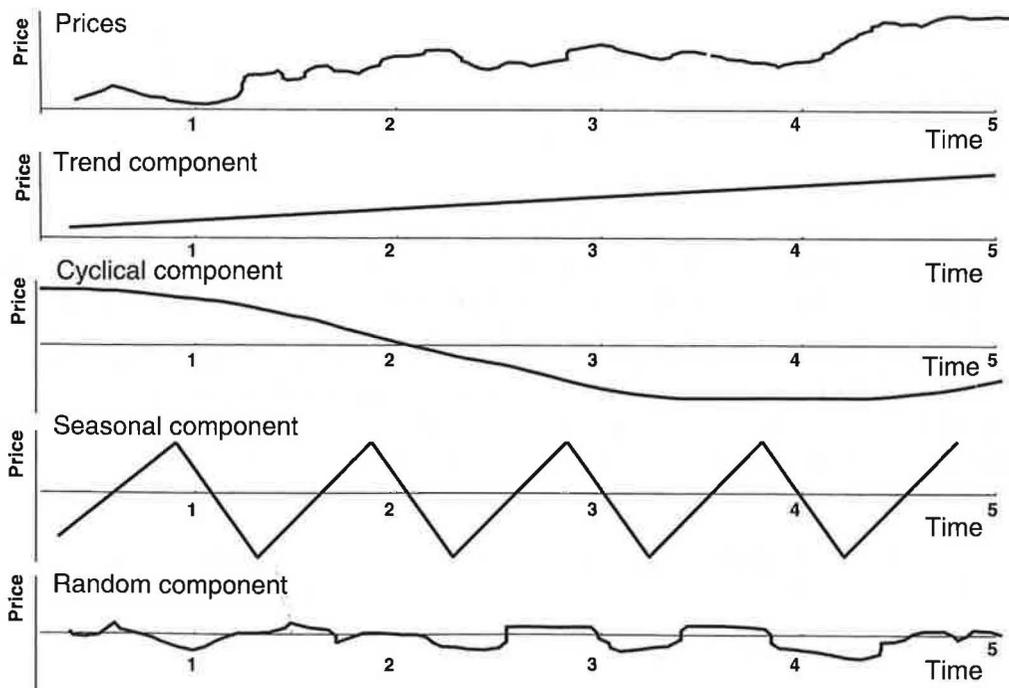


Figure 3 Time Series Price Decomposition

The most common method is to assume that the four components are linked multiplicatively

$$P_t = (T_t) \times (C_t) \times (S_t) \times (R_t) \quad (1)$$

where P_t is the price, at time t , T_t the trend component, at time t , C_t the cyclical component, at time t , S_t the seasonal component, at time t , R_t the random component, at time t , and t is one observation at day, week or month t .

This is a general approach adopted by government statistical agencies in producing seasonally adjusted economic data from the raw price series. A less common alternative is to assume that the components are linked additively, not multiplicatively

$$P_t = (T_t) + (C_t) + (S_t) + (R_t) \quad (2)$$

where P_t is the price at time t , T_t the trend component at time t , C_t the cyclical component at time t , S_t the seasonal component at time t , and R_t the random component at time t . Fuller and Lury (1977) suggest initially using both the multiplicative and additive models and continuing with the model that yields the more stable Seasonal Index.

More complex model specifications are possible using combinations of both additive and multiplicative terms. Here we use the multiplicative model only.

To isolate the seasonal component, the first step is to estimate the trend and cyclical components so that they can be removed. Removing the T_t and C_t components from P_t leaves us with a series with just S_t and R_t in it.

$$\begin{aligned} S_t \times R_t &= \frac{P_t}{T_t \times C_t} \\ &= \frac{S_t \times R_t \times T_t \times C_t}{T_t \times C_t} \end{aligned} \quad (3)$$

Once that is done, then R_t is removed and we are left with a series hopefully containing the S_t component alone.

Step One: Moving Seasonal Average (MSA)

The first step then is to estimate T_t and C_t . This is done jointly, as $T_t \times C_t$, in one step by creating a Moving Seasonal Average (MSA) of the P_t values. A moving average removes the random component and by making it one season in length, then the seasonal component is removed as well. That may not seem intuitively obvious. If the random component is truly random then the average of all the random components for all the observations should be zero. On average the random events cancel each other out. If we make the average a seasonal one, then the effects of seasonality are also cancelled out. 'Moving' refers to the fact that the seasonal average is not constant but changes (moves) with each observation. Each observation's seasonal average includes a half-season behind and a half season ahead. The seasonal average is centred on each observation.

What is left then is just the trend, T_t and cyclical, C_t , components. It is perhaps easiest to visualize it mathematically. Assuming monthly data and a season length of 5 months, it can be described as

$$\begin{aligned} \text{MSA}_t &= \frac{P_{t-2} + P_{t-1} + P_t + P_{t+1} + P_{t+2}}{5} \\ &= T_t \times C_t \end{aligned} \quad (4)$$

There is a computational problem when the season length is an even number of months, as with the common case of a 12 month season. The MSA needs to be centred on month t , which is automatic with seasons of an odd number of months as above, but is not automatic for seasons with an even number of months. For a 6 month season this is resolved as follows

$$\begin{aligned} \text{MSA}_t &= \frac{P_{t-3} + 2(P_{t-2}) + 2(P_{t-1}) + 2(P_t) + 2(P_{t+1}) + 2(P_{t+2}) + P_{t+3}}{12} \quad (5) \\ &= T_t \times C_t \end{aligned}$$

Essentially to compensate for our inability to centre the average on P_t , we average two different seasonal averages; one from $P_{t-3} \rightarrow P_{t+2}$ and one from $P_{t-2} \rightarrow P_{t+3}$. This results in the above equation. For a 12 month season the computation is analogous. The P_{t-6} and P_{t+6} values would be the only values not multiplied by 2 and the denominator would be 24 not 12. It may not be obvious initially but the moving average technique means that we 'lose' values at the beginning and end of the series; a half season in each case. The MSA series created will then be a full season shorter than the raw price series. For a lengthy series this is not problematic. However, for a short data series, especially for a product with a long season, this can mean significantly reducing the number of values that are carried on to Step Two.

Step Two: Seasonal Index (SI)

The first step of estimating $T_t \times C_t$ is then complete. The second step of estimating $S_t \times R_t$ and computing what Goetz and Weber call the Seasonal Index (SI), is easily handled because

$$S_t \times R_t = \frac{P_t}{T_t \times C_t} \quad (6)$$

$$= \frac{P_t}{\text{MSA}_t} \quad (7)$$

$$\text{Seasonal Index} = \text{SI}_t = (S_t \times R_t) \times 100$$

We have then created a fraction; what fraction P_t is of its own MSA_t . Then it is standardized to a percentage by multiplying by 100. If P_t equals its own MSA_t , then the SI_t will equal 100. There will be one SI_t for each P_t (except for the half season we have 'lost' at either end of the series). In economic literature this is sometimes referred to as the 'ratio to moving average method'. For a 12 month season, an SI_t value of say 114.5 would imply that month t is 14.5% higher than the 12 month moving average (one season moving average). If the same calendar month in each successive season (i.e. $\text{SI}_t, \text{SI}_{t+12}, \text{SI}_{t+24}, \dots$) is similar to 114.5, then we can be confident that this calendar month is significantly above the seasonal average of 100. If no seasonality exists we should expect that all the calendar month SI values would not be significantly different from 100.

Step Three: Grand Seasonal Index (GSI)

The third, and final, step is remove the random component, R_t , to produce what we call the Grand Seasonal Index (GSI). This is done by computing the average SI for each calendar month. There is then one GSI for each calendar month in the season. Mathematically this is as follows, for a season of 12 months and 6 years of data

$$\text{GSI}_m = \frac{\text{SI}_t + \text{SI}_{t+12} + \text{SI}_{t+24} + \text{SI}_{t+36} + \text{SI}_{t+48} + \text{SI}_{t+60}}{6} \quad (8)$$

where m is the calendar month.

It is the averaging over all the years of data that purges the random component. There is one minor computational complication. We would like the average of all the GSIs to equal 100, just as the average of the SIs in one season equals 100. In that way any calendar month's GSI deviation from 100 is then evidence of seasonality. However, due to rounding errors in the computation, the average of all the calendar month's GSIs may not exactly equal 100. Accordingly, all the GSIs are adjusted slightly to ensure that the average does, in fact, equal 100. The method of doing so is simple and can be seen in the next section which looks at the application of the techniques to the Indonesian rice data.

The GSI is then merely the mean of a set of SIs, all of the same calendar month across successive seasons. In addition to simply calculating the mean, one can also test for seasonal significance and look at the trend and variability in the SI series. How this is done is explained in the next section.

APPLICATION OF THE METHODOLOGY TO INDONESIAN RICE PRICES

Here we will look at just one price series from the Indonesian study; the Medium Retail Rice Price for the city of Surabaya in East Java. Medium Rice refers to a price series maintained by BULOG itself. It can be best viewed as the retail price of the modal variety in a particular location. It is then the retail price of the variety of rice most preferred by consumers at a certain time and location. Given consumer price sensitivity and consumer tastes in Indonesia, the most preferred variety changes with time and with geographic location. Therefore, the Medium Price in Surabaya may be based on the variety IR 64 II at one time and later, on Cisadane II. At the same time, the medium price in Jakarta may be based on IR 36 I.

Table 1 shows the Lotus 123 worksheet used to move from Step two to Step three. Steps one and two have already been computed. It perhaps appears rather daunting at first. There are four horizontal blocks of figures. The top box, Rows 1–11, contains the SI values which have already been calculated following Steps one and two. They are arranged by month and year. The second block, Rows 12-23, can be ignored for the moment. It is the series of longhand statistical calculations which are then used in the last two blocks. This method was employed in the spreadsheet to ensure that any changes to the underlying price series would automatically update all the statistical values.

The third block, Rows 24-29, gives the GSI, the results of the test for statistical significance of seasonality and the variability of the GSIs. The fourth block, Rows 30-32, gives the estimates for the trend of the GSI over the period of study and the result of the statistical test for the significance of the trend.

Let us take each procedure step by step.

GSI Calculation

First we take the average of all the SIs for a particular calendar month, say January. In Table 1 this is listed as 'Mean' (Row 26) and for January is equal to 106.08. However, if we sum across Row 26, all the Means do not sum to 1200 but rather 1198.39, as can be seen on the far right of the table under 'Sum'. The GSI, however, is defined as having an average value of 100 so that the sum of all calendar months summed together should equal 1200 (i.e. 12×100). Consequently, all the Means need to be corrected by multiplying each by $1200/1198.39$ to give the GSI.

Table 1 Spreadsheet for Seasonal Analysis of Indonesian Prices
Medium Retail Price, Surabaya

Row number			Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
1	Seasonal	1980	104.16	104.43	101.26	99.08	99.71	98.50	94.44	92.38	93.49	103.88	107.37	107.29	
2	index	1981	106.52	105.70	101.74	95.60	95.78	95.82	97.41	96.86	96.38	99.16	102.25	102.02	
3		1982	110.23	109.09	97.65	92.41	91.35	92.66	90.90	89.56	102.68	103.34	102.92	111.46	
4		1983	113.41	107.32	103.12	96.43	94.07	93.74	94.57	96.66	98.59	100.30	100.89	100.88	
5		1984	114.97	103.65	101.06	96.85	97.73	98.00	98.49	99.35	100.40	100.52	100.48	101.72	
6		1985	101.79	100.87	99.89	98.13	96.93	96.20	95.81	97.17	100.64	101.03	102.27	102.92	
7		1986	103.62	103.56	101.98	97.22	95.52	94.35	93.47	93.57	97.44	110.55	108.69	105.89	
8		1987	104.15	103.21	99.55	93.05	92.63	92.33	90.55	89.32	94.98	102.22	111.03	108.74	
9		1988	105.49	105.63	100.20	95.03	91.58	97.60	99.86	102.38	103.62	103.90	105.89	101.81	
10		1989	101.02	100.42	98.81	100.25	99.58	95.75	97.50	96.75	96.85	101.79	101.69	99.44	
11		1990	101.50	104.23	95.97										
12	N		11.00	11.00	11.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	
13	Sum X		66.00	66.00	66.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	55.00	
14	Sum X_2		506.00	506.00	506.00	385.00	385.00	385.00	385.00	385.00	385.00	385.00	385.00	385.00	
15	Sum Y		1166.86	1148.11	1101.23	964.04	954.87	954.94	952.99	953.99	985.08	1026.69	1043.48	1042.18	
16	Sum Y_2		124007.66	119896.92	110289.77	92992.53	91262.65	91233.45	90906.68	91166.78	97135.24	105501.14	109004.59	108751.53	
17	Sum XY		6921.77	6847.87	6570.67	5308.90	5241.44	5245.18	5259.95	5279.63	5437.52	5666.81	5759.22	5697.25	
18	S_{xx}		110.00	110.00	110.00	82.50	82.50	82.50	82.50	82.50	82.50	82.50	82.50	82.50	
19	S_{xy}		-79.40	-40.79	-36.74	6.69	-10.36	-6.98	18.49	32.67	19.60	20.01	20.08	-34.73	
20	S_{yy}		228.93	64.74	42.71	55.59	84.43	42.84	87.04	156.59	97.68	91.73	119.78	137.75	
21	Regression SS		57.31	15.12	12.27	0.54	1.30	0.59	4.14	12.94	4.66	4.85	4.89	14.62	
22	Residual SS		171.62	49.62	30.44	55.05	83.13	42.25	82.89	143.66	93.02	86.88	114.89	123.13	
23	Residual MS		19.07	5.51	3.38	6.88	10.39	5.28	10.36	17.96	11.63	10.86	14.36	15.39	
24	t (null=mean is 100)		4.21	5.70	0.18	-4.82	-4.91	-6.88	-5.04	-3.68	-1.51	2.79	3.97	3.59	
25	s.e. (mean)		1.44	0.77	0.62	0.75	0.92	0.65	0.93	1.25	0.99	0.96	1.09	1.17	Sum
26	Mean		106.08	104.37	100.11	96.40	95.49	95.49	95.30	95.40	98.51	102.67	104.35	104.22	1198.39
27	GSI		106.22	104.51	100.25	96.53	95.62	95.62	95.43	95.53	98.64	102.81	104.49	104.36	1200.00
28	GSI+ 1 s.e.		107.66	105.28	100.87	97.28	96.53	96.28	96.36	96.78	99.63	103.76	105.58	105.53	
29	GSI- 1 s.e.		104.78	103.75	99.62	95.79	94.70	94.97	94.49	94.28	97.65	101.85	103.39	103.18	
30	Trend coeff.		-0.72	-0.37	-0.33	0.08	-0.13	-0.08	0.22	0.40	0.24	0.24	0.24	-0.42	
31	s.e. (coeff.)		0.42	0.22	0.18	0.29	0.35	0.25	0.35	0.47	0.38	0.36	0.42	0.43	
32	t (coeff.)		-1.73	-1.66	-1.90	0.28	-0.35	-0.33	0.63	0.85	0.63	0.67	0.58	-0.97	

Test for Seasonality

Seasonality is the statistically significant deviation of *any* GSI from the average value of 100. The null hypothesis is that seasonality is not present, implying that the GSI is, in fact, 100. The alternative hypothesis is that the GSI does not equal 100. It is then a two-tailed test. The test statistic is t which is

$$\begin{aligned}
 t_{n-1} &= \frac{\text{GSI} - 100}{s \div n^{1/2}} \\
 &= \frac{\text{GSI} - 100}{\text{s.E. (Mean)}}
 \end{aligned}
 \tag{9}$$

where n is the sample size, here either 10 or 11 depending on the month, s the standard deviation (of that calendar month's SI series), $s \div n^{1/2}$ the standard error (s.e. (Mean) in Table 1), and t_{n-1} the Student's test statistic for degrees of freedom $n-1$. The two-tailed t_{n-1} value ($n=11$, 95% confidence level) is ± 2.23 . Values of t above ± 2.23 mean the null hypothesis of no seasonality is rejected. Row 24 gives the t values for each GSI. One can see that all months but March and September are significantly different from 100 because their t values are higher than ± 2.23 . Seasonality is then accepted.

Variability of the GSI

Underlying any GSI may be a highly variable SI series that has no central tendency. In such a case the GSI has little meaning. It is therefore worth reporting the standard error for each GSI as this gives the reader some idea of the variability. The variability of the GSI is also important when considering gross returns to storage. For any storage agent, a less variable gross return is preferable. Consequently, Table 1 includes the lines, GSI + 1 s.e. and GSI - 1 s.e. Statistically, approximately 60% of the GSI values should fall within this ± 1 s.e. band. If the band were widened to ± 2 s.e. then approximately 95% of the GSI values would fall within it.

Trend of the GSI and Testing for its Significance

If the data series is long enough, it is then worth looking at the trend for the GSIs. This will give an indication whether seasonality is becoming either more or less pronounced. Each calendar month's SI series is regressed on a monthly time variable. The significance of the trend coefficient is assessed using a t statistic, where the null hypothesis is that no trend exists and therefore that $\beta = 0$. The regression equation would be

$$\text{SI}_t = \alpha + \beta(\text{season}_s) + \varepsilon_t
 \tag{10}$$

where season_s is seasons 1 to the maximum number of seasons in the data set (in Table 1 either 10 or 11), SI_t the set of all the SIs for a particular *calendar* month, β the trend coefficient, ε_t the error term, and α the intercept term. Spreadsheet packages can handle this simple ordinary least squares regression quickly, automatically giving the trend coefficient and the t value for the trend coefficient. (Table 1 derives the t statistic and trend coefficients from first principles so that a new regression equation does not have to be run if data are changed. The spreadsheet then automatically updates all the calculations. The formulas can be found in any introductory statistics book, including those mentioned in the references.) Once again t values above ± 2.23 indicate rejection of the null hypothesis of no trend at the 95% confidence level.

Row 32 gives the t statistics for the hypothesis test of no trend. It can be seen that the null hypothesis is not rejected for any GSI month at the 95% confidence level. The t values are all below ± 2.23 . However, January, February and March have the most significant trends (highest t values). Although the null hypothesis is not rejected at the 95% confidence level, it is rejected at between the 85% and 90% confidence level. With moderate confidence the evidence suggests that the GSI is declining (because the coefficients are negative) in those three months. For instance January is the peak seasonal price month (highest GSI) and the GSI is declining at a rate of 0.72 GSI units/year.

Gross Real Storage Returns (GRSR)

Gross Real Storage Returns (GRSR) can be estimated from the GSI because it is a measure of the average change in the seasonal component of prices. Gross refers to the fact that no adjustments have been made for costs. Real refers to the fact that the trend, and hence inflationary trend, has been removed. It can be calculated by computing the percentage increase from seasonal price trough to seasonal price high. The computation is given in Equation 11.

We focus on only the seasonal component rather than all the price components because we want to ignore the influences of inflation, random events and production cycles. Our data base may only cover part of a cycle, say the rising part. In this case using, say, deflated prices, rather than the GSI, will bias the result upward. We should be clear, however, that the result we calculate using the GSI is not what the market actually faced (even in real terms) but what it would face (in real terms) in the long run (when the random and cyclical factors cancel out).

$$\text{Seasonal GRSR} = \frac{\text{Highest GSI} - \text{Lowest GSI}}{\text{Lowest GSI}} \times 100 \quad (11)$$

Row 27, Table 1, gives the GSI values. The low is July at 95.43 and the high is January at 106.22. Therefore, the gross storage margin is 11% per season. There are several points to make about this figure. The most important is that this is a real price margin not a nominal price margin. Because the trend has been eliminated from the raw price series in these computations, so essentially has inflation. Second, this is a gross margin completely unadjusted for storage costs and risks. Consequently, no judgements about profitability can be made at this stage. Third, this return is a seasonal one not an annual one. In our example, the 11% real price increase occurs within 6 months. When comparing this figure with the cost of borrowed funds which are quoted in percentages per year, proper adjustments need to be made. Often analysts talk of the percentage increase per month stored rather than per season. In our example, this would be just under 2% per month stored ($11\%/6$). Finally, this figure is sensitive to the shape of the GSI curve. It assumes implicitly that agents actually purchased at the seasonal low and sold at the seasonal high. Perfect forethought is an unlikely optimistic assumption. This can be misleading when the seasonal low (or high) is not pronounced but, as in Figure 4, essentially stretches from April to August. Using April instead of August as the low month greatly influences the results because it adds 4 months of storage costs but adds no price increase. In practice storage agents are more likely to purchase, not at the low of the year in July, but at harvest in April. Consequently, it can be argued that the 11% rise should be averaged over 9 months not 6 months. This, of course, cuts the gross real storage return *per month* in half.

There are drawbacks to following the method outlined here. Our example implicitly assumes that rice is stored at the retail level whereas storage actually is conducted more at the wholesale or producer level. As we will see in Section 3, producer prices exhibit more seasonality than urban retail prices. Consequently, if they are used, rather than urban retail prices, gross real storage margins are slightly higher. Lack of extensive and consistent producer price data precluded their use here.

DISCUSSION OF THE INDONESIAN RESULTS

Figure 4 presents most of the important points that the analysis produced. The GSI peaks in January before the largest harvest period which itself peaks in March. Prices decline quickly as the main harvest enters the market. Prices do not even begin to rebound until after the second harvest. The small third harvest in roughly November only stops the price rally in the lean season temporarily.

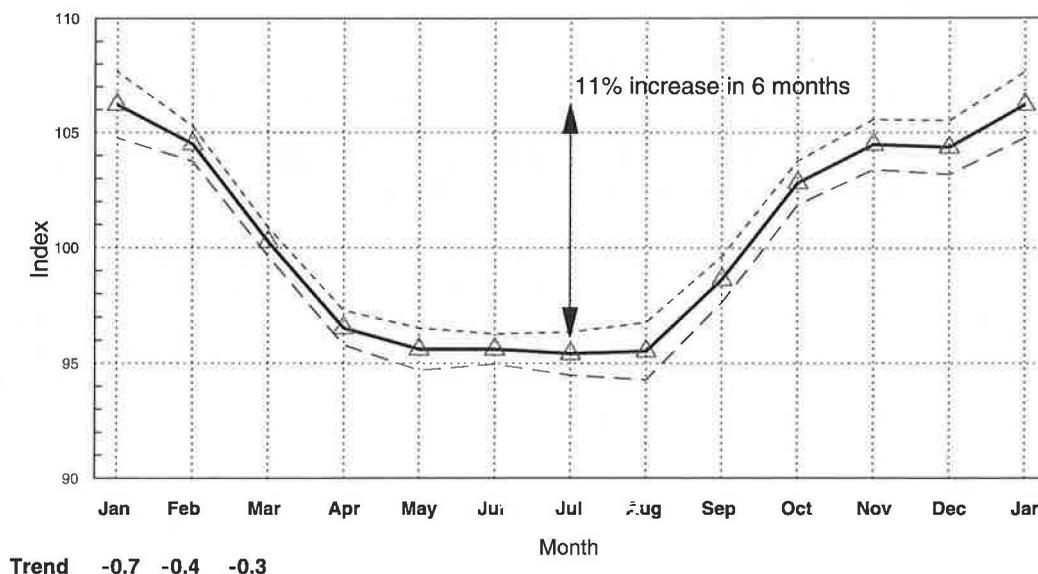


Figure 4 Grand Seasonal Index, Surabaya Medium Retail Rice Prices
Only trends of 80% confidence are given, in GSI units per year

—▲— GSI
- - - GSI plus 1 s.e.
- - - GSI minus 1 s.e.

The ± 1 s.e. bands are quite narrow. There is some anecdotal evidence that seasonal price behaviour in the 1980s was less volatile than either before or after this decade. The widening of the s.e. bands at the peak month indicates fluctuating harvest times.

The trends indicated in the caption suggest a decline in seasonality. Essentially the price spike in January is being eroded. This could be due to a number of factors. Shorter growing season varieties are more common and consequently the main harvest is slightly earlier. Also the cropping ratio (number of crops per year) has been increasing, suggesting that total production is more evenly spread throughout the year.

Another useful way of presenting the results is a real return per month stored rather than per season. Given the discussion in the last section about the difference between using the GSI and actual deflated prices to compute GRSRs, the latter are plotted in Figure 5. As can be seen, using actual (deflated) prices produces a slightly higher maximum storage return ($\approx 2.3\%$ per month stored) than using the GSI ($11\%/6 \approx 1.8\%$ per month stored). Goetz and Weber (1986) discuss other ways of assessing storage strategies and of presenting results.

Two other studies using this type of analysis have been done on Indonesian crops. One was on rice (Goldman, 1974) and the other on maize (Timmer, 1986). The rice study covered the years 1949 - 1970 for Surabaya and found seasonal increases of approximately 39% over a period of 6 months. The maize study covered the years 1973 - 1982 for rural prices and found increases of approximately 59% over a period of 7 months. Our results of 11% over 6 months are low compared to these studies.

Indonesia is uncommon amongst developing countries in having very high real interest rates. Although data are scarce, what do exist suggest that, at a minimum, *real* interest rates have ranged between 12.5% and 15.5% per annum (IMF). Given our finding of less than 11% gross real return to storage over 6 months there are indications that net real returns to storage may be negative. Storage involves other costs besides interest, such as inward and outward loading costs, physical losses, quality losses, warehouse costs, pesticides, revenue risk, and so on. These would be more than 1% per month. The costs of storage would then be greater than the revenue from storage.

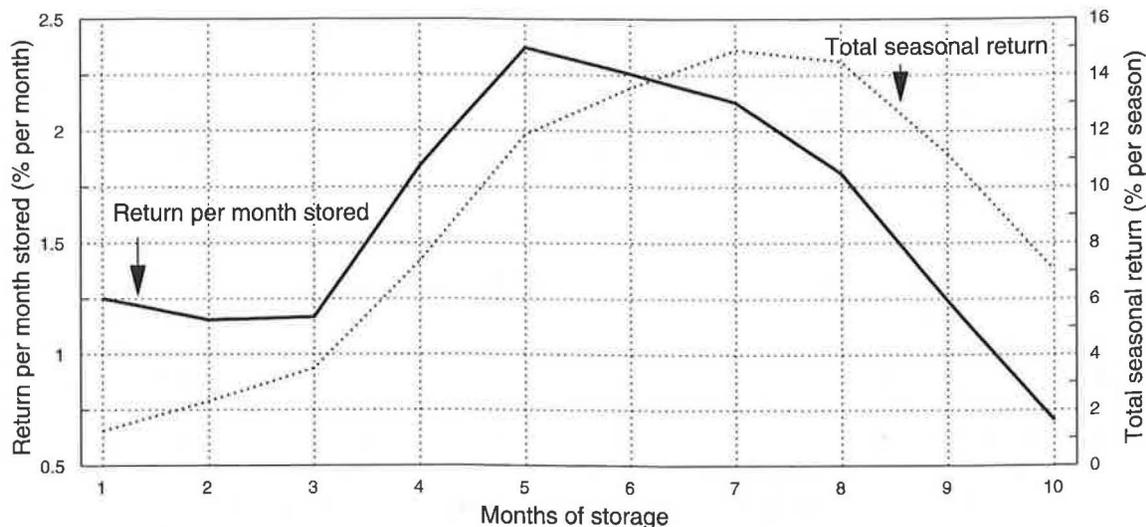


Figure 5 Gross Real Returns to Storage, East Java Medium Retail Rice Prices
 Purchase fixed at June, prices were constant 1977 Rp/kg Medium Retail Price
 ———— Return per month stored
 Total seasonal return

The evidence indicates that BULOG's existence and success at price stabilization may be a major reason for the low gross real returns and negative net real returns to storage. The older rice study (Goldman, 1974) covers a period mostly before BULOG's existence. The maize study (Timmer, 1986) is concerned with a market that, while nominally under BULOG control, is not one in which BULOG intervenes. The possibility of a parastatal causing negative net real storage returns, and yet a well-functioning private market still undertaking storage, is discussed in Appendix 1.

Section 3

Producer-Consumer Margins and Vertical Integration

INTRODUCTION

One is often interested in using producer-consumer margins as a means of assessing whether a market is functioning well. In its most simplistic form by subtracting producer prices from consumer prices, we can derive the gross producer-consumer margin. This can be compared to the costs of transporting the product from producer to consumer, and a net producer-consumer margin derived. This can be used as a measure of the existence of excessive profits. The technique is not limited to just producer-consumer margins but can be applied to any margin in the marketing chain.

It is perhaps best to view any product price as a conditional one. The price is conditional on the product having certain attributes. Often we fail to realize just how many attributes are important to the marketplace and how strongly they can affect price levels. For example, rice is often treated as a homogeneous product when, in the marketplace, it is clearly not. Market perceived quality differences for Indonesian rice (largely variety determined) can make a price difference of over 100% (Tabor, 1989). Any price in the marketplace is conditional on the product attributes: quantity, geographic location, time (particularly in relation to the season), level of processing, variety, moisture level, cleanliness, quality factors (for rice: whiteness, per cent broken, red and yellow grains) and age, to name but an obvious few. Changing any of those attributes will change the market's valuation of the product.

The problem for margin analysis is that in moving from the producer to the consumer we are not merely changing the geographic attribute of the product but also most other attributes upon which the price is conditional. The marketplace is adding value to the product by transforming the original attributes. The product is likely to have been dried, cleaned, bagged, graded, inspected, processed, stored, packaged, transported and marketed between the producer and the consumer. This is all the more true for urban consumers. This means that the amount of cost data we need in order to derive *net* producer-consumer margins, especially for time series analysis, is indeed large. It is also notoriously difficult to collect.

So, as with seasonal analysis, the almost universal problem will be the lack of access to cost data. Only gross margins but not net margins, and hence, not profitability, can be derived. Neither the level, nor changes in the level, of gross margins have any necessary implications for net margins. A decrease in the gross margin may not reflect a decrease in profitability but perhaps a decrease in transport costs due to better rural roads or lower fuel prices. A valid question then arises; is it worth the effort to compute gross producer-consumer margins?

The answer is still yes. Assuming appropriate producer and consumer price series exist then the computational effort is very low. One can still look at margin trends, variability, seasonality, reversals, as well as regional margin differences. In our case, examining producer-consumer margins, particularly seasonality, trends and regional differences, aided our understanding of the working of the Indonesian rice market.

COMPLICATIONS

Before computing producer-consumer margins, we would like to know what the expectation is. What benchmark are our results to be measured against? Much of the work on margins is predicated on one or both of the following assumptions (see Goetz and Weber, 1986). Firstly, it is usually assumed that producer prices are functionally dependent on retail prices so that the margin

between the two is then the transfer costs. Demand for the product at the producer level is derived demand; derived from the demand for the product at the retail level. Secondly, it is usually assumed that margins are constant, perhaps in nominal or deflated terms per unit of product. Margins would then be a constant flat fee (in nominal or deflated terms). Field results are then tested against this expectation of constant margins and conclusions drawn.

There are a number of complications with this view. The first arises simply because some services' margins are best represented as a percentage of the producer price (e. g. milling, drying), whereas others are best represented as a flat fee (e.g. bagging, transport). (Here we are talking of a product that is sold to an agent who then dries and/or mills it. We are not talking of margins for custom drying or milling where the product is not sold. In drying and milling a percentage of the original weight of the product is lost (water) or worth a new value (bran, brewer's grain). Although the percentage lost does not change, the base value of the original product is continually changing so the monetary value of the weight loss changes. Hence the monetary value of the service within the marketing chain also changes. Consequently, the cost of these services is essentially a fixed percentage and not a fixed absolute amount of money.) With the former type of services, the fee directly varies with changes in the producer price. With the latter, the fee does not. Since there is underlying variability (e.g. seasonality) in the producer price series, we should expect some variability in the margins even when two markets are fully integrated. We can avoid part of this problem by eliminating one source of variability in the producer price series, namely inflation. We would then deflate the nominal producer and consumer price data by an appropriate deflator (e.g. Consumer Price Index) and deal with constant or real prices only.

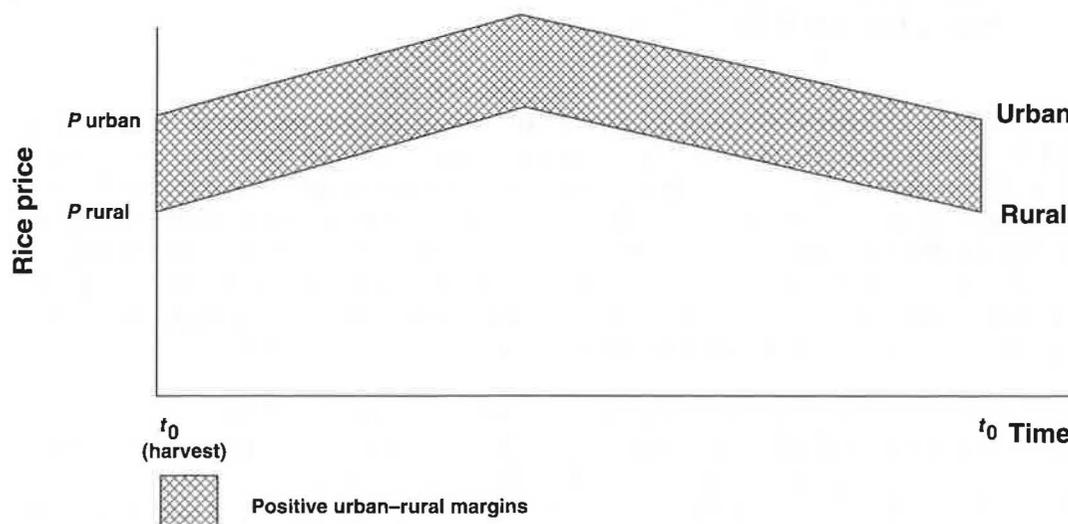


Figure 6 Constant Marketing Margins
Source Timmer (1974)

There are other reasons why margins may not be constant in a fully integrated market. The simplistic model for rural-urban margins, namely constant positive margins, is shown in Figure 6. However, as Timmer (1974) showed, the model assumes a rural to urban commodity flow. Take, for example, a case where a government parastatal intervenes only in the urban, and not the rural, sector (as in Indonesia) to prevent price rises above a certain level. We would no longer expect urban-rural margins to be constant. Additional supply is being added to the urban retail market and not to the rural market. Rural prices may continue their seasonal increase, urban prices may not and the margin narrows. Nor is it necessary to assume government parastatal intervention as the only possible reason. Private market imports could also be a cause for the increase in urban supply. World import prices (cost, insurance, freight (CIF)) would put a ceiling on urban prices. Both of

these situations can be represented by Figure 7. Urban prices are prevented from rising above either the parastatal's intervention price or the import parity price (P_{\max} urban in Figure 7) whereas no such restriction directly applies to the rural market. Consequently, only in the time periods $t_0 \rightarrow t_1$ and $t_2 \rightarrow t_0$, are the margins high enough to permit the markets to be connected. Producer prices then are not functionally dependent on retail prices. Averaging margins over the whole season ($t_0 \rightarrow t_0$) would underestimate the true level of margins.

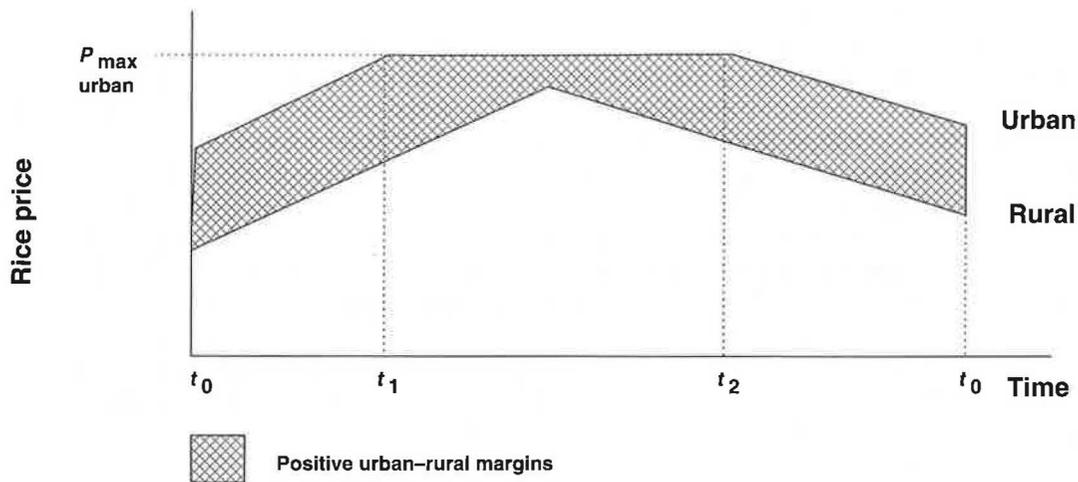


Figure 7 Non-constant Positive Margins
Source Timmer (1974)

Finally, if rural prices continue to rise above the urban price level, flows may reverse. This situation is depicted in Figure 8. Margins, of course, will reverse as well, reflecting the cost of transporting product from the urban to rural sector. The urban centre is supplying the rural sector in the later portion of the crop year. Essentially around the peak harvest period, say time period $t_0 \rightarrow t_1$ and time period $t_4 \rightarrow t_0$, the rural sector is supplying the urban centre. During time period $t_2 \rightarrow t_3$, the lean season, the urban sector is supplying the rural sector. In all the other time periods, the margins are insufficient for flows in either direction and the two markets are not physically connected. Averaging margins over a whole season could produce a zero or negative result.

Interestingly, Timmer (1974) found that Figure 7 often best represented the Indonesian rice market. However, his period of study coincided with one of large Indonesian rice imports. Accordingly, one might expect that result. On the other hand, our period of study was one essentially of self-sufficiency on trend. We would not, therefore, necessarily expect the same result.

However, there are other more general reasons why Figure 7 may still be the correct representation even when parastatals and imports are not the cause. Consider the case where there is not one homogeneous rural sector but several rural regions; the different harvest period of each region making each distinct. In such a case the seasonal price patterns in various rural regions would be different. The urban deficit sector might source supply from each rural region sequentially, according to the seasonal price lows in each. If we were to look at only one of the rural regions, rather than the rural sector collectively, Figure 7 might be the best representation. That particular rural region is only physically connected to the urban market around its own harvest period, $t_0 \rightarrow t_1$ and $t_2 \rightarrow t_0$. In the period $t_1 \rightarrow t_2$, the urban region is being supplied not by imports or a parastatal but another rural sector which is, at that time, in its own harvest period. One rural sector is displacing the other as the cheapest (CIF) supplier to the deficit urban sector.

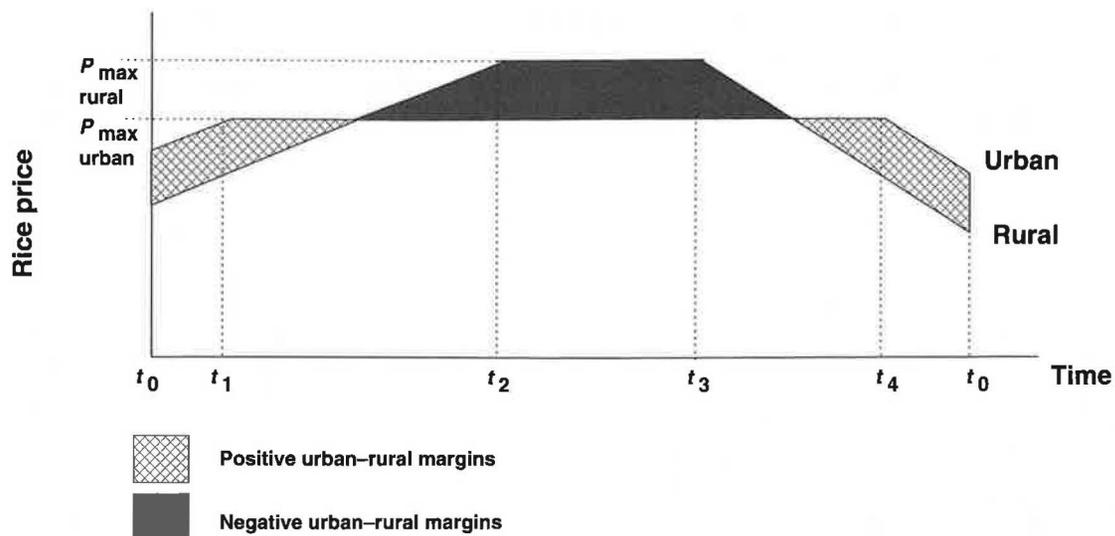


Figure 8 Negative Marketing Margins
Source Timmer (1974)

In Indonesia, the harvest period for surplus provinces is reasonably temporally synchronous but one important surplus province, South Sulawesi, has a different harvest period. The description in the previous paragraph could well then apply. There are two possible reasons for expecting Figure 7 to represent the Indonesian case; distinct rural regions and the operation of a parastatal, BULOG. If so, then we should not expect to see constant margins but rather seasonally varying margins.

The general point is that the expectation of a constant margin is predicated on the assumption of actual market connection, that there is a physical commodity flow, and on the uni-directional nature of that flow. Hence we should not expect markets that are only physically connected for, say, 2 months during peak harvest, to display constant producer-consumer margins over a full season. Functional dependence of producer prices on retail prices is not valid. Any seasonal averaging of margins would artificially underestimate true margin levels. Once again we see that time series analysis can only be an aid to understanding. To interpret the results will require considerable prior market knowledge.

METHOD AND APPLICATION TO INDONESIAN RICE PRICES

Figures 9a and b give the producer-consumer margins in milled rice terms for East Java, the major marketable surplus rice region in Indonesia and the source of some 60% of BULOG's floor price purchases. Figure 9a shows the trend in the margin, whereas Figure 9b shows the relative influence of producer and consumer prices on the margin. Their derivation is straightforward and is outlined below.

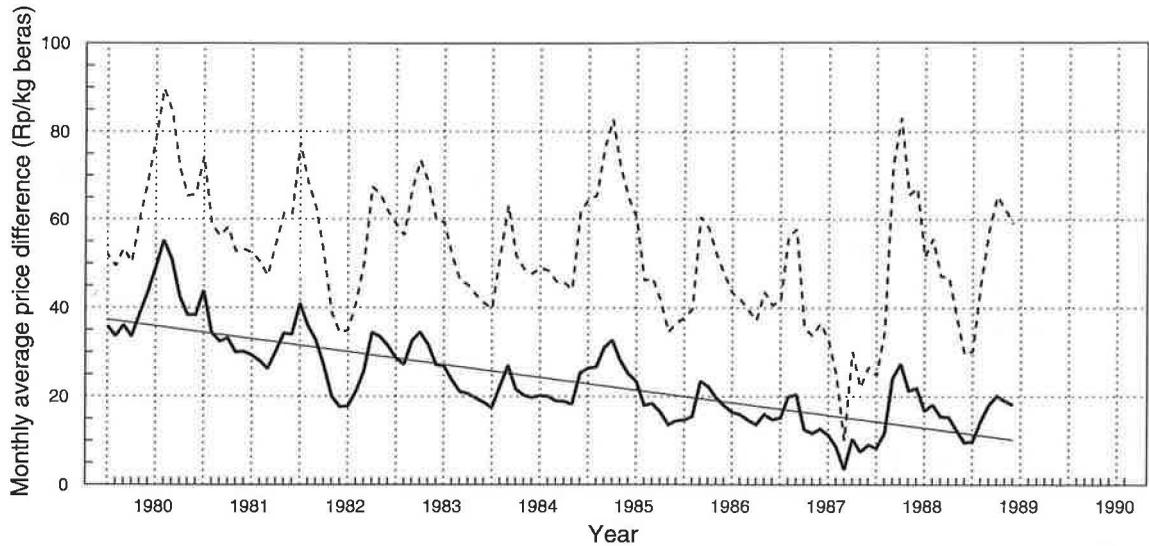


Figure 9(a) Producer-Urban Consumer Gross Margins, East Java
 Deflator: Indonesian CPI excluding rice, base = 1977
 Trend: $Y = 30.01 - 0.23 (X)$
 Grid lines are January and July
 - - - - - Nominal margins
 ——— Deflated margins
 ——— Deflated margin trend

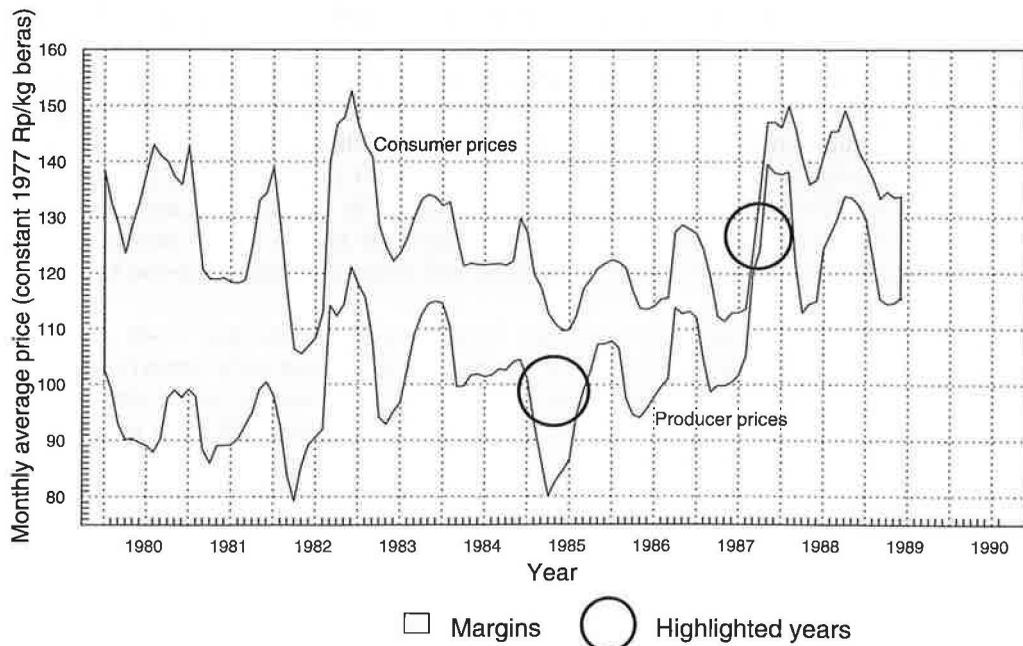


Figure 9(b) Real Producer-Consumer Margins, East Java
 Margins adjusted for milling by-product sales
 Constant 1977 Rp/kg beras

Given the discussion at the beginning of this Section concerning the conditional nature of all prices, we need to ensure that the producer and consumer series reflect a product with similar attributes and, to the extent that they do not, that this is adjusted for. The three major concerns are variety, moisture level and weight losses due to milling (by-products). The final concern is to remove inflation from the price series in order to concentrate on real margins and also in order to remove one source of margin variability.

Step One: Ensuring Compatibility

In this analysis we have used the IR II variety. It was the only series for which there were both producer and consumer prices for the whole period of study. That said, however, IR II is not a variety *per se* but a grade and class of varieties with similar attributes that change over the period of study. Accordingly, the quality of the data is not as high as one would have wanted.

The producer series needed no adjustment for moisture changes as it was referenced to dried paddy of a similar moisture content to that which is sold to consumers as milled rice. However, this is still likely to be a source of error because all prices, both in the milled rice series and paddy series, are unlikely to be the same moisture level or correctly adjusted for in this respect.

Step Two: Adjusting for Inflation

We also wanted to remove inflation from both producer and consumer prices as we wanted to look at real margins rather than nominal margins. Accordingly, both series were converted to constant Rupiah per kg by deflating each by a non-rice price Consumer Price Index (CPI) that was constructed. The standard CPI series was an inappropriate deflator because rice prices themselves were a major component of the CPI. However, with data on the relative weight of rice in the CPI, the index can be adjusted to exclude the rice component.

The first step is to produce a Rice Price Index (RPI) with the same base year as the CPI index, in this case 1976. This is done as follows.

$$\text{RPI}_{(1976=100)} = \frac{\text{Rice price}_t}{\text{Average rice price for 1976}} \times 100 \quad (12)$$

We now have an inflation index and an RPI with a common base year of 1976. To remove rice prices from the CPI we must multiply the RPI by its weight in the CPI calculation. Rice prices might be given a weight of 15% in the CPI calculation, so in the equation below we would use the 0.15 as the figure for 'Rice wt in CPI'. The non-rice CPI is produced in the following way

$$\text{Non-rice CPI}_{(1976=100)} = \frac{\text{CPI}_{(1976=100)} - (\text{Rice wt in CPI} \times \text{RPI}_{(1976=100)})}{1 - \text{Rice wt in CPI}} \quad (13)$$

where $\text{CPI}_{(1976=100)}$ is the Consumer Price Index, base year 1976 = 100, $\text{RPI}_{(1976=100)}$ the Rice Price Index, base year 1976 = 100, Non-Rice CPI the Consumer Price Index excluding rice, base year 1976 = 100, and Rice wt in CPI the weight given to rice prices in the CPI calculation.

Step Three: Adjusting for Weight Changes (By-products)

There are two ways to do this procedure; to convert milled rice into paddy equivalent prices, or to convert paddy into milled rice equivalent prices. We chose to do the latter because our target

audience thought in terms of milled rice rather than paddy. Goetz and Weber (1986) give an example for livestock where the former approach is adopted. Procedurally, one is the mirror image of the other.

When dried paddy is converted to milled rice the husk and bran are removed. There is a resulting weight loss. We used the official conversion rate of 0.65 (1 tonne of paddy = 0.65 tonnes of milled rice) for our calculations. This was less than ideal because this official rate has changed over the years and there has been a lively official debate as to what the actual conversion rate should be. Tabor (1989) reports survey data suggesting that millers achieve only an average conversion rate of 0.63. Without a doubt different millers achieve substantially different conversion levels which is a function of a wide variety of factors; the skill of the miller, millers' equipment, quality of the paddy, degree of whiteness desired in the milled rice, and so on. The conversion rate of 0.65 is really a simplifying assumption rather than a market reality. Consequently if the producer price series, in currency per kilogram of paddy, is divided by 0.65, it is then converted to a producer price series in currency units per kilogram of milled rice. This reflects the fact that 35%, on average, of the weight of paddy is lost in the conversion to milled rice. (This may not be obvious to readers. However, approach it like a miller buying dry paddy for milling and ask the question: 'If rice prices are \$200 per tonne of rice and 1 tonne of paddy makes 0.65 tonne of rice, what paddy price exactly compensates me for the loss of 0.35 tonnes of paddy in milling?' The answer is that

$$(1 \text{ tonne paddy}) \times (Y) = (0.65 \text{ tonne rice}) \times (\$200 \text{ per tonne of rice})$$

where Y is the equivalent paddy price. From this equation, $Y = \$130$ per tonne paddy. Or, as we have done in preceding sentences, the paddy price of \$130 per tonne paddy divided by 0.65 equals the rice price of \$200 per tonne rice.)

Now this new producer price series can be subtracted from the consumer price series because they are in the same units; currency per kilogram of milled rice. Initially, we used this result to represent producer–consumer margins, because we lacked any by-product revenue time series data. Implicitly we were then assuming that the by-products, the 35% by weight of paddy that is extracted in converting to milled rice, had zero value. Our measure of producer–consumer gross margin was an underestimate to the extent that the miller actually received additional revenue from by-product sales.

Step Four: Adjusting for By-Product Sales

This calculation of the producer–consumer margin resulted in negative gross margins at the time of peak harvest in several years. That is, it suggested that producer prices were higher than consumer prices (when corrected for weight losses in milling). Although from the discussion of Figure 8 this result is possible, it was not expected. It suggests that by-product sales were an important revenue source for millers. We then needed to adjust the margins for by-product revenue. Tabor (1989) reported survey data on bran and brewer's grains yields and prices. This was cross-sectional data rather than time series data. The results are then a snapshot of by-product revenue at one particular point in time. These revenue data, corrected for inflation, were added to the margin series.

This procedure was obviously less than ideal. Because of the lack of time series data we were forced to assume that these by-product yields and prices did not vary year to year or vary seasonally. Although their inclusion increases the accuracy of our estimate of margin levels and leaves margin trends unchanged, it biases downward the estimate of seasonal variability. This is simply the arithmetic effect of adding a constant to a seasonally varying margin; variability is decreased.

Step Five: Analysis of Margin Seasonality, Trend, Reversals and Variability

One can see very distinct trends and seasonality in the Indonesian results shown in Figures 9a and b. It is worthwhile to try to capture this information in a more systematic way. The simplest way is to treat the producer–consumer margin series as any other price series and undertake the analysis described in Section 2. Spreadsheet templates will most likely have been made already to handle the seasonality of other price series (retail, producer, wholesale). Consequently, approaching the issue this way is made easier. Secondly, it allows statistical tests to be done on the existence of the seasonality, its trend and standard errors.

Figure 10 shows the seasonal index and average real margins for East Java. One could easily include, as we did in Figure 4, the ± 1 s.e. bands for the GSI (East Java Margins) and the trend coefficients for any statistically significant trends. The margins can easily be tested for reversals by searching for negative margin levels. After we adjusted for by-product revenue we did not find any.

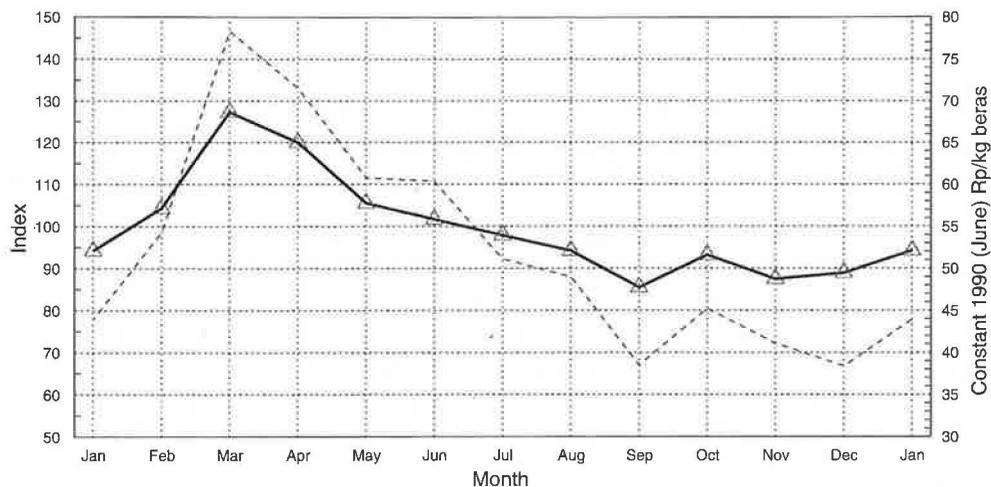


Figure 10 Gross Real Margin Seasonality, East Java
 —▲— GSI
 - - - - Gross margins

There is also the issue of comparing margins between regions. Figure 11 shows the gross real producer–urban consumer margins for the three major Javanese provinces.

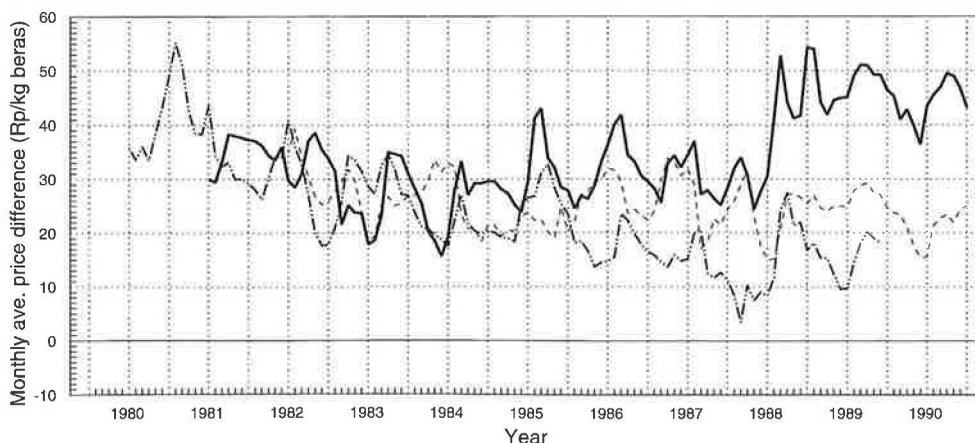


Figure 11 Gross Real Producer–Urban Consumer Margins, Indonesia.
 Deflator: Indonesian CPI excluding rice
 Price differences are in real terms
 Grid lines are January and July
 — West Java
 - - - - Central Java
 - . - . - East Java

DISCUSSION OF THE INDONESIAN RESULTS

Figure 9a and b depict a general declining trend in real margins for East Java from 1979–87, perhaps even to unsustainably low levels. This decline in real margins was due to both increasing real producer prices and declining real consumer prices. Two years are highlighted as they are anomalous ones. 1985 was a year in which BULOG had great difficulty in defending the floor price to producers. Its warehouses were largely full as a result of surplus harvests in the previous two years. In fact BULOG raised its quality standards at the time in order to reduce its purchase obligations. One can see the dramatic effect on margins, as a result of the sharp drop in real producer prices.

BULOG had difficulty in defending the ceiling price in 1987. Following the large carry-over of stocks in the 1984–85 crop year, there had been successive years of deficit (relative to consumption) harvests. By the main harvest of 1987, BULOG's stocks had been run down to a level where it was uncertain, especially given production estimates, of having enough rice to supply civil servants. It raised the floor price several times, relaxed buying standards and actually targeted intake procurement levels. It was acting in a price-destabilizing manner because it targeted volumes not prices. One can see the dramatic effect on both prices. The effect on real producer prices was particularly marked and as a result margins were reduced to very low (and unsustainable) levels. Following this, real prices have declined and margins have widened out to more historic levels.

The importance of Figure 10 can be seen when it is compared to the GSI for retail rice prices in East Java, Figure 4. There the GSI low was approximately 95 and the high 106, for a seasonal increase of 11% in 6 months. Here the low is approximately 86 and the high 127, for a seasonal increase of 48%. The seasonality is much more marked for the margins than for the retail prices. The highest margins also occur at the main harvest when farmers sell the largest percentage of their marketable surplus. This suggests that simple annual averages will grossly underestimate the margin levels farmers actually faced.

The simplistic assumption of constant margins is not borne out (Figure 6). Neither is the possibility of negative margins (Figure 8). No margin reversals (urban prices above rural prices) were found for any month. The results lend support to the margin model represented by Figure 7.

Figure 7 shows that West Java producer–urban consumer margins have not followed the trend in the other provinces. Since 1984, West Java margins have been increasing in real terms. Although the evidence is not presented here, this increase is not found in the West Java producer–*rural* consumer margins, suggesting that the costs (transport, marketing) or profitability of supplying Jakarta have increased.

Rural margins (not shown here) show convergence to a similar level over the period of study. This supports the view of a competitive market. However, the decline in margins is particularly marked for the major surplus province of East Java. Possibly the Indonesian market became more integrated over the period of study, allowing the East Java seasonal rice surplus to be absorbed with less pressure on margins.

Section 4

Vertical Integration

INTRODUCTION

Vertical integration of the market is a concept closely linked to margins. As a preliminary definition we state vertical integration to be the extent to which, within one geographic area, a price change in one product market is reflected in a price change in a vertically different market for the same product. Usually with producer-consumer margins we are dealing really with the combined effects of both vertical integration and spatial integration. Spatial integration is defined here as the extent to which, within one vertical market level, a price change in one product market is reflected in a price change in a geographically different market for the same product. Spatial integration we take up in detail in the next chapter but much of the discussion and methodology used in this section has application to that topic.

The importance of vertical integration can readily be seen in the Indonesian case. BULOG, as a price-stabilization body, intervenes to defend producer prices at a publicly announced level known as the floor price. The floor price, like any other, is a conditional one. In this case the conditions are that it is paddy (unmilled rice) of any variety or age, with minimum levels of cleanliness and quality and a maximum level of moisture. However, the floor price is merely BULOG's local producer price target. BULOG does not directly defend producer prices but instead intervenes in the local wholesale milled rice market in order to influence producer prices. BULOG's motivation in acting indirectly rather than directly is largely to minimize storage problems. It is easier with milled rice than with paddy to determine and control quality at procurement.

If the market is vertically well integrated, intervention in the wholesale milled rice market will have the desired effect on prices in the producer paddy market. However, if the markets are not well integrated, BULOG's actions in the wholesale milled rice market may be an inefficient, or even an ineffectual, means of achieving its producer price target. Considerably more milled rice may have to be bought than paddy to achieve the same affect on producer prices.

The two markets, producer paddy and wholesale milled rice, are connected by a series of value added services (drying, cleaning, transport, milling and so on). A total disruption in the supply of any of the services would sever the connection between the two markets, allowing prices in the two markets to diverge. For example, sun drying is employed to dry paddy before being milled. If continual rain prevents sun drying then it is not possible to convert a farmer's wet paddy into milled rice. The two markets would be independent of each other. The supply of sun drying is at that moment perfectly inelastic; a change in price elicits no supply response. The two markets would not be vertically integrated.

However, we do not need to restrict ourselves to the extreme case of perfect price inelasticity. Simply a relaxation of the common simplifying assumption of perfect price elasticity of supply of value added services is sufficient to reduce the level of vertical integration. There are reasons why the price of value added services is not constant and then why two markets will not be fully integrated. This will be true, particularly at peak harvest; the time when BULOG is defending the floor price. In Indonesia, between 60% and 70% of the rice is harvested in the March-June period. Obviously there is seasonally varying demand for services that convert wet paddy into milled rice; particularly drying and transport. That seasonality in the supply and demand balance implies seasonality in the price of the value added service, the margin and hence the level of integration.

What is happening is that the supply and demand balance for one of the value added services (drying, cleaning, milling, transporting), which physically connects the two markets, has changed. There is a resultant change in the implicit price for these services and hence a change in the producer-wholesaler margin. The margin is the implicit price for the value added services. Because of the concentration of the rice harvest in Indonesia, we should not expect to observe either fixed paddy-milled rice margins within one geographic location or full vertical integration.

METHODOLOGY (COINTEGRATION)

We want a methodology to assess the extent to which two markets are vertically integrated. Goetz and Weber (1986) suggest regressing the wholesale/retail price on the producer prices using the ordinary least squares method. A hypothesis test would be done on the slope coefficient, β , to determine if it is statistically different from 1. If actual nominal prices are used, then the test is for a constant flat fee mark up equal to α , the intercept term. The regression equation would be

$$RP_t = \alpha + \beta(PP_t) + \varepsilon_t \quad (14)$$

where RP_t is the retail price, at time t , PP_t the producer price, at time t , ε_t the error term, at time t , β the slope coefficient, and α the intercept term.

There are, however, major problems with such a test for vertical integration. It is worth going into some detail on two of the problems, because discussion of these problems leads to a better measure of vertical integration, namely cointegration. Also the problems here are ones common to other more complex approaches we will come across when discussing spatial integration in the next section.

Simultaneity

The first problem is that the equation violates ordinary least squares (OLS) assumptions. In reality, not only is RP a function of PP , but PP is a function of RP , i.e.

$$RP_t = \alpha + \beta(PP_t) + \varepsilon_t \quad (15)$$

but also

$$PP_t = \lambda + \mu(RP_t) + \gamma_t \quad (16)$$

As Timmer (1974) explained in a related context:

The problem is simultaneity. Price formation involves both supply (stalk paddy in the rural areas) and demand (for milled rice in the urban (and rural) retail markets. It is not strictly correct, then, to regard one price, e.g. the urban retail price, as functionally dependent on the other price, the rural stalk paddy price.

If, for example, the error term, ε_t , in Equation 14, increases, then RP_t automatically increases. However, because of Equation 15, an increase in RP_t means an increase in PP_t . That, in turn, means that ε_t and PP_t are correlated; an increase in ε_t increases PP_t (via Equation). In the regression of Equation 14, OLS will incorrectly attribute both effects on RP_t (by ε_t and PP_t) to PP_t . We have violated the OLS assumption that the independent variable, (PP_t), is uncorrelated with the error term, ε_t . This means that the OLS estimates will be biased (even asymptotically) and that OLS may not be the preferred technique. One then could use a different regression technique: often a two-stage least squares, which overcomes this problem. This is, of course, more complicated.

Integration and Cointegration

The second problem is that for series with trends one should test the individual series for 'integration' (used here in an econometric sense referring to stationarity of the series) and between the series for 'cointegration' (used here in an econometric sense) before modelling relationships between the series. These techniques establish whether there is, in fact, some relationship between the two series. Only if the two series are in some sense bounded does it make sense to model the relationship between the two. Acceptance of 'cointegration', in fact, itself determines the form a model should take which tests for the nature of the relationship between the two series. That form is specifically an error correction model. Those who have not come in contact with these

econometric terms before will find this paragraph confusing. However, it is important to try to come to grips with these concepts.

The 'integration' test concerns the stationarity of any time series. Stationarity means that the stochastic properties of a time series, Y_t (i.e. the mean, the variance of the mean and the covariance of the mean with values of Y_t), are stationary and do not vary with time. Most economic time series are not stationary because, for example, the mean of the series changes with time, if only because of inflation. Time series are made stationary usually by differencing the time series. This is where the term 'integration' comes from. Say, in forecasting Y , one must 'integrate' over the various forecast 'differenced' series (ΔY_t s) to obtain a forecast value for Y_t . The similarity to the nomenclature of calculus one supposes is intentional.

The first difference of a series, Y_t , would be the series, $Y_t - Y_{t-1}$, or ΔY_t . That is, from each value in the original series the previous value is subtracted from it. This produces a new series, ΔY_t . The second difference would be the differences of the first differences, $\Delta Y_t - \Delta Y_{t-1}$, which is the same as $(Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$. Here we have taken the new series, ΔY_t , and from each of its values subtracted the previous value. That series is then labelled $\Delta^2 Y_t$.

A series is integrated of order 0 if no differencing is needed to make it stationary. A series is integrated of order 1 if only one difference is needed to make it stationary. It is integrated of order 2 if two differences are needed to make it stationary. Usually an economic series will be made stationary within two differences.

Cointegration of order 1,1 tests whether there is some linear combination of two series, both of which are integrated of order 1, which is also integrated of order 1. If a linear combination of the two series is integrated of order 1, then the error term in the linear combination will be integrated of order 0. To understand the importance of the concept let us look at an example: the linear combination of RP_t and PP_t . First one needs to test whether each series is integrated of order 1. For convenience we will assume they both are integrated of order 1. The linear combination of the two series is

$$RP_t = \alpha + \beta(PP_t) + \varepsilon_t \quad (17)$$

The test for cointegration of order 1,1 is, in fact, a test of whether the series, ε_t , is integrated of order 0. Integration of order 0 means the series, ε_t , is stationary without the need for differencing. Why should that be important? Only if the ε_t series is stationary will it make sense to talk of some linear relationship between the two series, RP_t and PP_t . If the ε_t series is integrated of order 1 then the mean of the series ε_t is not constant and some trend exists in the series. If a positive trend exists in the error term, ε_t , then the two series are drifting further and further apart. It would make no sense to talk of some linear relationship between the two in that case.

If the two series are found to be cointegrated of order 1,1 then necessarily they are causally related. We should perhaps be more explicit about what is meant by causality, because we are not using it in its everyday sense. Proving a statistical relationship does not prove causality. In fact there is no test for causality in the everyday sense. We are using here 'Granger-causality', which is what econometricians mean by causality. One variable 'Granger-causes' a second variable if prediction of the *current* value of the second variable is improved by knowledge of the *past* values of the first.

Cointegration, Inflation and Causality

The existence of a causal relationship between, say, RP_t and PP_t , does not, however, preclude the existence of other causal relationships, perhaps between RP_t and an inflation series, or between PP_t and an inflation series. With integration we are interested in a causal relationship due to market forces eliminating profits above transfer costs, not integration due to inflation. Accordingly, each of the two series, RP_t and PP_t , can each be tested against an inflation index series for cointegration of order 1,1. If cointegration of either of the price series with the inflation index series does not exist, then we can conclude that inflation is not producing the causal relationship.

We are arguably a long way away from our starting point; problems with a simple OLS regression of retail prices, RP, on producer prices, PP, as means of testing for vertical integration. It is worth trying to summarize what we have been saying. First, a simple regression equation fails to recognize the simultaneity between RP and PP. Second, it is incorrect to regress RP on PP without first testing each series for integration and testing for cointegration between the series. Yet by doing so we have already gone a long way to answering the question that the simple regression was intended to address; are the two series causally related? To that extent the simple regression is not only incorrect but largely unnecessary.

Causality: Strength and Direction

We would also like some idea about the strength of the causality not just its existence. This is where the cointegration technique shows much promise. It can be extended not only to address the strength of (Granger-)causality but also the direction of the (Granger-)causality. This is very useful.

If two series are cointegrated of order 1,1 the Granger Representation Theorem suggests the two can be represented by a specific error correction mechanism (specifically, 'there exists a bivariate vector autoregressive representation of the first differences of the variables, with each equation augmented by one lag of the cointegrating residual', Taylor and Tonks, 1989). Error correction refers to the fact that markets usually are not in equilibrium and that some of the disequilibrium ('error') in one period is 'corrected' for in the next period. Mathematically it would take the following form

$$\Delta RP_t = \alpha_1 + \alpha_2(RP_{t-1}) + \alpha_3(PP_{t-1}) + \alpha_4(\Delta RP_{t-1}) + \alpha_5(\Delta PP_{t-1}) + \varepsilon_t \quad (18)$$

$$\Delta PP_t = \beta_1 + \beta_2(PP_{t-1}) + \beta_3(RP_{t-1}) + \beta_4(\Delta PP_{t-1}) + \beta_5(\Delta RP_{t-1}) + \gamma_t \quad (19)$$

where RP_t is the retail price, at time t , PP_t the producer price, at time t , ΔRP_{t-1} the change in retail price between time $t-2$ and $t-1$, ΔPP_{t-1} the change in producer price between time $t-2$ and $t-1$, ΔRP_t the change in retail price between time $t-1$ and t , ΔPP_t the change in producer price between time $t-1$ and t , α various regression coefficients, β various regression coefficients, and ε_t , γ_t are error terms.

Equation 18 states that the change in retail price (ΔRP_t) is a function of the previous level of the retail price (RP_{t-1}), the previous level of the producer price (PP_{t-1}), the previous change in the retail price (ΔRP_{t-1}), the previous change in the producer price (ΔPP_{t-1}), and a stochastic error term (ε_t). The equation is autoregressive because the change in retail price (ΔRP_t) is regressed on the past value of itself (ΔRP_{t-1}). (We have simplified the equation for clarity here by including only the one time lag for this autoregressive term when in practice several lags are included.) The equation has an error correction mechanism because of the disequilibrium term RP_{t-1} . In equilibrium prices are constant, so inclusion of RP_{t-1} accounts for the fact that markets are not in equilibrium and prices are not constant.

Because of the cointegration, (Granger-)causality must exist in at least one direction and possibly in both. We defined Granger-causality as 'one variable 'Granger-causes' a second variable if prediction of the *current* value of the second is improved by knowledge of the *past* values of the first'. This makes the problem tractable. The direction of causality can be determined by assessing the significance of the terms, lagged PP and ΔPP , in Equation 18 and the terms, lagged RP and ΔRP , in Equation 19. Here we are simply interested in whether the inclusion of these terms in the respective equations significantly improves the explanatory power of the equations. If they do then we can state that Granger-causality exists.

If, for say Equation 18, the coefficients of the lagged PP and ΔPP terms' are (jointly) significantly different from 0, then it indicates that they increase the equation's explanatory power. That would indicate that Producer Prices are (Granger-)causing changes in the Retail Prices. This flows

automatically from the definition of Granger-causality. In each case the null hypothesis is that the terms do not jointly improve the explanatory power of the equation (therefore in the equations above $H_0: \alpha_3=\alpha_5=0$, or $H_0: \beta_3=\beta_5=0$). The alternative hypothesis is that they do. To test whether PP are (Granger-)causing changes in RP we would use Equation 18. We would run one regression with all the terms included (the complete model), that is Equation 18. We would also run another regression without the PP terms (the reduced model). That equation would be: $\Delta RP_t = \alpha_1 + \alpha_2 (RP_{t-1}) + \alpha_4(\Delta RP_{t-1}) + \varepsilon_t$

An F test is used to compare the two equations. The test statistic is

$$F(\Delta P, df) = \frac{(SSE_{\text{reduced}} - SSE_{\text{complete}}) \div \Delta P}{SSE_{\text{complete}} \div df} \quad (20)$$

where SSE_{complete} is the error sum of squares, complete model, SSE_{reduced} the error sum of squares, reduced model, ΔP the change in the number of parameters, complete versus reduced model, df the degrees of freedom, complete model ($= N - (\text{number of parameters} + 1)$) and N is the sample size.

The test for direction of causality is then whether the lagged terms, PP and ΔPP , significantly help in explaining changes in RP. The strength of that causality can be inferred from the significance levels with which the null hypothesis is rejected. Namely, the higher the confidence level with which the null hypothesis is rejected, the stronger is the causality.

Cointegration requires more econometric understanding than other techniques at which we have looked, but is not a difficult technique to apply. It can address successfully the question of integration, vertical or spatial. It can determine the existence of (Granger-)causality. Additionally, it has the potential to address issues of the causal strength and direction. Cointegration is a recent econometric method that has been applied successfully to integration questions in financial studies (Hakkio and Rush, 1989; Taylor and Tonks, 1989). For those interested in looking at just one of the references on applying the technique, Taylor and Tonks (1989) is the shortest, simplest and clearest; for those wishing to understand the econometric justification for the technique, the papers by Granger (1969,1981) and Engle and Granger (1987) are the more readable. More recently, Alexander and Wyeth (1991) have applied it to the question of spatial integration in the Indonesian rice market. We will look at their results in the next section on spatial integration.

APPLICATION OF THE METHODOLOGY TO INDONESIAN RICE PRICES

We apply the methodology to East Java producer prices (dry paddy) and to East Java urban retail prices (milled rice). In all cases the natural logarithm (\ln) of the price is used not the price itself in the calculations. In econometrics the term 'log' is usually used to represent natural logarithms (base e) not common logarithms (base 10). This can be confusing as other disciplines, engineering for example, invariably use 'log' to refer to common logarithms and 'ln' to refer to natural logarithms. A natural logarithm (\ln) of a number, a , is the exponent or power, n , to which the base, e , must be raised in order to equal, a . Mathematically a natural log (\ln) can be described as follows: if $a = e^n$, then, $\log_e a = n$, where $e = 2.71828$. Transforming both the dependent and independent variables by using \ln allows non-linear relationships still to be handled by ordinary least squares. The standard example is the Cobb–Douglas production function

$$Y = AK^{\alpha}L^{\beta}\epsilon \quad (21)$$

where Y is the output, K the capital, L the labour, ϵ a disturbance term, and α, β are coefficients. In this form the equation is not linear and cannot be estimated by ordinary least squares (OLS). However, if we transform both sides of this equation by \ln then the result is a linear equation that can be estimated by OLS

$$\ln Y = \ln A + \alpha(\ln K) + \beta(\ln L) + \ln \epsilon \quad (22)$$

In our case whether the actual prices or the \ln of prices should be used here depends on whether one believes that PP is equal to RP minus a constant mark-up or whether RP is constant proportion of PP. We have chosen the latter and therefore used \ln of prices. Other work on integration (Heytens, 1986; Wyeth, 1991) used \ln of prices but did not find significant differences if actual prices were used. The interpretation of the coefficients will vary depending on which approach one adopts. The coefficient for a term like ΔPP , where $\ln PP$ is used instead of PP, will represent the *percentage* change in PP.

Step One: Testing for (Econometric) Integration of Order 0

Here we take each series separately (producer prices, retail prices and non-rice CPI series) and test for the order of integration. The regression equation is

$$\Delta Y_t = \alpha_0 + \alpha_1(Y_{t-1}) + \alpha_2(\Delta Y_{t-1}) + \alpha_3(\Delta Y_{t-2}) + \alpha_4(\Delta Y_{t-3}) + \epsilon_t \quad (23)$$

where $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ and α_4 are coefficients, ϵ_t is an error term, Y_t the value in the series Y , time t , $\Delta Y_t = Y_t - Y_{t-1}$, and $\Delta Y_{t-1} = Y_{t-1} - Y_{t-2}$. The null hypothesis is that the series Y_t is integrated of order 1; namely that the series must be differenced once before stationarity is achieved. The alternative hypothesis is that the series is integrated of order 0; namely that no differencing of the series is needed to produce stationarity. The test for integration is the Augmented Dickey–Fuller Test (Dickey and Fuller, 1979). The 'Augmented' refers to the fact that the regression equation includes, or is 'augmented by' the ΔY_{t-n} terms. These are added in order to ensure there is no autocorrelated error. Essentially, enough lagged ΔY_{t-n} terms are included to avoid autocorrelated error. We have included three as a worst case scenario. One or two lags may be enough. First-order autocorrelation occurs when the disturbance term in one period, ϵ_t , is a proportion of the disturbance in the previous period, ϵ_{t-1} . One disturbance term is correlated with the other, hence the term autocorrelation. (Higher order autocorrelation refers to correlation of ϵ_t with $\epsilon_{t-2}, \epsilon_{t-3}$, and so on. With monthly data the twelfth order correlation is one to watch for.) Autocorrelation violates the OLS assumption that error terms are spherical, have a common variance (homoskedastic) and are independent (not correlated with each other). The almost universal test for *first order* autocorrelation in statistical packages is the Durbin–Watson statistic, d . However, it is biased towards accepting the null hypothesis in cases where there is a lagged value of the dependent variable as an independent variable (as above in Equation 23). The general Lagrange Multiplier (LM) test is an alternative in this situation for any order correlation and the Ljung–Box or Box–Pierce Q test is an alternative for higher order correlation. Both estimators have chi squared distributions (see Kennedy, 1985).

In the regression of Equation 23, it is the t statistic of the coefficient α_1 in which we are interested. The critical values, however, are not those from a t distribution, as would normally be the case for a t statistic. Rather, critical values specifically calculated for the Augmented Dickey–Fuller Test are used. These are given in Table 2.

Table 2 Critical Values for Augmented Dickey–Fuller Test

Sample size	Confidence level		
	1%	5%	10%
50	-3.58	-2.93	-2.60
100	-3.51	-2.89	-2.58
250	-3.46	-2.88	-2.57
500	-3.44	-2.87	-2.57
∞	-3.43	-2.86	-2.57

Source: Engle and Yoo (1987) p. 157.

If the t statistic for the coefficient α_1 is greater (a larger negative number) than the critical values given in Table 2, the null hypothesis can be rejected. The alternative hypothesis of the series being integrated of order 0 is accepted. As we will see later, with all our series, the t values were below the critical values and the null could not be rejected. This is the likely case as few economic time series will have a constant mean and be integrated of order 0. If the null is not rejected one must go on to test whether the series is of higher order of integration than just 1, possibly of order 2.

Step Two: Testing for (Econometric) Integration of Order 1

Here we run a similar regression to Equation 5 but all terms differenced once

$$\Delta^2 Y_t = \beta_0 + \beta_1(\Delta Y_{t-1}) + \beta_2(\Delta^2 Y_{t-1}) + \beta_3(\Delta^2 Y_{t-2}) + \beta_4(\Delta^2 Y_{t-3}) + \gamma_t \quad (24)$$

where $\beta_0, \beta_1, \beta_2, \beta_3$ and β_4 are coefficients, γ_t is an error term, $\Delta Y_{t-1} = Y_{t-1} - Y_{t-2}$, $\Delta^2 Y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = \Delta Y_t - \Delta Y_{t-1}$, and $\Delta^2 Y_{t-1} = (Y_{t-1} - Y_{t-2}) - (Y_{t-2} - Y_{t-3}) = \Delta Y_{t-1} - \Delta Y_{t-2}$.

The null hypothesis is now that the series, Y_t , is integrated of order 2; namely that the series needs to be differenced twice to be made stationary. The alternative hypothesis is that the series is of order 1. The procedure is the same. Enough lagged ΔY_{t-n} terms are included to avoid autocorrelation. The t statistic of the coefficient of the ΔY_{t-1} term, β_1 , is compared to the critical values in Table 2. Only if the values are greater (a larger negative number) can the null hypothesis be rejected and the alternative hypothesis of integration of order 1 be accepted. As we will see, all our series were integrated of order 1.

Step Three: Testing for Cointegration of Order 1,1

Once we have established that two series are integrated of order 1 we can test whether they are cointegrated of order 1,1. To do that here we use the Engle–Granger Two-Step Procedure (Engle and Granger, 1987). The first step is to regress one series on the other and save the residuals from that regression. This is a very simple regression and is used only for this procedure (no other use should be made of the coefficients)

$$Y_t = \alpha_0 + \alpha_1(X_t) + \varepsilon_t \quad (25)$$

where Y_t = series one, X_t = series two, and ε_t = residuals.

The second step is to test the residuals themselves for integration of order 0. We treat the residuals just like any other series. The testing procedure is exactly the same as we did in Step One; the same regression equation and hypotheses. Essentially we are testing for stationarity of the error terms.

The null hypothesis is that the residuals are integrated of order 1. The alternative hypothesis is that the residuals are integrated of order 0. If the two series (Y_t and X_t) are each integrated of order 1 and are related, then the error terms (ε_t) must be stationary and integrated of order 0. If they are not, then the two series “will tend to drift apart without bound” (Taylor and Tonks, 1989). In that case there is no long-run linear relationship between the two series. If we reject the null hypothesis, we can accept cointegration of order 1,1.

If we find that our two price series, say producer and retail prices, are cointegrated we still need to know if this is a result of inflation. In Steps One and Two we also tested the inflation series for integration. If we had found the inflation series to be integrated of order 0, inflation could not be the cause of the cointegration between producer and retail prices. If, however, the inflation series is integrated of order 1, then the cointegration could be a result of inflation. Accordingly, we then need to test for cointegration between the producer prices series and the inflation series and for cointegration between the retail price series and the inflation series. This is done using the Engle–Granger Two-Step Procedure outlined above.

Discussion of the Indonesian Integration and Cointegration Results

Table 3 shows the integration results for East Java producer prices, urban retail prices and non-rice CPI series. For all three series the null hypothesis in Step One, namely that the series is integrated of order 1, cannot be rejected. The regression estimates of the t statistics for the coefficients, α_1 , are all below the critical Augmented Dickey–Fuller (ADF) values. For all three series the null hypothesis in Step Two, namely that the series is integrated of order 2, is rejected at the 99% confidence level. All the values are well above the critical ADF value of 1%. The same critical ADF values are used in both steps.

Table 3 Integration Results, East Java

	Step One	Step Two	Critical ADF value	
			1%	5%
Producer prices	-1.47	-5.72	-3.51	-2.89
Retail prices	-1.45	-6.01	-3.51	-2.89
Non-rice CPI	-1.66	-5.97	-3.51	-2.89

Notes:

Step One: $H_0: I(1)$ versus $H_1: I(0)$, Regression equation: $\Delta Y_t = \alpha_0 + \alpha_1(Y_{t-1}) + \alpha_2(\Delta Y_{t-1}) + \alpha_3(\Delta Y_{t-2}) + \alpha_4(\Delta Y_{t-3}) + \varepsilon_t$

Step Two: $H_0: I(2)$ versus $H_1: I(1)$, Regression equation: $\Delta^2 Y_t = \beta_0 + \beta_1(\Delta Y_{t-1}) + \beta_2(\Delta^2 Y_{t-1}) + \beta_3(\Delta^2 Y_{t-2}) + \beta_4(\Delta^3 Y_{t-3}) + \gamma_t$.

Table 4 gives the cointegration results. Because the inflation series (non-rice CPI) was integrated of order 1, not order 0, it cannot be ignored in the cointegration analysis. The results show that all the series are cointegrated. Consequently, we can conclude there is (Granger-)causality in at least one direction between producer and urban retail prices in East Java. However, because the inflation series is also cointegrated with them, it is possible that the relationship we established is not direct but an indirect one via an inflationary process. Secondly, we do not yet know the direction of that causality or its strength. We need to test all these when looking at causality.

Table 4 Cointegration Results, East Java

Variable		α_1	Critical ADF value	
Y	X	<i>t</i> statistic	1%	5%
Producer price	Retail price	-4.28	-3.51	-2.89
Producer price	Non-rice CPI	-5.14	-3.51	-2.89
Retail price	Non-rice CPI	-4.19	-3.51	-2.89

Notes:

H_0 : $I(1)$ versus H_1 : $I(0)$; H_0 : non-cointegration, Regression equation: $Y_t = \alpha_0 + \alpha_1(X_t) + \varepsilon_t$

Step Four: Testing for Causal Direction and Strength

The acceptance of cointegration between two series ensures causality in at least one direction. Earlier (p.26) we discussed, (i) the meaning of Granger-causality, (ii) the standard F test that can be applied to test causal direction, and (iii) the Granger Representation Theorem which dictates that the two cointegrated variables will have an error correction representation of the following form

$$\Delta RP_t = \alpha_1 + \alpha_2(RP_{t-1}) + \alpha_3(PP_{t-1}) + \sum_{i=1}^n \chi_i(\Delta RP_{t-i}) + \sum_{i=1}^n \delta_i(\Delta PP_{t-i}) + \varepsilon_t \quad (26)$$

$$\Delta PP_t = \beta_1 + \beta_2(PP_{t-1}) + \beta_3(RP_{t-1}) + \sum_{i=1}^n \varphi_i(\Delta PP_{t-i}) + \sum_{i=1}^n \lambda_i(\Delta RP_{t-i}) + \gamma_t \quad (27)$$

where RP_t is the retail price at time t , PP_t the producer price at time t , ΔRP_{t-i} the change in retail price between time $t-i-1$ and $t-i$, ΔPP_{t-i} the change in producer price between time $t-i-1$ and $t-i$, ΔRP_t the change in retail price between time $t-1$ and t , ΔPP_t the change in retail price between time $t-1$ and t , $\alpha, \beta, \chi, \delta, \varphi, \lambda$ are various regression coefficients, and ε_t, γ_t are error terms.

To test for causality in the direction of producer prices (Granger-) causing retail prices (PP→RP) we need to do an F test on the complete model, Equation 26, versus the reduced model of the same equation where $\alpha_3 = \sum \delta_i = 0$. The reduced model then only has RP terms left in it, because the coefficients of the PP terms are assumed to be zero.

However, to test for causality in the opposite direction, retail prices (Granger-) causing producer prices (RP→PP), we need to do an F test on the complete model, Equation 27, versus the reduced model of the same equation where $\beta_3 = \sum \lambda_i = 0$. In this case the restricted model has only PP terms left in it. Some econometric software packages have this Granger-causality test as an automated procedure.

Discussion of the Indonesian Causality Results

The number of lags (n in Equations 26 and 27) is determined by the need to avoid autocorrelated errors. In the Indonesian work, three time lags were used ($n = 3$). These F tests need to be repeated for each set of series in which we are interested. In our case this is six, because we have three variables (producer prices, retail prices and non-rice CPI) and want to understand the causality between any of them. Table 5 gives a matrix of the results of F tests for causality. The causing variables are across the top (the 'From' variables) and the caused variables are listed vertically (the 'To' variables).

Table 5 Granger-causality Results, East Java

To	From			F critical values		
	Producer prices	Retail prices	Non-rice CPI	0.1%	1%	5%
Producer prices		0.49 (0.74)	4.31 (0.003)	5.02	3.51	2.46
Retail prices	4.24 (0.003)		3.22 (0.015)	5.02	3.51	2.46
Non-rice CPI	6.19 (0.0002)	0.94 (0.45)		5.02	3.51	2.46

Notes:

The matrix is $F_{(4,101)}$ -statistics for joint significance of the coefficients of lagged levels and changes in the 'From' variables in an OLS regression of the form of Equation 26 with $n=3$ and change in the 'To' variable as the dependent variable.

H_0 : coefficients of the lagged levels and changes in the 'From' variables jointly equal zero.

Figures in parentheses are the marginal significance.

Approximate $F_{(4,101)}$ critical values: 0.1% = 5.02, 1% = 3.51, 2.5% = 2.92, 5% = 2.46.

If we look at the vertical columns in Table 5 we can see the direction and strength of the (Granger-) causality. Producer prices (Granger-) cause both retail price (99% confidence level) and non-rice CPI changes (99.9% confidence level). Retail prices do not (Granger-) cause either of the other two variables. The non-rice CPI (Granger-) causes both producer prices (99% confidence level) and retail prices (97.5% confidence level). The results then suggest that: (i) inflation is important in the link between producer and retail prices, (ii) producer prices (Granger-) cause changes in retail prices, but (iii) retail prices do not (Granger-) cause changes in producer prices.

This latter finding is interesting because, as we noted on p.16, the usual assumption is that producer prices are functionally derived from retail prices. That suggests that causality should be unidirectional; retail prices cause changes in producer prices but not vice versa. Our results indicate the opposite; producer prices cause changes in retail prices but not vice versa.

CONCLUSIONS

What has the technique been able to conclude about vertical integration in East Java? It has established that producer prices and retail prices are causally related and the direction of causality is from producer prices to retail prices. However, it has suggested that inflation is important in the causal link of producer and retail prices; but just how important? Alexander and Wyeth (1991) state

If it is found that each price series is cointegrated with a retail price index (calculated in such a way as to exclude prices from the market being investigated), and if it is found that causality runs from this price index to both market prices, the apparent market integration is merely an artifact of inflation, which is driving both prices.

The suggestion is that if the causality exists from the inflation index to both of the market price series, then market integration does not exist, and this is the situation we face. The conclusion then is that the East Java producer and retail rice markets are not integrated. The apparent vertical integration is spurious and due to inflation.

This is an odd result and one wonders whether the statement made by Alexander and Wyeth (1991) is not overly categoric. Does the existence of causality from the inflation series to the two market price series perhaps imply the importance of inflation as *one* causal factor rather than denying the possibility of any other causal factors?

Within the technique there is no means to assess whether the vertical integration may be 'spurious' for another reason; parastatal intervention. BULOG intervenes in both producer and retail markets so the vertical integration could be indirectly a result of their actions and not private market forces connecting the two.

As with other techniques, it is not clear if this technique can handle at all well cases where two markets are physically linked only sporadically or where vertical margins reverse (Figures 7 and 8).

Cointegration is not the only technique available to test for integration. A simpler, and more common, technique is the use of bivariate correlation coefficients. With that technique, inflation can directly be eliminated from the price series before the technique is applied, and we can avoid this whole issue of the strength of inflation in the market integration found.

If one is to adopt the more complex technique, in this case cointegration, there needs to be an information reward; increased insight, firmer conclusions, increased sensitivity or some such. Our results suggest that the reward is insufficient in this particular instance. However, correlation coefficients are certainly not without their own problems and we turn to those now in Section 5 when discussing spatial integration.

Section 5

Spatial Market Integration

INTRODUCTION

One may be concerned with spatial market integration for several reasons. Ravallion's (1986) concern was with the question of how long a localized scarcity can be expected to persist?. Wyeth (1991) suggests lack of spatial integration as an indicator of general vulnerability to famine. However, it is often used as an indicator of market efficiency. In the Indonesian context, spatial integration is particularly important. BULOG operates a vast, and expensive, network of countrywide storage facilities in order to defend producer prices. If the Indonesian (producer) rice market was spatially integrated, then BULOG would be able to influence producer prices countrywide by operating in a small number of individual (producer) rice markets. Measures of spatial integration might not only suggest the general possibility of this organizational streamlining but also which locations one could dispense with.

Spatial integration is preliminarily defined here as the extent to which, within one vertical market level, a price change in one product market is reflected in a price change in a geographically different market for the same product. As we will see, this definition is insufficient. The economic process we are concerned with is the ability of the market to eliminate spatial price differences in excess of transfer costs.

The existence of spatial integration is not a sufficient condition for Pareto optimality. Pareto optimality is the economic condition where no-one's utility can be increased without decreasing the utility of someone else. It is often used as the welfare benchmark. Takayama and Judge (1971) pointed out that, generally, a spatial competitive equilibrium will be Pareto optimal. However, Newberry and Stiglitz (1984) pointed out that the existence of Pareto optimality rests not only on the competitiveness of markets but also crucially on the existence of a complete set of competitive markets, including those for risk (futures, crop insurance, securities markets). Particularly in developing countries, these do not exist. So although spatial integration may have importance it cannot be used by itself to claim Pareto optimality.

In this Section we will discuss four different methodological approaches to measuring spatial integration: correlation coefficients, the Ravallion model, a variant of that model, the Index of Market Connection proposed by Timmer (1986) and finally, cointegration which we looked at in Section 4.

METHODOLOGIES

Correlation Coefficients

In an integrated market, prices in different geographic locations will move together. It is understandable then that the bivariate correlation coefficient, a statistical measure of association, is the most usual methodological approach to spatial integration. The mathematical definition of the correlation coefficient, r , is

$$r = \frac{\sum(X_t - \bar{X})(Y_t - \bar{Y})}{\sum^{1/2}(X_t - \bar{X})^2 \cdot \sum^{1/2}(Y_t - \bar{Y})^2} \quad (28)$$

where X_t is the price observation for location X , $X_t - \bar{X}$ the deviation of actual observation from the average for location X , Y_t the price observation for location Y , and $Y_t - \bar{Y}$ the deviation of actual observation from the average for location Y .

The correlation coefficient is a scale-free measure of association ranging from -1 for perfectly negatively correlated variables, to +1 for perfectly positively correlated ones. Zero is the expected result for statistically independent variables. The percentage of price variation of market X associated with the other market Y is the square of the correlation coefficient, namely R^2 . Intuitively, it perhaps is not obvious why the correlation coefficient is a good measure of correlation. In view of the attacks that have been made on correlation coefficients as measures of spatial integration, it is worth understanding, r better.

The numerator in Equation 28 is, on its own, a good measure of correlation. When the prices in *both* locations X and Y are at the same time much higher than their respective averages, the numerator will be a large positive number. If they are *both* much smaller than their respective averages, the numerator will be a large positive number as well. So if the two price series are positively correlated, the numerator will be large. The problem with using just the numerator as a correlation measure is that the scale of prices in X and Y may not be the same. Prices in location X may be twice those in location Y. In that case the numerator is not giving equal weight to the two locations' deviations: the higher valued price series is given more weight. Secondly, because the numerator is scale-dependent, we would have a trouble comparing our results for locations X and Y with another set for A and B. The denominator in Equation 28 above merely serves the purpose of correcting for these problems of scale to produce a value that always ranges between -1 and +1. (I am indebted to Wonnacott and Wonnacott (1985) for this intuitive explanation.)

Figure 12 may help to make this clearer. This is a scatter diagram of the retail rice prices for two Indonesian locations, Jakarta and Ujung Pandang. Each black dot represents one month's observation. The average values for X (Ujung Pandang), 133.6, and for Y (Jakarta), 139.8, are depicted as a grid which separates the graph into four quadrants. The grid allows us to measure quickly any observation's distance from the average value of X and Y. The observations are concentrated in the upper right and lower left quadrant. Observations in the upper right quadrant show that positive deviations from the average value of X are associated with positive deviations of Y. Observations in the lower left quadrant show that negative deviations from the average value of X are associated with negative of Y. If any two series are positively correlated, the values should be in these two quadrants. If any two series are negatively correlated, the values should be in the upper left and lower right quadrants. If two series are not correlated, but independent, the values should be randomly scattered through the four quadrants.

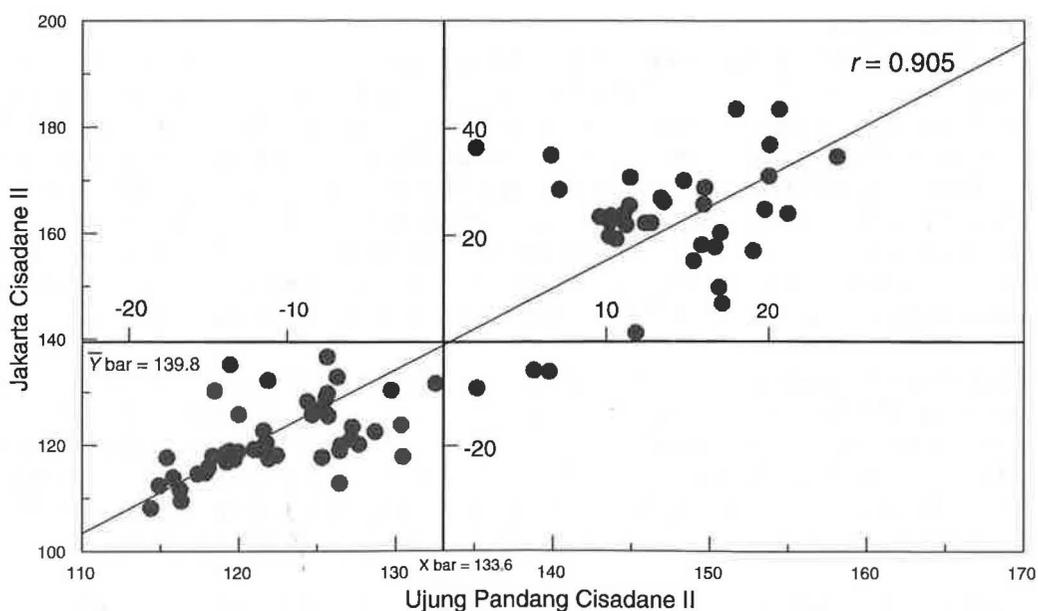


Figure 12 Scatter Plot of Values; Deflated and Deseasonalized Cisadane Prices, Jakarta-Ujung Pandang

The use of correlation coefficients for measuring spatial integration has been vigorously attacked. The articles by Harriss (1979) and Blyn (1973) are good examples. Some of the concerns raised are not specific to this technique but are more general, particularly data problems. However, there are two major problems we want to address here; false positives and negatives, and sensitivity to trends.

False negatives and false positives

This first problem is one we have encountered in a different guise already with margins; what is the expected result? It is not clear what level of r we should expect to find in the real world situation:

even if markets are well integrated, correlation coefficients may not be high because these markets are not simply supply centres but also centres of importance for local consumption. In this circumstance it is possible for equilibrium price to be anywhere between a low which just makes it worthwhile to export grain from the local centre and a high which just makes it worthwhile to import grain from other markets. Unless markets have consistently large supply relative to demand, making them exporters, or the opposite, making them importers, price series correlation coefficients will be lower than otherwise, despite the integration which occurs at prices outside the export–import range. (Blyn, 1973)

We have here a situation where correlation coefficients would give a false negative and suggest integration does not exist when it does. Blyn's comment is similar to the case put forward by Timmer (1974) concerning margins and discussed previously in Section 3. Unless the two markets are physically connected, testing for integration would appear problematic.

However, correlation coefficients are more likely to give false positives and indicate integration exists when it does not. Two markets may be physically disconnected and show high correlation coefficients because they trade through a common third market. On the other hand, the operation of a parastatal agent maintaining a pan-territorial price or merely defending a narrow price band (narrow spread between floor and ceiling price) could give rise to high correlation coefficients without one wanting to say spatial integration exists.

Sensitivity to trends

The second major problem with correlation coefficients is that they are sensitive to underlying trends in the price series themselves. If the trend and seasonal components of two price series are strong and similar, then high correlation coefficients will be a result of these influences rather than short-term integrating market forces. If one refers back to the formula for the correlation coefficient, it is easy to see that inflation and seasonality can produce 'spurious' false positive results. Both series, X and Y , will be increasing over time due to inflation. So for both series, any observation of X and Y in the latter half of the period of study will be above the respective X and Y mean. Similarly, for observations in the first half of the study period, they will be below their respective means. Consequently, the deviations of both X and Y will tend to have both the same sign and relative size.

Do these problems preclude the use of correlation coefficients? The answer I would suggest is, not necessarily. The second point, sensitivity to trends, can largely be countered as Blyn (1973) suggested: "time-series correlations should be restricted to residuals remaining after the trend and seasonal components have been removed". In that sense this attack on correlation coefficients is more an attack on indiscriminate application than the technique itself. If one has already done the seasonal analysis in Section 2, Blyn's points can all the more easily be taken on board.

The first point, false negatives and positives, is less easily handled. However, it would seem to be a more extreme example of a general problem that exists with seasonal analysis, margin analysis and vertical integration. For example, seasonal analysis is susceptible to false positives because it cannot isolate the effect of a parastatal on net storage margins. In margin analysis we do not know if zero net margins are a result of competition eliminating prices above costs or a result of flow

reversals. In fact, as Heytens (1986) pointed out, this discussion is as much one about the definition of integration (which sadly is rarely defined) as it is about correlation coefficients as a measure of it. Correlation coefficients, in a sense, do not produce 'spurious' integration results. Rather, people have artificially restricted the definition of integration such that correlation coefficients are no longer a good measure. It is, in fact, unclear whether the definition of integration should allow for the possibility of two physically disconnected markets still being labelled integrated (via a third market).

There is a trade-off with correlation coefficients; they are easy to compute but it is felt that they provide less market insight than other techniques which we will discuss next. At the end of the day, there is still a desire for "a model that can pick up the more subtle spatial differentials and not be overwhelmed by common trends" (Heytens, 1986). With that point we move on to the discussion of the Ravallion model.

Ravallion Model

This discussion of the Ravallion model ties closely with the previous discussion of cointegration in Section 4. The model developed by Ravallion (1986) is very similar to the type the Granger Representation Theorem would prescribe. Those who have not read the section on cointegration are advised to do so before proceeding with this discussion.

Ravallion assumed a radial market structure such that there was a single reference market which dominated trade and price formation. Mathematically this assumption is

$$R = f(P_1, P_2, P_3, \dots, P_n, X_r) \quad (29)$$

$$P_i = f_i(R, X_i) \quad (30)$$

where R is the reference market price, P_i a local market price in the i th local market, X_r other factors affecting the reference market price, X_i other factors affecting local market prices, and $i = 1 \dots n$ are the various local markets.

Nested Hypothesis Testing

The reference market price is then a function of the various local market prices and a vector of other factors. Any local price is a function of the reference market price and a vector of other local factors (e.g. seasonality, drought). In converting this function to an equation, three things are done. First, it is assumed that a linear equation is the correct specification. Second, the equation is made dynamic (with lagged price change terms) to take account of expectations formation and adjustment costs. Finally, the equation is made in a general form so that hypotheses involving a more restricted model form can be tested. The restrictions can then be nested within the general model form. This hypothesis testing using the F test would be the same as we used in Section 4 (p.25) discussing cointegration. For ease of comprehension, the equations below are (artificially) restricted to only one local market and one time lag

$$R_t = \alpha R_{t-1} + \beta_0 P_t + \beta_1 P_{t-1} + \chi X R_t + \gamma_t \quad (31)$$

$$P_t = a P_{t-1} + b_0 R_t + b_1 R_{t-1} + c X_t + \epsilon_t \quad (32)$$

where R_t is the reference market price at time t , P_t the local market price at time t , $X R_t$ other factors affecting the reference market at time t , X_t other factors affecting the local market at time t , and ϵ_t, γ_t are disturbance terms.

Market segmentation Ravallion suggested testing various hypotheses: market segmentation, short-run integration and long-run integration. Heytens (1986) suggested also testing for the absence of local factors affecting local prices. If the two markets are segmented, the reference market does not influence local prices. For Equation 32 this implies that the coefficients $b_0 = b_1 = 0$. The general model would then reduce to

$$P_t = aP_{t-1} + cX_t + \varphi_t \quad (33)$$

This restricted model (Equation 33) can be tested against the general model form (Equation 32) using an F test. This test determines whether the extra terms in the general model increase the explanatory power of the model. (This F test procedure was outlined in Section 4, p.26 when discussing the methodology of cointegration.)

Short-run integration The other hypotheses can be tested in a similar manner. Short-run integration was taken by Ravallion to mean that a change in the reference market price will be fully passed on to local prices within one time period. In Equation 32 this implies that the coefficient $b_0 = 1$. It further implies that the coefficients $a = b_1 = 0$. This ensures that there will be no lagged effects on future prices offsetting the full change in central prices being passed on. (If we had included further time lagged variables for R and P beyond just $t-1$, those coefficients would also need to equal 0.) This restricted model is then

$$P_t = R_t + cX_t + \mu_t \quad (34)$$

Again this restricted model (Equation 34) can be tested against the general model (Equation 32) using a F test.

Absence of local factors The absence of local factors implies that, in Equation 32, the coefficient $c = 0$. The restricted model would then take the form

$$P_t = aP_{t-1} + b_1R_t + b_1R_{t-1} + \lambda_t \quad (35)$$

As before, this restricted model (Equation 35) can be tested against the general model (Equation 32) using the F test.

Long-run integration Long-run integration implies there is a long-run equilibrium such that prices are constant with no stochastic effects. For Equation 32 this means that all values of R and P are constant (denoted by $*$) and that the error term $\epsilon_t = 0$. The general model then reduces to

$$P^* = aP^* + (b_0 + b_1)R^* + cX_t \quad (36)$$

However, this means that $a + b_0 + b_1 = 1$. This then is the parameter restriction of long-run integration on the general model.

Problems of multicollinearity

There are likely to be problems of multicollinearity in any of the equations above. Multicollinearity exists when there is a linear relationship between the independent variables themselves. The independent variables are then highly correlated. OLS uses the variation unique to each variable to compute the coefficient estimate for that variable. If there is no correlation between the independent variables then all the variations can be attributed to specific variables uniquely. Accordingly, OLS has much information upon which to estimate the variable coefficients. However, when there is high correlation between the independent variables, most of the variation is common between variables and not unique to individual variables, so OLS has very little information upon which to estimate coefficients. This is reflected in the higher variance of the coefficient estimates (higher standard error). OLS is not invalidated but merely inefficient. More seriously, the inefficiency leads to misspecification errors (including wrong variables, excluding correct variables) because OLS cannot determine the specific impact of one variable as opposed to another as so much is common.

Ravallion (1986) recognized this and suggested using the change in local prices (ΔP_t) rather than the level of local prices (P_t) as the dependent variable in Equation 32. If long-run integration is accepted, the following equation is the equivalent form to Equation 32

$$\Delta P_t = (a-1)(P_{t-1} - R_{t-1}) + b_0(\Delta R_t) + (a + b_0 + b_1 - 1)(R_{t-1}) + cX_t + \varepsilon_t \quad (37)$$

Problems of simultaneity

In Equation 32, R_t is unlikely to be an exogenous variable. P_t is a function of R_t (Equation 32) but R_t is a function of P_t (Equation 31). There is a problem of simultaneity. This problem was explained in more detail in the previous section. In this case OLS is a biased (even asymptotically) and inconsistent technique. There are a number of options open to potential users. First, it can be argued that OLS is still acceptable because other techniques, although consistent, are also biased (Kennedy, 1985). Heytens continued with OLS in the Ravallion model even though he recognized the simultaneity problem: "Simultaneous equation bias will always exist in theory, necessitating instrumental variables or faith that it is not 'too large' (Heytens, 1986).

Second, one can follow Ravallion's own example. He employed two-stage least squares (2SLS). Wyeth (1991) argues that this then makes the Ravallion model altogether too complex, arguing in favour of adopting cointegration as an alternative technique. Indeed most readers are likely not to have used 2SLS. However it is easy to overestimate the *relative* complexity, as cointegration is not a particularly simple technique either. Ravallion (1986) himself states "simultaneity in the system can be dealt with easily". 2SLS is often the preferred choice in dealing with simultaneity, largely because it is easy.

Wyeth (1991) suggests several other options. Third, one can use the Ravallion technique only when the reference price is exogenous rather than endogenous. As he recognized, this is unlikely to be possible in most cases.

Fourth, one can alter Equation 37, excluding the endogenous term ΔR_t which is causing the simultaneity problem, giving rise to the following equation

$$\Delta P_t = \alpha(P_{t-1} - R_{t-1}) + \beta(R_{t-1}) + \chi X_t + \varepsilon_t \quad (38)$$

The problem with this approach is that by dropping the ΔR_t term we lose the major benefit that the Ravallion technique offers; the ability to assess short-run integration. Only if this term is in the equation can we determine whether a current change in the central market price is transmitted to the local market.

Problems of complexity

The equations given above are artificially simple, employing only one local market and only one time lag. Ravallion's analysis used up to 17 markets and 6 time lags. If one also includes the complication of having to use 2SLS, the Ravallion model is a reasonably complex procedure.

As Hendry (1980) states "whether or not 'econometric escalation' is justifiable will depend on whether it facilitates clearer findings or camouflages tenuous evidence". Of particular interest is the Ravallion model's ability to delineate short-run integration from long-run integration. Long-run integration may be a result of general economic trends and inflation. It is long-run integration that correlation coefficients are capturing. Short-run integration, it is hoped, is capturing the effects of actual product flows eliminating prices above transfer costs, and it is this that we are really interested in. Timmer (1986) suggests focusing on what we call here short-run integration (and he calls connection) rather than long-run integration. The increased complexity of the Ravallion model then does have an information dividend, short-run integration. Whether that dividend is high enough will depend critically on the econometric skill of the practitioner.

Applicability

We noted that underlying the Ravallion model is the assumption of a radial market model; a single central market dominating trade and price formation. If there is a large degree of local to local trade we can no longer state that $P_1 = f(R, X_1)$. A more appropriate specification would be something along the lines $P_1 = f(R, \Sigma P, X_1)$. Also, if there are multiple central markets, the model is also inappropriate. In situations where knowledge of the marketplace is limited, it may be difficult to know if this assumption is valid. Unexpected results may indicate the true situation or may be due to the fact that the assumption is not applicable. Have we proved that the market is integrated or have we proved that the radial market model is inappropriate? This makes interpretation difficult. No matter what, because the Ravallion model requires a considerable commitment of skill and time, users should be sure at the outset that the assumptions fit their situation. (Faminow and Benson (1990) have been able to extend the Ravallion model beyond just a radial market structure.)

There is also a potential data problem. Usually monthly data are used, largely because they are all that are available. However, market forces may respond to price changes in well under 1 month. Then, with monthly data, there is little captured; the price response to, say, a current month reference price change has occurred within the current month period. We then need more sensitive data to capture these more sensitive short-run market forces; namely weekly data. These may not be available. The model, particularly for testing short-run integration, may have poor applicability to monthly data.

Testing for integration and cointegration

As mentioned in Section 4 any trending series should be tested for integration and cointegration before suggesting a model form. This was not done in the Ravallion model. If cointegration of the two series does not exist, the two series are not bounded and suggesting a linear relationship between them does not make sense. This can easily be made an argument in favour of using cointegration itself as a measure of spatial integration. It is similar to the argument presented for vertical integration. If integration and cointegration must be tested for in any event, it is simpler to continue with that technique than start anew with the Ravallion model. In the cointegration approach, only two steps would remain if cointegration was found: (i) testing the prices series with an inflation series for cointegration, and (ii) testing for the direction and strength of causality. However, the cointegration approach cannot, by itself, address this question of short-run integration.

Timmer's Index of Market Connection (IMC)

Timmer (1986) employed a simplified version of the Ravallion technique to address the question of spatial integration in the corn market in Indonesia. The equation he used was the one we discussed above that avoids the multicollinearity problem:

$$\Delta P_t = (a-1)(P_{t-1} - R_{t-1}) + b_1(\Delta R_t) + (a + b_0 + b_1 - 1)(R_{t-1}) + cX_t + \varepsilon_t \quad (37)$$

or, in Timmer's simpler notation where the intercept term (d_0) is explicitly included

$$\Delta P_t = d_0 + d_1(P_{t-1} - R_{t-1}) + d_2(\Delta R_t) + d_3(R_{t-1}) + d_4X_t + \varepsilon_t \quad (39a)$$

After the regression and the coefficients are estimated, the equation is rearranged to the following (by simply adding P_{t-1} to both sides of the equation)

$$P_t = d_0 + (1 + d_1)(P_{t-1}) + d_2(\Delta R_t) + (d_3 - d_1)(R_{t-1}) + d_4 X_t + \varepsilon_t \quad (39b)$$

If we make the assumption that the central market is in long-run equilibrium then prices are not changing, so that $\Delta R_t = 0$. If we further assume that local factors have no influence, then $d_4 = 0$ as well. All that remains is the restricted model which has two terms, lagged local price and lagged reference price

$$P_t = d_0 + (1 + d_1)(P_{t-1}) + (d_3 - d_1)(R_{t-1}) \quad (39c)$$

Consequently $(1 + d_1)$ and $(d_3 - d_1)$ are "the relative contributions of local and reference market price history to the formation of the current local price level" (Heytens, 1986, p. 30). Timmer suggested using the ratio of these two contributions, dubbed the Index of Market Connection (IMC), as an indicator of short-run integration

$$\text{IMC} = \frac{1 + d_1}{d_3 - d_1} = \frac{\text{Lagged local market coefficient}}{\text{Lagged reference market coefficient}} \quad (40)$$

If the lagged reference market coefficient is strong, then the IMC will be low. If the lagged local market coefficient is strong, then the IMC will be high. For short-run integration, the reference market coefficient should dominate. Timmer suggested, as a guide-line, that an IMC of less than 1 indicates short-run integration, or connection in his terminology.

The Ravallion model, as we have seen, does allow for a nested hypothesis test of short-run integration, so it is not immediately clear what benefit this IMC confers. However, the definition of short-run integration which Ravallion used is quite restrictive; namely that changes in the reference price are *fully* communicated to the local market within *one* time period. One could conceivably conduct an alternative nested hypothesis test with a less restrictive short-run integration definition; e.g. by eliminating the restriction of 'within one time period'. However, it can only give a yes or no answer, no matter what the definition of short-run integration. It cannot then be a measure of the *degree* of short-run integration. This is what the IMC purports to do: measure the degree of short-run integration. It is thus more sensitive.

Problems with the IMC

There are severe problems with the IMC as a measure of short-run integration. First, Timmer chose one of Ravallion's equations, Equation 37, that does not correct for simultaneity. We must be quite clear on this. Ravallion (1986) corrected for simultaneity by using 2SLS with Equations 31 and 32. Heytens (1986), on the other hand, noted the simultaneity problem but chose to use the same equation as Timmer (1986), Equation 37, that does not make any correction for it. Presumably he had "faith that it is not 'too large'" (Heytens, 1986) and that OLS was the preferred regression technique. Timmer (1987) did not even note the simultaneity problem. For those, like Wyeth (1991) and Alexander and Wyeth (1991), who do not accept the use of OLS in these instances, Equation 37 simply cannot be used.

Second, because Timmer's work is just an extension of the Ravallion model, it is open to the criticisms of the Ravallion model: lack of testing for integration and cointegration, applicability of a radial market model and so on.

Third, for the IMC to measure what it purports to, Timmer needed to make two implicit assumptions. One, is that the long-run integration of the markets is accepted. Timmer did not test for it but merely assumed it. Second, is that local factors are absent. To be fair, as we have seen, it is possible within the Ravallion model to test these two assumptions. That is, one can test for the validity of these assumptions and only apply the IMC when the assumptions are true. However, this means that the Ravallion nested hypotheses tests will need to be done as well. We then lose a large part of the attractiveness of the IMC: its inherent simplicity and universal applicability.

APPLICATION AND DISCUSSION OF THE METHODOLOGIES TO INDONESIAN RICE PRICES

Correlation Coefficients

The analysis was carried out in stages. First, nominal prices were used and correlation coefficients determined for all locations and varieties. Second, all the nominal price series were then seasonally adjusted and correlation coefficients recomputed. The seasonal component of the series had already been computed following the analysis laid out in Section 2. Accordingly this step was reasonably simple. Thirdly, all the nominal price series were deflated and correlation coefficients computed. Finally, the nominal series were both seasonally adjusted and deflated and the correlation coefficients computed once again.

Table 6 Correlation Coefficients for Seasonally Adjusted, Deflated Medium Prices, Indonesia

	Jakarta	Medan	Bandung	Semarang	Yogyakarta	Surabaya	Pontianak	Ujung Pandang	Jayapura
Jakarta	1	0.86	0.89	0.84	0.56	0.86	0.79	0.86	0.61
Medan		1	0.89	0.78	0.56	0.81	0.77	0.80	0.59
Bandung			1	0.90	0.64	0.86	0.82	0.80	0.56
Semarang				1	0.66	0.88	0.81	0.85	0.33
Yogyakarta					1	0.60	0.60	0.61	0.52
Surabaya						1	0.82	0.88	0.55
Pontianak							1	0.77	0.50
Ujung Pandang								1	0.47
Jayapura									1

Table 6 shows the correlation coefficients for the final stage; seasonally adjusted and deflated Medium Prices. The numbers in bold indicate coefficients greater than 0.8, indicating strong correlation, whereas italic entries indicate coefficients less than 0.8 but greater than 0.6, indicating moderate correlation. This delineation into strong, moderate and weak follows other studies, for example, Jones (1974). See also Appendix 2 for a discussion of hypothesis testing of correlation coefficients). It is nonetheless arbitrary. Generally, the Javanese locations (the first five locations along the top, excluding Medan) show strong correlation amongst themselves. The intra-Java correlations (excluding Yogyakarta) all range between 0.84 and 0.90. It is doubtful that the technique is sensitive or accurate enough to make any statements about the small correlation differences for Java locations. Yogyakarta, however, is anomalous which possibly is a result of manipulation of the rice variety chosen for the Medium Price series. We will return to this point.

Off-Java locations (the last three on the top row) generally show strong correlation with Javanese locations (except Yogyakarta), but moderate or poor correlation with themselves. Jayapura is an exception as expected. It was expected to show low correlation with all locations because it is geographically isolated with high import costs, chronically in rice deficit and largely supplied by BULOG. It receives the highest per capita supply of BULOG rice of any Indonesian province (Wyeth, 1991).

Table 7 Effects on Trends on Jakarta Correlation Coefficients (Medium Price)

	Nominal	Seasonally	Deflated seas. adjusted	
	prices	adjusted	Prices	+ Deflated
Medan	0.98	0.98	0.86	0.86
Bandung	0.98	0.98	0.89	0.89
Semarang	0.98	0.99	0.80	0.84
Yogyakarta			0.59	0.56
Surabaya	0.98	0.98	0.87	0.86
Pontianak	0.98	0.98	0.79	0.79
Ujung Pandang	0.99	0.99	0.86	0.86
Jayapura	0.94	0.95	0.57	0.61

Note: Strong correlation (>0.8) in bold, moderate (0.6 – 0.8) in italic.

Table 7 shows the progressive effect on the correlation coefficients as the series were adjusted for seasonality and inflation. Adjusting for inflation has a marked impact as expected. However, seasonally adjusting has virtually no effect. This may appear counter-intuitive because there are different seasonal patterns in Indonesia. However, the insensitivity of correlation coefficients to seasonal adjusting may itself be an indicator of spatial integration. If all the markets are well integrated then the price effect of, say, a different seasonal pattern in one location, is diminished because the other markets help absorb the impact. Harvest surpluses, lean season deficits and their respective local price changes are now spread over the other markets inducing synchronous changes in prices. Correlation is then high. However, if the markets are not integrated, the effect of local seasonality must be absorbed by local market prices alone. We then have an asynchronous price change: local market prices declining at harvest say, with no corresponding change in prices in other markets. Correlation will be lower.

Table 8 Jakarta Correlation Coefficients (Seasonally Adjusted and Deflated)

	Medium price	IR	Cisadane
Bandung	0.89	0.90	–
Semarang	0.84	0.91	0.95
Yogyakarta	0.56	0.92	0.96
Surabaya	0.86	0.91	–
Ujung Pandang	0.86	0.90	0.91

Note: Strong correlation (>0.8) in bold.

Table 8 shows the effect of variety on the correlation coefficients for some selected locations. The Medium Price series is not consistent with respect to varieties between locations or over time. We would then expect it to be a poorer measure than would individual rice varieties. This is borne out, because using specific varieties increases the correlation coefficients relative to using the Medium Price. The effect is very dramatic for Yogyakarta and indicates that the Medium Price series is not a good guide to rice price behaviour.

Some work was also done on the trend and seasonality of the correlation coefficients. Figure 13 presents some examples of the seasonal nature of the correlation between Surabaya in East Java and other Java locations. Interestingly, the weakest correlation is at the end of the lean season and the start of the main harvest. This is expected, at least to some degree, because the seasonal drop in price is very sharp and correlation is easily influenced by local timing of the start of harvest. Accordingly, if one region harvests a month earlier than another its prices will start to decline sharply while prices in other regions are still increasing. This will lead to lower correlation than if harvests were completely synchronous. During peak harvest, correlation is much higher and increasing. Peak harvest nationally is March–April and the effect on retail prices might be expected to lag by about a month.

Figure 13 may also give us some insight into whether BULOG is a major cause of the high correlation coefficients. One would expect BULOG's effect on the coefficients to be largest when it is the most interventionist; namely at harvest when it is purchasing and at the end of the lean season when it is reselling. However, the period of highest correlation is not at either of those times but when BULOG is least interventionist; after the main harvest and up until after the second harvest.

No significant trends were found in the correlation coefficients over time.

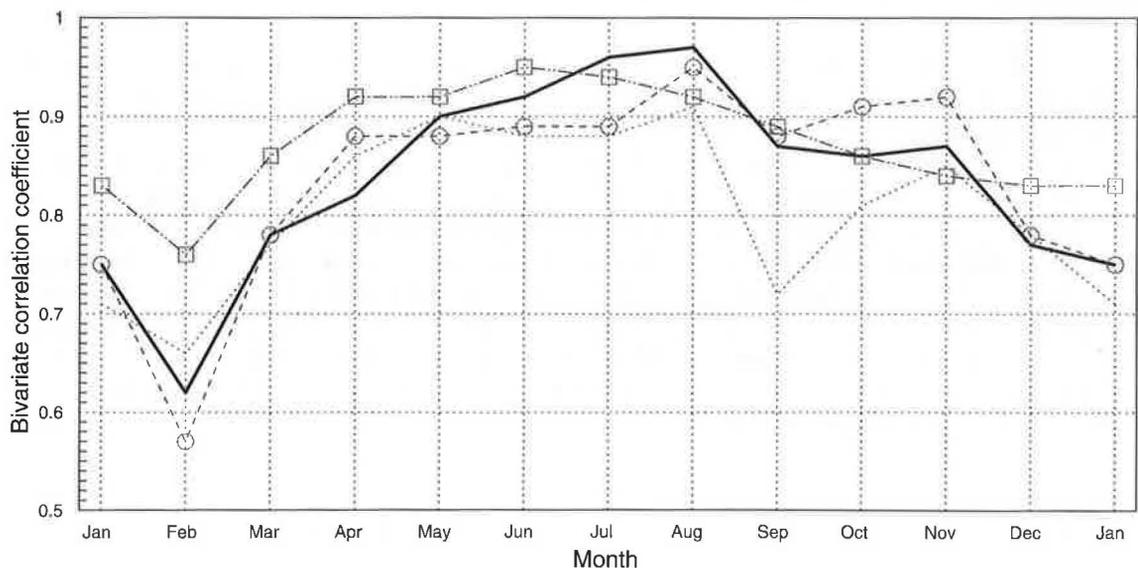


Figure 13 Seasonality of Correlation, Surabaya
 Medan
 ————— Jakarta
 -○- Bandung
 -△- Semarang

Ravallion Model and Timmer's Index of Market Connection (IMC)

The analysis done on the Ravallion model and for Timmer's Index of Market Connection made no correction for simultaneity. The approach adopted by Heytens (1986) was followed and Equation 37 was used

$$\Delta P_t = (a-1)(P_{t-1} - R_{t-1}) + b_0(\Delta R_t) + (a + b_0 + b_1 - 1)(R_{t-1}) + cX_t + \varepsilon_t \quad (37)$$

The equation states that the change in local prices is a function of the spatial price spread, the change in the reference market price, the previous level of local prices and a vector of local factors (e.g. seasonality). This approach avoids the use of two-stage least squares (2SLS). One can refer to a number of sections that discuss the applicability of this equation (pp38, 40 and 41). This work was carried out prior to knowledge of the cointegration technique.

It was felt that the retail price adjustments between provinces would occur quickly, in much less than a month. Price adjustments would then occur before the data could capture them. Assessing short-run integration (price changes in the reference market being fully passed on to the local markets) could then not be done with monthly data. However, we did not have weekly data. It was thus decided to use variety specific *producer* prices in one province and Jakarta *retail* prices of the same variety, as the local and reference prices, respectively. The adjustment time would be significantly longer in this case and more adequately fit the data available.

There were then three local markets (producer prices in East, Central and West Java) and one reference market (Jakarta retail prices). This is then no longer strictly a spatial, but also a vertical, integration test. In all cases the natural log of prices (ln) was used, not the price level itself. Models were run with seasonal dummies for X_t . Seasonal dummies are qualitative rather than quantitative variables and attempt to measure the impact of differences between the various seasons. Statistical software packages will generate these easily. The word 'seasonal' is a bit of a misnomer, because if one is using monthly data one should use monthly dummy variables: a dummy variable for each month rather than each season.

Table 9 Ravallion, Timmer Results. Jakarta Retail Prices versus Java Provincial Producer Prices

	East Java	Central Java	West Java	F and t Critical values	
				1%	5%
Market segmentation	9.9	21.0	19.9	3.10	4.84
				<i>F</i> (2,99)	
Absence of local factors	7.3	7.8	7.5	1.89	2.43
				<i>F</i> (11,99)	
Short-run integration	-5.9	-5.6	-5.8	-2.63	-1.98
				<i>t</i> (99)	
Index of Market Connection (IMC)	16.0	6.3	8.1		

For the market segmentation and absence of local factors, values are *F*-statistics using Equation 37 and following hypothesis tests outlined on p.39. Market segmentation: H_0 : markets are segmented. Absence of local factors: H_0 : local factors not significant.

For short-run integration a simpler and less restrictive null was used because short-run integration clearly did not exist.

Short-run integration: H_0 : ΔR coefficient = 1, markets are short-run integrated.

IMC ≤ 1 is indicative of short-run integration or market connection.

Nested hypothesis tests were conducted (as outlined on p.39) for market segmentation, short-run integration and the absence of local factors. Also the Index of Market Connection was derived. Table 9 shows the results. The null hypothesis of market segmentation is rejected very strongly for all Java provinces. The null hypothesis of short-run integration is also strongly rejected for all provinces. The null hypothesis of local factors not being significant is rejected strongly for all provinces. Seasonality is therefore important because the seasonal dummies are jointly significant. However, not all individual monthly dummies are. As others have found, none of the coefficients of the R_{t-1} terms were significant (at the 5% level) (Heytens, 1986).

The IMCs are high, indicating the strong influence of lagged local prices as opposed to lagged reference prices in local price formation. Although it was an arbitrary level, Timmer (1986) suggested an IMC level of less than 1 as a guide-line for short-run integration. The IMC results suggest lack of spatial integration (short-run). However, the last two points in the previous paragraph call into question the applicability of the IMC. Use of the IMC assumes that local factors are insignificant. As we have noted, this is not the case here. Also, the IMC uses the coefficient of the R_{t-1} term minus the coefficient of the $(P_{t-1} - R_{t-1})$ term as the denominator. In no case was the former significant and in one case, East Java, neither was the latter. That suggests that the very high East Java IMC value may have little meaning. Also, in using the IMC, we have assumed rather than tested for, the existence of long-run integration.

Finally, the acceptance of the assumption of a radial market structure inherent in the Ravallion and Timmer analysis is suspect. As we will see from the work of Alexander and Wyeth (1991), there was much bidirectional (Granger-)causality in Indonesia. With a radial market structure there should be more unidirectional causality from the reference market to the local market. Further, the Jakarta market was largely a price taker not a price maker. As such it makes little sense to suggest it as the reference market.

In conclusion then, if one can accept the assumptions upon which the analysis is based, the results suggest that the markets are not segmented, are not integrated in the short-run and that local factors (seasonality) are important.

Cointegration

The cointegration technique was not applied to the question of spatial market integration by the author. For the Indonesian rice market this has recently been done by Alexander and Wyeth (1991) and Wyeth (1991). We will summarize some of their findings here. The reader is referred to p.29 for an application, within this paper, of cointegration to the question of vertical integration.

Alexander and Wyeth (1991) used the Medium Price series from seven Indonesian locations (1979-90) and applied the cointegration technique to address the question of spatial integration. They found all price series were integrated of order 1. However, the inflation series was found to be order 0. The latter is an odd result and is attributed to the fact that logs were used in all cases, including the inflation series. Only if the inflation series had been order 1 would the question of inflation causing changes in the market price series arise. However, to be rigorous, they in any event proceeded as if the inflation series was integrated of order 1 and still did not find any causality from the inflation series to any of the market series.

Virtually all the locations were cointegrated with each other. The major exception was that Jayapura was not cointegrated with any other location. That exception would be expected, as we noted previously (p.44). A minor exception was that Surabaya was not cointegrated with two off-Java locations. The conclusion is that the Indonesian rice market is spatially integrated (with the exception of Jayapura).

Turning to causality, there are some interesting results. There was little causality running to Surabaya from other locations. However, there was causality running from Surabaya to the other locations, suggesting Surabaya's importance as a price leader. Also there was no causality running from Jakarta, the largest deficit area, to two of the three largest surplus provinces (Surabaya and

Ujung Pandang) but only to the geographically adjacent surplus area, Bandung. This suggests Jakarta is largely a price taker, at least on the national scale. For many of the other locations there was bidirectional causality.

Alexander and Wyeth also tested the market relations for exogeneity. In the Ravallion model, only if the reference market is exogenous with respect to the local one, can the problem of simultaneity be avoided. Only 5 of 26 market sets were found to be exogenous.

CONCLUSIONS

Having applied four different techniques to the question of spatial integration, what can we conclude and which technique performed best?

The conclusion of spatial integration is clouded somewhat by the fact that the different techniques attempt to address and measure essentially different definitions of spatial integration. Correlation coefficients and cointegration address what might be called long-run integration. The Ravallion model attempts to address both that and short-run integration. Timmer's Index of Market Connection attempts to address only short-run integration.

Both correlation coefficients and cointegration come to similar conclusions as to long-run integration on Java and off-Java. The latter technique is, however, more sensitive and, significantly, can address the direction and strength of causality. Both the Ravallion model and Timmer's IMC conclude that short-run integration cannot be accepted. However, there are doubts about the applicability of the assumptions (radial market, accepting OLS despite simultaneity problems and so on) in the analysis.

Which technique is best? As one might expect, there is no categorical answer. The answer will be a function particularly of three things: (i) the exact definition of integration to be tested, (ii) one's existing market knowledge, and (iii) the resources (econometric skill, software packages and time) available.

Correlation coefficients are still worth pursuing, largely because they are easy to compute and therefore the cost low. The price data can first be purged of inflation and seasonality. They require no assumptions about market structure or which markets are to be the dependent and independent variable. Little pre-knowledge of the market is then required. Also, if the analysis covers the seasonality, trend and volatility in the correlation coefficients, more information can be gained. However, the technique cannot address short-run integration or the direction and strength of causality. Also, in the final analysis, the cut-off level for acceptance of integration is necessarily arbitrary.

It is hard to avoid employing cointegration. If one wants to do any modelling of the market relationships, the series need to be tested for integration (econometric) and cointegration anyway. Then the direction and strength of causality is just an F test away. If one employs an econometric software, as opposed to a general statistics package, Granger-causality tests are likely automated within the package, cutting down on effort. Soon, perhaps, the Augmented Dickey-Fuller test will be too. Like correlation coefficients it does not require assumptions about market structure and dependent variables. It is then more readily applied where existing market knowledge is lower. The great advantage is its ability to address causal direction and strength, which none of the other techniques can. Its weakness is its inability to address short-run integration. Integration for the cointegration technique is the existence of cointegration between two price series that is not (Granger-)caused by inflation. That said, however, the technique can readily be extended to address exogeneity of price series and hence the applicability of using the Ravallion model (using OLS) to address short-run integration. In actual application there are still doubts about its ability to return useful information when inflation is causally important (see p.34).

If one wants to address short-run integration then, in one shape or another, the Ravallion model is the one to employ. Within the nested hypothesis testing one can use various definitions of short-

run integration: particularly less stringent ones than used by Ravallion. Integration for Ravallion was defined as whether price increases were fully passed on within one time period to the local market and that there is no lagged effect on future local prices. Also nested hypothesis testing allows one to address a variety of other issues (e.g. importance of seasonality, long-run integration) which other techniques may not be able to. However, there are several drawbacks. Strictly speaking one needs to be able to use 2SLS, so the demands on the skill of the practitioner are higher. Also strictly speaking, integration (econometric) and cointegration tests need to be performed before the Ravallion model is tested. That puts further calls on resources (both skill and time). Finally, one needs to know more about the market to begin with, because the model assumes both a radial market structure and that one knows which market(s) is(are) in fact the reference market(s). Even if one has good market knowledge, the radial model still may not apply. Finally, the model is probably sensitive to whether the data are weekly or monthly. To capture short-run integration, weekly data may be needed but are rarely available.

The Timmer Index of Market Connection is merely an extension of the Ravallion model that focuses solely on short-run integration. In that sense it is the most limited of all the techniques so it is hard to see it as the only technique to adopt. If, however, one is already doing the nested hypotheses in the Ravallion model then the IMC is very little extra effort: just one calculation away. In that case it is worth doing. However, the IMC, of course, suffers from all the problems of the Ravallion model outlined above (need for 2SLS, integration and cointegration testing, assumption of a radial market, pre-knowledge of the market). Strictly speaking, it can only be used where long-run integration exists and local factors are unimportant. That will limit its applicability. Finally, just as the cut-off level for integration with correlation coefficients is arbitrary, so is the level for the IMC. There is no intrinsic justification for an IMC of less than 1 being the criterion.

One will see from the discussion that more than one technique will need to be employed in most cases. Also it is fair to say that none of the techniques adequately address the problem of markets intermittently being integrated or connected. This problem has been raised a number of times in this publication (see pp.16 and 38). It would appear the implicit assumption is that if markets are connected at all they are connected all the time. As Timmer (1974) found for the Indonesian rice market, it is unlikely to be true. All the techniques should then suffer from the bias of reporting false negatives in this respect.

The techniques, even correlation coefficients if properly carried out, are not particularly susceptible to producing false positives due to the effect of inflation. Some are susceptible to false positives due to the effect of parastatals. As pointed out previously (p.38) a parastatal's actions, say in defending a ceiling price, may give the illusion of spatial integration. This was one of the factors that prompted the change in focus from long-run integration to short-run integration by Heytens and Timmer. It would appear that at least correlation coefficients and cointegration, because of their focus on long-run integration, are susceptible to false positives from this source.

References

- ALEXANDER, C. and WYETH, J. (1991) Cointegration and market integration. (Unpublished)
- BLYN, G. (1973) Price series correlation as a measure of market integration. *Indian Journal of Agricultural Economics*, **28** (2): 56-59.
- BRENNAN, M.J. (1958) The supply of storage. *American Economic Review*, **47**: 50-72.
- DICKEY, D.A. and FULLER W.A. (1979) Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, **74** (366): 427-431.
- ELLIS, F., MAGRATH, P. and TROTTER, B. (1991) *Indonesian Rice Marketing Study 1989-91. Final Report. Main Report*. Vol. I. Jakarta: BULOG.
- ELLIS, F., TROTTER, B. and MAGRATH, P. (1992) *Rice Marketing in Indonesia: Methodology, Results and Implications of a Research Study*. Marketing Series 4. Chatham: Natural Resources Institute.
- ENGLE, R.F. and GRANGER, W.J. (1987) Co-integration and error correction: representation, estimation, and testing. *Econometrica*, **55** (2): 251-276.
- ENGLE, R.F. and YOO, B.S. (1987) Forecasting and testing in co-integrated systems. *Journal of Econometrics*, **35**:143-159.
- FULLER, M.F. and LURY, D.A. (1977) *Statistics Workbook for Social Science Students*. Oxford: Philip Allan.
- GOETZ, S. and WEBER, M.T. (1986) *Fundamentals of Price Analysis in Developing Countries' Food Systems: A Training Manual to Accompany the Microcomputer Software Program "MSTAT"*. MSU International Development Papers. Working Paper No. 29. East Lansing: Department of Agricultural Economics, Michigan State University.
- GOLDMAN, R.H. (1974) Seasonal rice prices in Indonesia, 1953-69: an anticipatory price analysis. *Food Research Institute Studies*, **13** (2): 99-141.
- GRANGER, C.W.J. (1969) Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, **37** (3): 424-438.
- GRANGER, C.W.J. (1981) Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, **16**: 121-130.
- HAKKIO, C.S. and RUSH, M. (1989) Market efficiency and cointegration: an application to the sterling and Deutschmark exchange markets. *Journal of International Money and Finance*, **8**: 75-88.
- HARRISS, B. (1979) There is method in my madness: Or is it vice versa? Measuring agricultural market performance. *Food Research Institute Studies*, **17** (2): 197-218.
- HENDRY, D.F. (1980) Econometrics – alchemy or science. *Economica*, **47** (188): 387-406.
- HEYTENS, P. (1986) Testing market integration. *Food Research Institute Studies*, **20** (1): 25-41.
- IMF (various). *International Financial Statistics Yearbook*. Washington: International Monetary Fund.
- JONES, W.O. (1974) Regional analysis and agricultural marketing research in tropical africa: concepts and experience. *Food Research Institute Studies*, **13**: 3-28.

- KEMPSON, R.E. (1987) *Statistics for Economists*. London: Wye College, University of London.
- KENNEDY, P. (1985) *A Guide to Econometrics*, 2nd edn. Oxford: Blackwell.
- MAGRATH, P. (1992) *Methodologies for studying agricultural markets in developing countries*. Marketing Series 2. Chatham: Natural Resources Institute.
- MONKE, E. and PETZEL, T. (1984) Market integration: an application to international trade in cotton. *American Journal of Agricultural Economics*, **66** (4): 481-487.
- NEWBERRY, D. and STIGLITZ, J. (1984) Pareto inferior trade. *Review of Economic Studies*, **51**: 1-12.
- RAVALLION, M. (1986) Testing market integration. *American Journal of Agricultural Economics*, **68**: 102-109.
- TABOR, S.R. (1989) *Price and Quality of Rice in Java: An Investigation into the Demand for Closely Related Goods*. Amsterdam: Ree University Press.
- TAKAYAMA, T. and JUDGE, G.G. (1971) *Spatial and Temporal Price and Allocation Models*. Amsterdam: North-Holland.
- TAYLOR, M.P. and TONKS, I. (1989) The internationalisation of stock markets and the abolition of UK exchange control. *The Review of Economics and Statistics*, **71**: 332-336.
- TIMMER, C.P. (ed.) (1986) In: *The Corn Economy of Indonesia*, pp. 201-234. Ithaca: Cornell.
- TIMMER, C.P. (1974) A model of rice marketing margins in Indonesia. *Food Research Institute Studies*, **13** (2): 145-167.
- WYETH, J. (1991) *Market Integration in Price Stabilisation and Food Security Policies*. Brighton: Institute of Development Studies.
- WONNACOTT, R.J. and WONNACOTT, T.H. (1985) *Introductory Statistics*, 4th edn. New York: Wiley.
- WORKING, H. (1948) The theory of price of storage. *American Economic Review*, **39**: 1254-1262.

Additional Reading

BEACH, C.M. and MACKINNON, F. G. (1978) A maximum likelihood procedure for regression with autocorrelated errors. *Econometrica*, **46** (1): 51-58.

ENGLE, R.F., HENDRY, D.R. and RICHARD, J. F. (1983) Exogeneity. *Econometrica*, **51** (2): 277-304.

FAMINOW, M.D. and BENSON, B.L. (1990) Integration of spatial markets. *American Journal of Agriculture Economics*, **72** (1): 49-62.

GRANGER, C.W.J. and NEWBOLD, P. (1974) Spurious regression in econometrics. *Journal of Econometrics*, **2**: 111-120.

LELE, U.J. (1967) Market integration: A study of sorghum prices in western India. *Journal of Farm Economics*, **49**: 147-159.

MADDALA, G.S. (1987) *Econometrics*. Singapore: McGraw-Hill.

MAGRATH, P. (1989) *Measuring the Integration of the Rice Marketing System in Indonesia*. M.A. Thesis, University of East Anglia.

MENDENHALL, W. and McClave, J.T. (1981) *A Second Course in Business Statistics: Regression Analysis*. San Francisco: Dellen.

MONKE, E. and PETZEL, T. (1984) Market integration: an application to international trade in cotton. *American Journal of Agricultural Economics*, **66** (4): 481-487.

RAVALLION, M. (1985) The performance of rice markets in Bangladesh during the 1974 famine. *Economic Journal*, **98**: 15-29.

RAVALLION, M. (1987) *Markets and Famines*. Oxford: Clarendon Press.

Appendix 1

Negative Storage Margins in a Competitive Market

CONVENIENCE YIELD

In Section 2 discussing seasonal analysis, we mentioned the possibility that negative net storage margins may exist in a well-functioning market with positive levels of storage. Intuitively this is unexpected because it implies storage agents lose money storing. Also, our Indonesian results suggested the possibility that the parastatal, BULOG, itself may be the cause of the negative net storage margin levels.

In this Appendix we want to follow up both of these issues and provide the theoretical framework behind these statements. Working (1948) had attempted an explanation of 'inverse carrying charges'; where the expected price in the next time period is below the current price. He introduced the concept of convenience yield to explain this.

Another important condition is that for most of the potential suppliers of storage, the costs are joint; the owners of large storage facilities are mostly engaged either in merchandising or in processing, and maintain storage facilities largely as a necessary adjunct to their merchandising or processing business. And not only are the facilities an adjunct; the exercise of the storing function itself is a necessary adjunct to the merchandising or processing business. Consequently, the direct costs of storage over some specified period as well as the indirect costs may be charged against the associated business which remains profitable, and so also may what appear as direct losses on the storage operation itself. (Working, 1948)

The stocks themselves then are a 'convenience' and provide a 'yield' to the rest of the firm's operation. Firms are not then irrational in storing at negative prices for storage (net storage margins) because storage is not a separate economic activity but an economic activity joint with another (e.g. processing, marketing).

Brennan (1958) developed a theory for the supply of storage which incorporated this idea of a convenience yield and could be applied to products for which there was no known future price (i.e. products without futures markets). It followed the classical assumption that firms attempt to maximize net revenue (profit). They will supply that level of storage which equates the marginal cost of storage with the expected revenue from storage. Again following classical theory, the supply curve of the firm is the (net) marginal cost curve and the industry supply curve is summation of all the individual firms' supply curves. Brennan broke the firm's total cost function into three components: the gross cost of storage (interest, insurance, in and out loading charges, rent of storage space, etc.), a risk-aversion and the convenience yield. The (net) marginal cost curve is then the summation of these three components: the marginal gross storage cost plus the marginal risk-aversion and minus the marginal convenience yield. (The convenience yield is a benefit not a cost so it must be subtracted, not added, in the derivation of the net marginal cost of storage.) These are shown in Figure A1. The supply of storage curve is the (net) marginal cost curve; the vertical summation of the three curves. The shapes of the marginal convenience yield curve and the marginal risk aversion curve are important. Without this marginal convenience yield, the supply of storage curve would be linear at low levels of storage, and without the marginal risk aversion curve, the supply of storage curve would be linear at high levels of storage.

At low levels of storage the marginal value of the convenience yield is very high, whereas at moderate levels of storage it is approximately zero. At low levels of storage the probability of having to shut down a (high overhead) processing plant from lack of raw product, or failing to perform on processed product sale contracts, or of being unable to accommodate even a small increase in customer demand, is high. Therefore, the convenience arising from avoiding these problems is high. However, with higher levels of stocks, the probability of these problems diminishes rapidly.

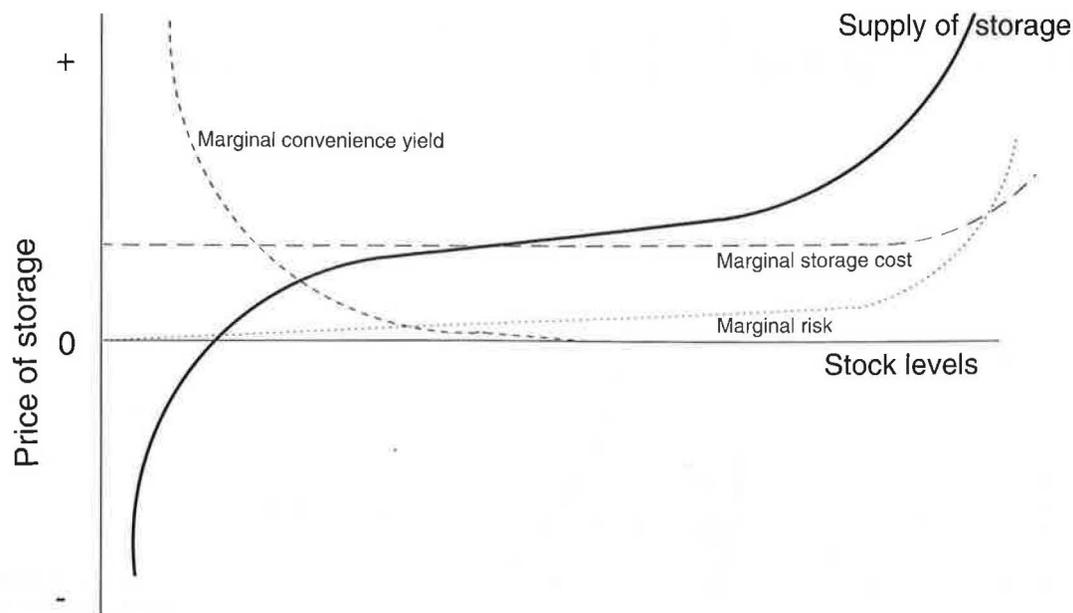


Figure A1 Derivation of the Supply of Storage Curve
Source: Brennan (1958)

The marginal risk aversion curve is asymptotic at high levels of storage. This is because at high levels of storage even small price decreases (in the stored product) have extreme effects on the financial well-being of the company. The probability of large losses is then high.

The final point is that from the supply of storage curve it can be observed that even at negative price of storage levels (net return to storage), storage is still supplied.

IMPLICATIONS FOR THE INDONESIAN CASE AND BULOG

Our results suggest there are negative net returns to rice storage in Indonesia over the period of study, 1980–90. Goldman's (1974) study of the Indonesian rice market prior to BULOG's effective operation and Timmer's (1986) more recent study of the Indonesian maize market in which BULOG does not intervene, found no suggestion of negative margins. There is the possibility that the existence and success of the parastatal, BULOG, is a contributing factor to these negative net returns to storage. The discussion above provides the theoretical framework for why positive levels of storage can consistently occur in a well-functioning market with negative net returns to storage. We now turn to the question of how BULOG's actions might contribute to negative net storage margins and what would happen to margins in the absence of BULOG.

Figure A2 depicts the possible situation in the absence of BULOG. This is non-farm storage, in a balanced crop year and is for the situation at the end of the main rice harvest (May). The private market must store all the rice, intra-seasonally. Changes in inter-seasonal storage are assumed to be zero because of the balance crop year assumption. The equilibrium position is in the linear portion of the supply of storage curve at 4.5 million tonnes of milled rice.

However, what happens if we introduce BULOG into the marketplace? Because BULOG is a price-insensitive supplier of storage, the introduction of BULOG can be viewed as a downward shift in the demand curve. We are not saying BULOG is insensitive to the price of rice; it clearly is not, because it operates a floor price support programme. We are saying it is insensitive to the price of storage. BULOG essentially reduces the *private* market demand for storage by 1.3 million tonnes of milled rice. In a balanced crop year, BULOG buys approximately 1.8 million tonnes of milled rice during the main harvest but redistributes 0.5 million tonnes to budgets groups within that 4 month period. By the end of the main harvest it has increased its stock position by 1.3 million tonnes.

Consequently, the introduction of BULOG to the private market for non-farm storage can be viewed as a reduction in the private demand for storage of some 1.3 million tonnes.

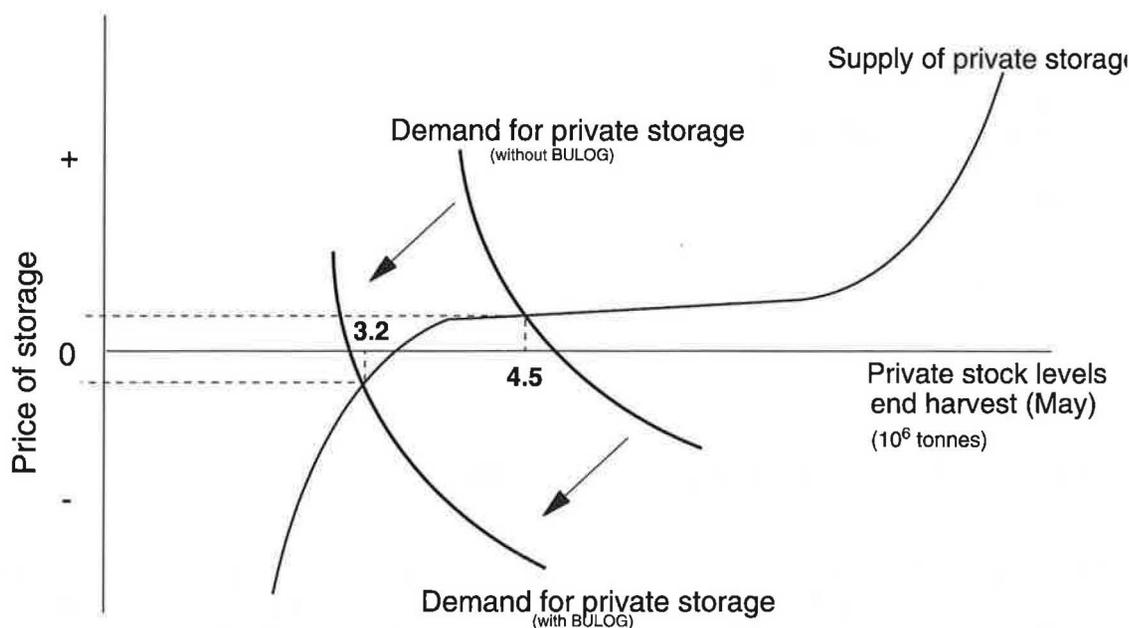


Figure A2 Supply and Demand for Rice Storage
Source: Ellis *et al.* (1991)

That inward shift of the demand for storage curve may be large enough for the equilibrium to occur in the non-linear portion of the supply curve and at a negative price of storage. The question then is whether the quantity BULOG removes from the private storage market is large enough, relative to the overall size of the private storage market, to push the equilibrium to negative price levels. At first glance it would seem unlikely. BULOG's total purchases are only 6% of the annual net harvest. Looked at in this manner it might indicate that the shift would not be large enough to induce negative storage margins. However, the 6% misrepresents BULOG's importance.

The annual net harvest size of 26.5 million tonnes is, however, (i) not the quantity the private market stores, and (ii) covers the three harvests within any year. Accordingly we want to know what percentage BULOG is of the private market storage, not what percentage it is of the annual harvest. Ellis *et al.* (1991) found that farmer household storage behaviour is insensitive to the price of storage. Farmers' storage motivation is to ensure their own food security. Because it is price insensitive demand it has been excluded from the discussion (and graph). Secondly, the 26.5 million tonne annual net harvest is not from one, but three, crops. Because the production is from three crops, less storage is needed than if the annual production of 26.5 million tonne came from one crop. If one then focuses on the main harvest season of February–May, the period in which BULOG buys approximately 80% of its procurement, BULOG is storing approximately 30% of the non-farm stocks (Ellis *et al.*, 1991). From the storage perspective this percentage more accurately reflects BULOG's importance.

BULOG, then, is not a minor storage agent. It may indeed reduce private storage demand sufficiently to shift the private market price equilibrium from a positive to a negative level. Neither Figure A1 nor Figure A2 has been tested for the case of Indonesian rice, but it does provide a framework to interpret results of both the time series analysis and survey data done within the Rice Marketing Study (RMS). It also suggests some areas of profitable research.

As a final point we have only looked at the stylized case of BULOG's intervention in a balanced crop year, where domestic demand exactly equals domestic supply. The analysis can be extended to include years of excess or deficit supply. Excess supply would be represented by an outward shift in the demand curve from its balanced crop year position. Deficit supply would be represented by an inward shift of the demand curve. Because even in a balanced crop year the equilibrium position may already be in the non-linear portion of the supply curve, deficit years, by further shifting the demand curve inward, should have a marked negative impact on the price of storage.

Appendix 2

Hypothesis testing and correlation coefficients

TESTING FOR THE ABSENCE OF CORRELATION, $H_0: \rho = 0$

In this publication we do not discuss hypothesis testing of the correlation coefficients. This is because the information gained from hypothesis testing is low. We instead simply use a level of greater than +0.8 as the acceptance region for spatial integration. However, other spatial integration studies do use hypothesis testing of correlation coefficients and the reader may like to know how to apply them.

As Ravallion (1986) points out, most papers use a t test for assessing the significance of the correlation coefficient results found. This is also what computer statistical packages use in producing the significance levels of correlation coefficients. In this approach the estimated correlation coefficient, r , is transformed to create the following t statistic

$$t_{n-2} = \frac{r(n-2)^{1/2}}{(1-r^2)^{1/2}} \quad (\text{A1})$$

The null hypothesis of this test is that the actual (population) correlation coefficient, ρ , is equal to zero. This is then a test for the absence of correlation. The alternative hypothesis is that some negative or positive correlation exists. A high t value, which is almost universally found, leads to rejection of the null hypothesis and the absence of correlation. The alternative hypothesis is then accepted; some negative or positive correlation exists.

To be very clear on this, rejection of the absence of correlation is not, however, the same as acceptance of *strong* correlation. Our problem here is that the alternative hypothesis is, for our purposes, too weak. It simply indicates that some, not necessarily strongly positive, correlation exists. Essentially we need to redo the hypothesis test using a different null hypothesis, namely that the actual (population) correlation coefficient, ρ , is +1.

TESTING FOR PERFECT CORRELATION, $H_0: \rho = +0.99$

The problem is that the t statistic used above is not a valid if the actual (population) correlation coefficient, ρ , is known not to be zero. If we have already done the t test in the section above, we will know that ρ is non-zero. That is exactly what we tested for. An alternative statistic must be used. There are two steps in this procedure. First, we must transform our estimated r value in a specific manner. Second, we must then use the transformed value in a z test.

The first step is the transformation. r can be transformed by taking its inverse hyperbolic tangent. This is called Fischer's z transformation. The inverse hyperbolic tangent has a normal distribution. All that we are doing here is transforming r , which has a complicated distribution, to another system where the transformed value has a much simpler distribution. We then have the following transformation

$$z = 0.5 \ln \left(\frac{1+r}{1-r} \right) \quad (\text{A2})$$

where \ln is the exponential logarithm. z , the transformed value of r , is distributed normally with a variance of $1/(n-3)$ (i.e. $\sigma^2 = 1/(n-3)$) and a mean ($\mu = \zeta$) equal to a transformed value of the actual (population) correlation coefficient, ρ . For those familiar with statistical notation, the transformation has a distribution $N(\zeta, 1/(n-3))$. We should say right at the outset that it is

not possible to use a null hypothesis of $\rho = +1$ because the denominator in the transformation then becomes 0. However, one can use a null hypothesis of $\rho = +0.99$.

Because the transformed values of r are normally distributed and we know the actual population variance, we can use a z rather than a t test. This is the second step. We use a standard z test to compare the r value we found, with the r value we choose as our null hypothesis. The general z test statistic is

$$z = \frac{\bar{X} - \mu}{\sigma} \quad (\text{A2})$$

where \bar{X} is the estimated sample mean (X bar), μ the actual population mean, σ the standard deviation = $\sqrt{\text{variance}}$.

We use our transformed values in this z test rather than the r value we estimated. We know that the variance is $1/(n-3)$ so that the standard deviation will be $1/(n-3)^{1/2}$. The actual population mean, μ , will be the transformed value of the ρ we use in our null hypothesis (e.g. $\rho = +0.99$). The estimated sample mean, \bar{X} , is the transformed value of the r we estimated in our correlation analysis. It is perhaps easiest to see if we do an example.

HYPOTHESIS TESTING EXAMPLE: JAKARTA-SEMARANG

The correlation coefficient for the largest rice deficit region, Jakarta, with Semarang, the capital of the third largest rice production province (Central Java) was +0.95 (for seasonally adjusted, deflated Cisadane prices). One can readily see that there must be some positive correlation but we can nonetheless test for the absence of correlation. The null hypothesis in that case will be $H_0: \rho = 0$. The alternative hypothesis will be $H_1: \rho \neq 0$. The sample size was 129, so $n-2 = 127$. It is thus a two-tailed test using the t_{n-2} statistic given on p.58.

$$\begin{aligned} t_{127} &= \frac{+0.95 (127^{1/2})}{[1 - (0.95)^2]^{1/2}} \quad (\text{A4}) \\ &= 34.3 \end{aligned}$$

The rejection region for the H_0 , at the 95% confidence level for t_{127} (two-tailed), is any value greater than ± 1.98 . We can see that the null hypothesis of the absence of correlation is very strongly rejected indeed. The alternative hypothesis of some correlation, either positive or negative, is then accepted.

We would now like to test whether the positive correlation is very strong. The null hypothesis will be that the two price series are perfectly correlated. Because we cannot use a null of $\rho = +1$ we use $\rho = +0.99$. The alternative hypothesis is that ρ is less than +0.99. This is then a one-tailed test. To use the z test we need to transform both our null value of $\rho = +0.99$ and our estimated r value of $r = +0.95$ using Fischer's z transformation (as detailed in the last section). The transformed value of ρ is 2.646 and for r is 1.832. The standard deviation, σ , ($\sigma = 1+126^{1/2}$) is 0.089. Therefore

$$\begin{aligned} z &= \frac{1.832 - 2.646}{0.089} \quad (\text{A5}) \\ &= -9.15 \end{aligned}$$

The rejection region at the 95% confidence level (one-tailed) is any value greater (more negative) than -1.64. The null hypothesis of perfect correlation of the two price series is strongly rejected. This may seem odd because the correlation coefficient level of +0.95 is high indeed relative to our minimum acceptance level of +0.8. It is also relatively close to our null of +0.98. Nonetheless, perfect correlation is rejected. We are then left with the conclusion that the two price series are neither uncorrelated nor perfectly correlated.

We are, of course, free to choose alternative null hypotheses. The one we chose, perfect correlation, is an especially rigorous one. We should expect that in practice even very strongly correlated price series would fail this test. Put another way, even if our two series had a correlation coefficient of +0.985, the null hypothesis of perfect correlation ($\rho = +0.99$) would still be rejected.

CONCLUSIONS

The problem with using hypothesis testing of correlation coefficients as a test of spatial integration can now be seen. On the one hand testing for the absence of correlation is a virtual formality in most cases. The acceptance of the alternative hypothesis of some correlation is not particularly revealing.

When the null hypothesis is changed to test for perfect correlation, the result is equally unrevealing. With any normal sample size we will be certain that the two price series are not perfectly correlated.

The tests thus confirm what we already know; that the two series are neither totally uncorrelated nor perfectly correlated. Choosing a different null hypothesis, essentially any level greater than 0 and less than +0.99, is effectively arbitrary.

The problem is not a statistical one but a theoretical one. We do not know exactly what r value to use in the null hypothesis. This is because in reality, markets are not continuously connected and our adjustment for the effect of trends on correlation coefficient values is imperfect. We should not then expect r values of +1.0 from spatially integrated locations. Just what values we should expect is unknown. One can put forward arguments for different r levels as minimum points for acceptance of spatial integration. In our analysis we have followed other studies in using a level of greater than +0.8 as evidence of strong association and by implication the region of acceptance of spatial integration. However, there are few arguments to counter readers who would choose a different level.

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3

There is pressure in developing countries for less regulated staple food markets. Public sector parastatals are being asked to justify their operations, streamline their operations and costs and to release many of their previous functions to the private market.

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Applying Price Analysis to Marketing Systems: Methods and Examples from the Indonesian Rice Market is intended as a comprehensive training manual for the various methodologies available to address the question of market integration. All methods are applied in a step-by-step, easy-to-follow manner to Indonesian rice market data.

The book assumes only a rudimentary level of statistical knowledge and will be of interest to researchers and organizations concerned with the assessment of agricultural market performance in developing countries.