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Abstract

This present study investigates the inter-relationships between food and oil prices, and an exogenous variable (rainfall). The analysis is based on monthly and annual price data for long periods at the global level. It is supplemented by similar analyses of annual food prices in China and India. While comovements of prices imply integration of different markets, their efficiency implications are far from obvious. First, there is robust evidence confirming comovements of different food prices. Second, oil price has a significant positive impact on agricultural commodity prices. Third, rainfall has a negative impact on agricultural commodity prices. Finally, in some cases, the price shocks are persistent but in several others they are short-lived. While these findings raise serious concerns about reversal of progress in rural poverty reduction, any temptation to draw pessimistic conclusions must be resisted. Much of course will depend on what governments in emerging economies and elsewhere do to promote smallholders, technical change and easier access to credit and insurance.

Key Words: cereals, oil, prices, cointegration, shocks, poverty
JEL Codes: C22, O13, Q11

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Food and Oil Prices[1]

I. Introduction

The last eighteen months have witnessed sharp spikes in the prices of food (e.g. cereals, fruits and vegetables, and meats) and oil. The FAO food price index rose by 9 per cent in 2006 compared to the previous year. By September, 2007, the index rose to 172 points, representing a year-on-year increase of about 37 per cent[2]. The surge in prices is led by dairy and grains, but prices of other commodities have also increased (e.g. oils/fats). For example, price of wheat rose from $212/tonne in October, 2006, to $352/tonne in October, 2007; of (basmati) rice from $525/tonne to $713/tonne; of maize from $135/tonne to $180/tonne; of soyabeans from $269/tonne to $445/tonne; and of palm oil from $506/tonne to $875/tonne.[3]

Some of these spikes spilled over into the futures prices. The wheat futures prices for December delivery on the Chicago Board of Trade (CBOT), for example, hit a record high of $350/tonne on 28th September, 2007. However, by late October, wheat futures for March 2008 delivery at the CBOT went down to $299/tonne, although still 60 per cent more than in the corresponding period last year. Feed shortages, combined with a buoyant wheat market, have sustained high maize prices. By late October, 2007, the CBOT March maize 2008 futures stood at $151/tonne, about $20 above the corresponding period in 2006. The unprecedented surge in maize prices has spilled over to the oilseeds and meal market and, in particular, the soyabean complex.

[1] We are grateful to T. Elhaut for his encouragement and advice at all stages. Raghbendra Jha's help with the econometric analysis is greatly appreciated, as also valuable research assistance by Valentina Camaleonte and Sundeep Vaid. The views expressed are, however, those of the authors' and do not necessarily represent those of the organisations to which they are affiliated.

[2] *The Economist* commodity-price index (with 2000=100) registered a sharper rise in food prices over the period January 2007-January 2008- an increase of about 48 per cent (January 19, 2008).

[3] As each commodity has several variants, our illustrations refer to specific commodities. For details, see *FAO Outlook* (November, 2007).

Besides, steadily increasing biodiesel demand is linked to rising demand for vegetable oils, notably soyabean, rapeseed and palm oil. This trend, combined with rising vegetable oil consumption and weak growth of total oil production in 2006/07, has resulted in a gradual tightening in global supplies, and the recent surge in vegetable oil prices. In the first half of October, 2007, the CBOT March contract for soyabeans traded at $150/tonne, 67 per cent higher than in the corresponding period in 2006 (*FAO Outlook*, November, 2007).

The mismatch between supply and demand has worsened. The world wheat stock-to-use ratio, for example, fell from 29.0 per cent in 2005/06 to 22.5 per cent in 2007/08. A more marked reduction is reflected in the major exporters' stock-to-disappearance ratio-from 23.8 per cent to 10 per cent over the same period. For oilseeds, the stock to utilisation ratio dropped-from 15 per cent to 11 per cent.

There are two distinguishing features of rising food prices. One is that it is not just a few but nearly *all* food and feed commodities that have recorded sharply rising prices. As a result, there are strong ripple effects through the food value/supply chain, manifested in rising retail prices of such basic foods as bread, meat and milk. Another feature is the higher price volatility of food prices (e.g. cereals and oilseeds)[4]. While tightness of supplies is often associated with price volatility, the current situation

[4] Volatility could be measured in two ways: historical and implied. The first is based on past price movements and the second on the market's expectation of likely price movements in the future. The latter is preferred to the extent that past price movements may not reflect crop expectations and other changes. For wheat, maize and soyabeans, the CBOT is widely viewed as the major centre for their price discovery. Volatility measured as standard deviation of the expected price six months ahead has been computed for the last 10 years and the previous 22 months. Volatility of wheat and maize prices has been creeping up during the last decade. More importantly, since the beginning of 2006, implied volatility of wheat and maize prices has often touched 30 per cent, and since October, 2007, has been about 27 and 22 per cent, respectively. These estimates imply that there is a 68 per cent certainty that prices will rise or fall by 27 per cent for wheat and 22 per cent for maize (*FAO Outlook*, November, 2007).

differs from past experience in so far as price volatility has lasted much longer. In fact, what underlies this phenomenon is the strengthening of relationships between agricultural commodity markets and other markets in a rapidly globalising world.

Soaring petroleum prices (West Texas Intermediate traded at $96.90 per barrel on January 8th , 2008, an increase of about 79 per cent over the price a year ago) have contributed to higher agricultural prices in two ways: by raising input costs and by boosting demand for agricultural crops used as feedstock for alternative energy sources (e.g. biofuels)[5]. In addition, freight rates have risen, reflecting higher fuel costs, stretched shipping capacity, port capacity and longer trade routes. The Baltic Exchange Dry Index-a measure of shipping costs for bulk commodities such as grains and oilseeds-recently crossed the 10000 mark with freight rates jumping by about 77 per cent during 2006-07 (*FAO Outlook*, November, 2007, and IGC, 2007)[6].

Issues

An overview of demand and supply factors is given below to motivate our analysis.

Some recent assessments (*Financial Times*, January,18, and 21, 2008, *The New York Times*, 19 January, 2008, *Economic and Political Weekly*, January, 2008, *The Economist*, 6 December, 2007, IFPRI, 2007) point to dire consequences of the unabated food price inflation and its persistence in the near future. Reports of unrest among urban and rural areas abound. "In some poor countries, desperation is taking hold. Just in the last week, protests have erupted in Pakistan over wheat shortages, and

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[5] For details, see *FAO Outlook* (November, 2007) and *The Economist* (19th January, 2008).

[6] This index rose from 3960 in October, 2006, to 10944 in October, 2007 (IGC, 2007).

in Indonesia over soyabean shortages. ……China has put price controls on cooking oil, grain, meat, milk and eggs" (*The New York Times*, 19 January, 2008[7]).

Both demand and supply factors are involved in the so-called "agflation". The growing use of grains and other agricultural products as feedstock to produce biofuels (ethanol and biodiesel) has been a key factor in the surge in their prices. A sharp increase in the price of fossil fuels has triggered a search for alternative sources of energy, and biofuel is seen as a viable alternative. In the US, for example, one-fifth of total corn output is now used for biofuel production and this may rise to 30 per cent by 2010. Global food reserves are disappearing fast mainly on account of this substitution. Based on the IMPACT model simulations under two scenarios (the second assuming a doubling of expansion of biofuels under the first), IFPRI (2007) shows that wheat prices in 2020 would rise by 8-20 per cent over the baseline, sugar prices by 11.5-26.6 per cent, oilseeds prices by 18.1-44.4 per cent, and maize prices by 26.3-71.8 per cent.

A second demand factor is the shift in dietary patterns towards livestock and high-value agricultural products (fruits, vegetables and dairy products) in rapidly growing emerging and highly populous countries such as China and India. Higher consumption of livestock products (e.g. meat) requires several kilos of grain to produce one kilo of livestock.[8] In China, consumers in rural areas continue to be

[7] Food riots in recent months have been widespread-Guinea, Mauritania, Mexico, Morocco, Senegal, Uzbekistan and Yemen.

[8] Calorie for calorie, you need more grain if you eat it transformed into meat than if you eat it as bread: it takes three kilograms of cereals to produce a kilo of pork, eight for a kilo of beef. So a shift in diet is multiplied many times over in the grain markets. Since the late 1980s an inexorable annual increase of 1-2% in the demand for feedgrains has ratcheted up the overall demand for cereals and pushed up prices (*The Economist*, 6 December, 2007).

more dependent on grains than consumers in urban areas. However, the increase in the consumption of meat, fish and aquatic products, and fruits in the rural areas has been faster than in the urban areas over the period 1990-2006. In India, while cereal consumption remained unchanged over the period 1990-2005, those of oil crops, meat, milk, fish, fruits and vegetables rose more than moderately (IFPRI, 2007)[9].

On the supply side, world production of cereals has stagnated around 2100 million tonnes after 1996, whereas world population has been growing by 78 million per year. As a result, per capita production of cereals has declined from 362 kg. in 1997-99 to 336 kg in 2005-07. After 1996, cereal production was at its lowest in 2005-06 and 2006-07. Wheat production suffered because of a drought in Australia and unfavourable weather conditions in eastern Europe. So apart from the growing mismatch between demand for and supply of foodgrains, what has pushed up food prices is higher price of oil (by raising the cost of oil- based fertiliser, for example). Stocks as a proportion of output are the lowest ever recorded, accentuated in part by the decisions of USA and China to reduce stocks to save money. What is indeed remarkable is that the present bout of 'agflation' has persisted despite optimistic projections of cereals crop this year (*The Economist*, 6 December, 2007). This is of course consistent with the view that demand factors and the surge in oil prices have played a more important role[10].

How long is this surge in food prices likely to last? The emerging economies' boom and rising demand for oil and its substitutes are unlikely to slacken in the near future

[9] On the dietary changes in Asia, see Pingali (2007).

[10] It is arguable that the 1973 jump in oil prices doubled the trend level of grain prices, and again oil is set to change the nature and trend in grain prices, but this time due to the search for a substitute for oil (*Economic and Political Weekly*, 12 January, 2008).

(*The Economist*, 6 December, 2007, IFPRI, 2007). Consequently, demand pressures on cereal prices will continue to be strong. Some recent assessments (e.g. *Financial Times,* 21 January, 2008, *The Economist*, 6 December, 2007, and IFPRI, 2007) are emphatic that supply constraints will exacerbate 'agflation'. Aggregate price elasticity of supply is low-typically, agricultural supply rises by 1-2 per cent when prices increase by 10 per cent (IFPRI, 2007). This supply response is weaker if prices are volatile but stronger with better rural infrastructure and access to technology and rural finance. A recent report by Bidwells (2007) highlights tightening of supply constraints-specifically, in addition to land scarcity, lack of water would hamper agricultural productivity. China and India, for example, would have no other option but to provide more water to their rapidly growing urban populations at the expense of agriculture. These constraints are already beginning to bite as yields have plateaued, after more than doubling from 1.1 tonnes per hectare in 1950 to 2.7 tonnes per hectare in 2000 (*Financial Times*, 21 January, 2007).

These concerns are reflected in the projections of food prices. Although there is a consensus that 'agflation' is likely to persist for a few years or more, price projections vary. The Economist Intelligence Unit (EIU, 2007) predicts an 11 per cent increase in the price of grains in the next two years and only a 5-percent rise in the price of oilseeds. The OECD-FAO outlook (2007) projects higher price increases-the prices of coarse grains, wheat, and oilseeds are expected to increase by 34, 20, and 13 per cent, respectively, by 2016-17. The Food and Agricultural Policy Research Institute (FAPRI, 2007) predicts that corn demand prices will rise up to 2009-10, and thereafter corn production growth will be on par with consumption growth. Nor does it expect biofuels to have a large impact on wheat markets, and predicts that wheat prices will stabilise. Only the price of palm oil- a biofuel feedstock-will spike by 29 per cent. IFPRI's (2007) projections, based on its IMPACT model, point to an increase of 10 to 20 per cent in cereal prices during 2006 to 2015 in current dollars. So in the event the dollar depreciates the prices will be higher in dollar terms (IFPRI, 2007). *The Economist* (6 December, 2007) is emphatic "Whatever the exact amount, this year's agflation' seems unlikely to be, as past rises have been, simply the upward side of a spike".

If this scenario prevails, the effects of costlier food will be felt everywhere but the impact is likely to be uneven. Let us first consider the macro effects.

- Net cereal exporters will benefit from improved terms of trade while net importers will face higher costs of food imports for meeting domestic cereal demand. As the number of net importers is four times that of net exporters of cereals, the losers are likely to predominate. China, for example, is a net importer of cereals while India is a net exporter. Almost all African countries are net importers (IFPRI, 2007).
- The share of food in consumer price indices varies in developing countries. For example, in China and other emerging markets, food is about 30 per cent of what consumers buy, and, in many low-income countries it is 50 per cent or more. This implies that conditional upon transmission mechanisms a given increase in global prices of corn, wheat, milk and meat will translate into higher inflation of varying rates in poorer countries. Inflation in food prices in emerging markets nearly doubled in 2007, to 11 per cent; meat and egg prices in China, for example, have gone up by about 50 per cent (although this is partly because of a sharp rise in pork prices due to a disease in pigs). Overall

inflation rose from 6 per cent in 2006 to 8 per cent in 2007 (Johnson, 2007, *The Economist*, 6 December, 2007)[11].

- In emerging markets, rural-urban disparities have widened as a consequence of diversification away from agriculture towards industry and services. In the process urban wages have outstripped rural wages. In China, for example, the Gini coefficient of income distribution rose from 0.41 in 1993 to 0.47 in 2004. A similar change is recorded for India (Sen and Himanshu, 2005).
- Global food aid is less than 7 per cent of global official development assistance and less than 0.4 per cent of total food production. Over the years food aid has declined. In 2006, for example, it was 40 per cent lower than in 2000 (WFP, 2007). Unavoidably, therefore, food aid is increasingly targeted to fewer countries-mainly in Sub-Saharan Africa-and to specific segments of the population (IFPRI, 2007).
- At the micro-level, whether a household benefits or loses from higher food prices depends on whether the household is a net seller or buyer of food. Since food accounts for a large share of household expenditure among low income households -agricultural and other labourers, and smallholders- a staple crop price increase translates into lower quantity and quality of food.[12] The impact, however, varies with the crop and the country. For example, two thirds of rural households in Java own between 0 and 0.25 hectares of land, and only 10 per cent of households would benefit from a higher rice price (IFPRI, 2007). A recent analysis of rural poverty in India also corroborates a strong positive

[11] In India, the retail price of rice went up by 15-25 per cent in 2007, and the edible oil price touched the Rs 100 mark per litre (*Business and Finance*, 13 January, 2008).

[12] A recent estimate of the share of food in the consumption basket of the rural poor in India is about 65 per cent (Deaton, 2008).

effect of rising food prices (Jha et al. 2007a). Another study (Jha et al. 2007b) confirms direct and indirect effects of food prices on rural populations through lower agricultural wages and reduction of calorie and micronutrient intake. Lower agricultural wages result in higher poverty and this effect is accentuated by lower nutritional status. It is further demonstrated that in rural labour market with efficiency wages and rationing of jobs, those with weak nutritional status are likely to have a lower probability of participation. Thus a food price shock is likely to perpetuate their poverty (Dasgupta, 1993).

So whether this bout of agflation-even if it persists for 5-10 years if not longer-is necessarily a *threat* to the poor and vulnerable sections or an *opportunity* for smallholders and others to secure better livelihoods warrants a careful analysis. The present study is part of a larger project designed to address this concern. What, however, must be emphasised is that the slew of measures undertaken by many emerging and poor developing countries is unlikely to help from a longer-term perspective except perhaps to buy time and a longer lease of life for present governments. Some illustrations are given below of the measures undertaken from this perspective. China, for example, has imposed several measures to curb inflation but with little effect. These include (i) large food producers must obtain government permission to raise prices, and merchants must report increases in retail prices; (ii) to make these requirements credible, it is emphasised that the government can roll back any price increases that are deemed “unreasonable”; (iii) there is a price freeze on cooking oil, airline tickets and electricity; and (iv) elsewhere restrictions have been put on food exports -in a dozen countries including India, Vietnam, Ukraine- there are export taxes or quantitative restrictions on their exports;.[13] (v) India is considering cutting import duties on edible oil, while Indonesia has subsidised cooking oil refiners and suspended a 10 per cent duty on imported soyabeans (*International Herald Tribune*, 21 January, 2008).

Some general remarks are in order. First, price subsidies or controls, and quantitative restrictions on imports and exports seldom work even as short-term palliatives. Subsidies to food producers may increase supplies but distort the allocation of resources, while subsidising retail prices lead to smuggling.[14] Income subsidies, on the other hand, avoid distortions associated with price subsidies but could affect adversely labour supply if expectations about their continuance persist. So there is little choice for governments other than higher investments in rural infrastructure, agricultural technology and market access, expansion of credit and insurance, and elimination of trade barriers (IFPRI, 2007, *The Economist*, 6 December, 2007).

Scheme

As stated earlier, the following analysis is part of a larger project on the impact of the surge in food and energy prices on agriculture and rural poverty. In focusing on the latter, our objective is to analyse both the effects on net buyers of food in rural areas as well as on the supply response of smallholders. While much of the analysis is based on global prices of food and oil, detailed applications are carried out for China and India to understand better the transmission of global prices to national prices, the food

[13] Argentina and Russia have done both (*The Economist*, 6 December, 2007).
[14] This is a problem for Malaysia, where cooking oil sells for much less than in neighbouring Singapore and Thailand (*International Herald Tribune*, 21 January, 2008).

supply responses and the income distributional effects (taking into account both income inequality and rural poverty).

The present analysis focuses on (i) food and oil price dynamics, taking into account the lagged effects of prices of specific food items (e.g. wheat, rice and maize) and oil, and rainfall; (ii) as there are direct and indirect effects of oil prices on food prices -the search for alternative sources of energy induced by strong crude oil prices (a case in point is surge in the demand for biofuels), rising maize/ corn prices, higher wheat and rice prices (through higher costs of oil-based fertilisers and transportation), and supply responses feeding into energy demand from various sources. So we analyse co-movements of these prices (using cointegration and vector autoregression methods). (ii) This is then supplemented by an analysis of Granger causality of these prices, both globally and for China and India. (iii) Impulse functions are computed to trace the effects of shocks to various food prices (say, the effect of a higher oil price on the price of maize, wheat and rice or of a higher maize price on wheat and rice prices). The methodology draws upon Johansen' method for cointegration analysis (Johansen ,1988, 1991; Johansen and Juselius, 1990) and Vector Autoregression (VAR) for monthly and annual time series data of agricultural commodity prices. The rest of the paper is organised as follows. The next section briefly describes the data and their sources. Section III gives an exposition of the econometric methodology used. The econometric results are discussed in Section IV. The final section offers concluding observations from a broad policy perspective.

II. Data

The present study draws upon the commodity price data series both at global and at country levels for India and China. The former is based on the IMF Primary Commodity Prices data compiled by the Commodities Unit of the Research Department of IMF.[15] Four monthly price data series from January 1980 to October 2007 are used: (i) maize (US$ per metric tonne), (ii) wheat (US$ per metric tonne), (iii) rice (5 percent broken milled white rice, Thailand nominal price quote, US$ per metric tonne), and (iv) oil (Crude Oil (petroleum), simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh, US$ per barrel). The latter is based on FAO-STAT and UNCTAD commodity price statistics.[16] Annual price data are compiled from these sources, and rainfall data from the Tynadall Climate Research Centre at University of East Anglia.

III. Econometric Methodology

We first apply unit-root and co-integration tests for both monthly and annual data series and then estimate a multi-variable vector autoregressive (VAR) model, whereby the determinants of agricultural commodity prices are analysed.

(1) Unit-root tests

First, in order to verify if the monthly data are stationary, we carry out the augmented Dickey-Fuller test whereby the differenced variable of price is regressed on its lag and some number of lagged differences of the variable with or without a constant or a

[15] The IMF commodity price data are available on http://www.imf.org/external/np/res/commod/index.asp (accessed on 27th November 2007).

[16] The new version of FAO-STAT data (from 1990 to 2005) is available on http://faostat.fao.org/site/570/DesktopDefault.aspx?PageID=570 and the old version (since 1966) is on http://faostat.fao.org/site/408/DesktopDefault.aspx?PageID=408 (both accessed on 27th November 2007).

trend term. Then, a variant of the augmented Dickey-Fuller test is performed in which the time-series is transformed via a Generalized Least Squares (GLS) regression based on Elliot, Rothenberg, and Stock (1996). The latter has significantly higher power than the previous versions of the augmented Dickey-Fuller test.

(2) Cointegration test

If time series have the same order of integration and if a linear combination of these time series exists that is stationary (integrated of order one), these series are referred to as cointegrated. Originally, Engle and Granger (1987) proposed a two-step procedure to estimate cointegration relations. However, as Engle-Granger procedure has some requirements[17] (e.g. a large sample, appropriate choice of independent and dependent variables, and a two-step estimator), the present study relies on an alternative method to test for cointegration based on a vector autoregressive (VAR) model proposed by Johansen (1988, 1991, and 1992) and Johansen and Juselius (1990). A brief summary of Johansen's cointegration test is given below.[18]

Consider a vector autoregression of order k, VAR(k),

$$X_t = \Pi_1 X_{t-1} + \ldots + \Pi_k X_{t-k} + \varepsilon_t \qquad \text{where } t = 1, \ldots, T \tag{1}$$

where the vector X_t contains endogenous stochastic variables and has dimension n × 1, where n is the number of endogenous variables. Each variable follows a process that is influenced by its own lagged variables and the lagged variables of the other endogenous variables. The matrix of coefficients Π_k has dimension n × n. Based on (1), the VAR can be transformed to a VAR of first differences. For this purpose, the lagged variables of the endogenous variables are subtracted from both sides.

[17] See Enders (1995), for example.
[18] This is based on Kuhl (2007).

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \qquad (2)$$

where $\Gamma_i = -I + \Pi_1 + ... + \Pi_i$ with $i = 1, ..., k-1$ and $\Pi = -(I - \Pi_1 - ... - \Pi_k)$. Here the matrices Γ_i contain information on the short-run adjustment coefficients of the lagged differenced variables. Additionally, the expression ΠX_{t-1} comprises the error correction term, *i.e.* it includes the long-run relationships between the time series.[19]

The Johansen procedure adopts the idea of determining the rank of matrix Π. In general, the rank of a matrix shows the number of linearly independent processes that is equivalent to the number of linearly independent columns. According to the definition, departing from the relevant case of I(1) variables in levels, both the differences of the endogenous variables and their lagged differences are stationary where the number of matrix is equivalent to the number of cointegration vectors. For this reason, a test for cointegration aims at testing the rank of Π. If the rank of matrix Π is greater than zero and less than the number of endogenous variables n, the matrix with dimension $p \times r$ can be decomposed into the matrices α and β, so that $\Pi = \alpha\beta'$. Using the cointegration vector, the non-stationary vector process X_t can be made stationary by generating linear combinations βX_t (Johansen, 1988, p. 232). In this case, the system in (2) becomes a vector error correction model and, in doing so, the matrix α describes the adjustment speed for each variable after a deviation from the long-run relationship. In other words, the elements in α weight the error correction term in each row of the VECM. Furthermore, the matrix β contains the coefficient of the cointegration relation, i.e. the weights within the linear combination. Subsequently, the VECM is a reduced form of the VAR in (1). Only the hypothesis of a restricted

[19] Stock and Watson (2001) provide a comprehensive review of VAR.

matrix Π is implemented. The cointegration rank can be tested by using the procedures outlined by Johansen (1988, 1991). On the basis of these considerations, the test statistics for the statistical significance of the rank of the matrix Π can be derived (Johansen, 1995, p. 89-95). The first test weights the hypotheses of, at most, r cointegration vectors, i.e. Rank(Π) = r, against the alternative of Rank(Π) >r, that is to say, there are r or more cointegration relations. According to Johansen (1988, 1991) this test is based on a likelihood ratio test and is called `*trace statistic*`.

$$\lambda_{trace} = -T\sum_{i=r+1}^{p}\ln\left(1-\hat{\lambda}_i\right) \qquad (3)$$

Additionally, Johansen proposes a second test to determine the cointegration rank. As in the case of the first test, it is based upon a likelihood ratio test but can differentiate more precisely between two alternatives, i.e. the ranks of matrix Π. This means, it is tested if there are exactly r cointegration relations or if there is just one more. Since this test departs from the eigenvalues that are arranged by their magnitude, the test is called 'maximum eigenvalue test'.

$$\lambda_{max} = -T\ln\left(1-\hat{\lambda}_{r+1}\right) \qquad (4)$$

Both test statistics are distributed asymptotically as χ^2 with p - r degrees of freedom (Johansen and Juselius, 1990, pp. 177-179; Johansen, 1991, pp. 1555-1556). As suggested by Johansen and Juselius (1990), both test statistics should be used simultaneously, although different conclusions can be drawn. In order to the cointegration vector, adjustment coefficients or eigenvalues, the Maximum Likelihood Procedure is used.

(3) Vector Autoregressions, Impulse Functions and Other Dynamic Issues

Here the focus is on inter-relationships among various cereal and non-cereal food prices, and oil prices at the global level, and for India and China.

A VAR makes minimal theoretical demands on the structure of a model. Two requirements are: (i) the variables (endogenous and exogenous) that are supposed to interact and should therefore be included as part of the economic system that we are trying to model; and (ii) the largest number of lags needed to capture most of the effects that the variables have on one another.[20] Letting $x_1, x_{2,} ....x_n$ be the endogenous variables and $z_1, z_2, ...z_m$ be the exogenous variables. A general form of the VAR is given below:

$$x_t = A_0 + A_1 x_{t-1} + ...A_p x_{t-p} + B_0 z_t + B_1 z_{t-1} + ...B_r z_{t-r} + \varepsilon_t \qquad (5)$$

where A_0 is an n x 1 vector of intercept terms, $A_1, ...A_p$ are n x n matrices of coefficients that relate lagged values of the endogenous variables to current values of those variables, $B_0, ...B_r$ are n x m matrices of coefficients that relate current and lagged values of exogenous variables to current values of the endogenous variables, and ε_t is an n x 1 vector of error terms. Here p is the number of lags for the endogenous variables and r is the number of lags for the exogenous varables. This model can be estimated by OLS (i) since there are no unlagged endogenous variables on the right hand side, and (ii) right side variables are the same in each case (in this case, OLS is a consistent and efficient estimator). As an extension, we will examine the interrelationships between each agricultural commodity price, annual rainfall, and

[20] The actual choice of number of lags is based on Schwarz Information Criteria (SIC).

oil price by including rainfall and oil price (with their lags) as additional exogenous variables.

The important issue here is whether we can apply VAR even if the variables are I(1) and they are cointegrated. Toda and Yamamoto (1995) show that, even if the processes is integrated or cointegrated of an arbitrary order, a lag-selection procedure by estimating (k+ d_{max})th-order VAR where k is determined as a lag length determined by Akaike Information Criteria (AIC) or Schwarz Information Criteria (SIC), for example, is feasible, and d_{max} is the maximal order of integration.[21]

IV. Econometric Results

(1) Unit-root tests

First, we plot the levels and first differences of monthly prices for maize, wheat, rice, and oil in Appendix 1. Prices of wheat (and its log) and oil (and its log) saw steep hikes after 2001, implying an upward trend. Hence, we try the augmented Dickey-Fuller test with or without a constant or a trend term. All the price series are I(1) or non-stationary and their first differences are I(0). Any pair of price series co-moves generally but the degree or the speed of each price responding to large positive or negative shocks varies over the years, as shown in the last six graphs.

Table 1 reports the results of unit root tests for monthly commodity prices from Jan 1980 to Oct 2007. Most of the price series are I(1) with a few exceptions (maize and log of maize for ADF test with intercept /without trend and for DF-GLS test with trend where the series is I(0)).

[21] Awokuse and Yang (2003) examines whether commodity prices provide useful information for formulating monetary policy by applying Toda and Yamamoto (1995) procedure.

Table 1 Unit Root Tests for World Monthly Commodity Prices (Jan 1980- Oct 2007)

	Augmented Dickey-Fuller (ADF) Test						DF-GLS Test			
	With trend & intercept		Without trend / with intercept		Without trend / without intercept		With trend		Without trend	
	Test Statistics [a, b]	Lags[c]	Test Statistics [a, d]	Lags[c]	Test Statistics [a, e]	Lags[c]	Test Statistics [a, f]	Lags[g]	Test Statistics [a, f]	Lags[g]
Level										
Maize	-2.923	6	-3.062 *	7	-0.256	6	-3.454 *	1	-3.331	1
log (Maize)	-3.106	1	-3.159 *	1	0.074	6	-3.365 *	1	-3.299	1
Wheat	-0.879	1	-0.753	1	0.64	1	-1.211	1	-1.064	1
log (Wheat)	-1.771	1	-1.69	1	0.506	1	-1.681	1	-1.621	1
Rice	-2.484	2	-2.712	2	-0.904	1	-2.29	1	-1.498	1
log (Rice)	-2.411	2	-2.62	2	-0.303	2	-2.296	1	-1.363	2
Oil	0.057	2	0.961	2	1.372	2	-0.212	1	0.003	1
log (Oil)	-1.577	2	-2.28	2	0.339	2	-1.297	1	-1.297	1
First Difference										
Maize	-8.194 **	5	-8.14 **	5	-8.149 **	5	-5.862 **	2	-2.41 *	6
log (Maize)	-7.919 **	5	-7.871 **	5	-7.882 **	5	-6.087 **	2	-3.947 **	2
Wheat	-13.564 **	0	-13.413 **	0	-13.397 **	0	-9.88 **	1	-8.748 **	1
log (Wheat)	-13.868 **	0	-13.774 **	0	-13.776 **	0	-10.548 **	1	-9.476 **	1
Rice	-12.287 **	1	-12.235 **	1	-12.25 **	1	-11.68 **	1	-11.27 **	1
log (Rice)	-12.617 **	1	-12.572 **	1	-12.589 **	1	-12.162 **	1	-11.946 **	1
Oil	-13.085 **	1	-12.705 **	1	-12.66 **	1	-12.024 **	1	-11.628 **	1
log (Oil)	-12.507 **	1	-12.36 **	1	-12.365 **	1	-12.202 **	1	-11.667 **	1

a. ** = significant at 1% level. * = significant at 5% level.
b. Critical Values: 1% -3.987, 5% -3.427. d. Critical Values: 1% -3.453, 5% -2.877. e. Critical Values: 1% -2.58, 5% -1.9
c. Lag length is determined by AIC (Akaike Information Criterion).
f. Critical Values are based on Elliot et al. (1996): With trend: 1% 3.48, 5% 2.89, Without trend: 1% 2.58, 5% 1.95.
g. Lag length is determined by LR test statistics.

(2) Cointegration Test

Table 2 reports the results of Johansen Cointegration Tests for World Monthly Commodity Prices from Jan 1980 to Oct 2007. As a general rule, we can conclude the pair of the price series is cointegrated if in the first row for each test we reject the null hypothesis that r = 0 against the alternative that r is at most 1 (i.e. the test statistic exceeds the critical values or it is significant) and, in the second, we do not reject the null hypothesis that r = 1 against the alternative that r is at most 2 (i.e. the test statistic does not exceed the critical value or it is not significant). In most cases, regardless of the specifications (with or without trend or constant) or of the statistic we use (trace statistic or the max-lambda statistic), the test statistic exceeds the critical value, which leads to the rejection of the null hypothesis that r = 0 against the alternative that r is at most 1. That is, in most cases, two sets of price series are cointegrated with a few exceptions where the hypothesis cannot be rejected for the pairs of 'wheat-rice', 'log(wheat)-log(oil)', 'rice-oil' and 'log(rice)-log(oil).

Moving on to testing the null hypothesis that r =1, in all the cases, regardless of the specification or the assumptions, the test statistic is smaller than the critical values and, as a result, we cannot reject the null hypothesis that there is 1 cointegrating vector.

Table 2 Johansen Cointegration Tests for World Monthly Commodity Prices (Jan 1980- Oct 2007)

T= 332		Lags[c]	H_0 : r <=	Model 1: [a, b] With Constant (in CE (Cointegration Equation)) λ_{trace}	λ_{max}	Model 2: [a, b] Without Constant λ_{trace}	λ_{max}	Model 3: [a, b] With Linear Trend in levels λ_{trace}	λ_{max}
Maize	Wheat	2	0	33.51 **	32.95 **	43.5 **	43.43 **	35.92 **	35.2 **
		2	1	0.57	0.57	0.07	0.07	0.73	0.73
log(Maize)	log(Wheat)	2	0	35.28 **	32.44 **	32.67 **	32.4 **	37.46 **	34.5 **
		2	1	2.84	2.84	0.27	0.27	2.96	2.96
Maize	Rice	2	0	35.28 **	32.44 **	32.67 **	32.4 **	32.46 **	34.5 **
		2	1	2.84	2.84	0.27	0.27	2.96	2.96
log(Maize)	log(Rice)	2	0	25.46 **	18.83 **	18.7 **	18.69 **	25.42 **	19.61 **
		2	1	6.63	6.63	0.002	0.002	5.82	5.82
Maize	Oil	2	0	18.66 **	17.65 **	11.72	10.24	18.08 **	18.23 **
		2	1	1.01	1.01	1.48	1.48	0.14	0.14
log(Maize)	log(Oil)	2	0	18.15 **	17.54 **	8.53	8.21	19.68 **	18.48 **
		2	1	0.6	0.6	0.32	0.32	1.21	1.21
Wheat	Rice	2	0	12.84	12.26	12.44	12.16 **	15.88	15.16
		2	1	0.58	0.58	0.28	0.28	0.72	0.72
log(Wheat)	log(Rice)	2	0	16.93 **	14.36 **	14.42 **	14.28 **	19.89 **	17.47 **
		2	1	2.57	2.57	0.13	0.13	2.42	2.45
Wheat	Oil	2	0	16.15 **	14.86 **	15.29 **	13.97 **	13.94	13.41
		2	1	1.3	1.3	1.32	1.32	0.53	0.53
log(Wheat)	log(Oil)	2	0	14.25	14.1 **	9.74	9.25	14.46	13.88
		2	1	0.15	0.15	0.49	0.49	0.58	0.58
Rice	Oil	2	0	10.4	9.98	6.5	5.16	10.78	10.78
		2	1	0.42	0.42	1.33	1.33	0.002	0.002
log(Rice)	log(Oil)	2	0	11.67	10.44	4.77	4.72	13.8	11.94
		2	1	1.23	1.23	0.04	0.04	1.86	1.86

a. ** = significant at 1% level. * = significant at 5% level.
b. Critical Vaues are based on Johansen and Juselius (1990).
c. Lag length is determined by LR test statistics.

Table 3 reports the unit root tests for annual price variables where P denotes price. D denotes first differences. For simplicity, only DF-GLS tests are tried for logarithm of annual prices and (untransformed) annual prices. Most of the variables are I(1) but with a few exceptions. In the world agricultural commodity price series, wheat, rice, fruit, vegetable, and crude oil are I(1). Price of maize is I(1) in the case without trend, but cannot be confirmed as I(0), I(1) or I(2) in the case with trend, as the test statistic is not significant for its level, and the first and second differences. Oilseeds are not available at the global level. For India, all the price series are I(1) except the maize price, which is I(0). The wheat price is I(1) in case with trend and its order of integration cannot be confirmed in case without trend. For China, all the agricultural commodity prices are I(1).

Table 3 Unit Root Tests for Annual Variables (World, India, and China: 1966- 2005)

	World (Annual)								India (Annual)								China (Annual)							
	DF-GLS Test								DF-GLS Test								DF-GLS Test							
	With Trend				Without Trend				With Trend				Without Trend				With Trend				Without Trend			
	Test Statistics [a, b]		Lags [c]		Test Statistics [a, b]		Lags [c]		Test Statistics [a, b]		Lags [c]		Test Statistics [a, b]		Lags [c]		Test Statistics [a, b]		Lags [c]		Test Statistics [a, b]		Lags [c]	
I. Price -Levels																								
log (P_Wheat)	-3.022		1	I(1)	-1.781		1	I(1)	-2.631		1	I(1)	-1.143		2	NA	-2.121		1	I(1)	-1.803		1	I(1)
log (P_Maize)	-1.964		1	NA	-1.771		1	I(1)	-3.339	*	1	I(0)	-3.753	**	1	I(0)	-1.356		1	I(1)	-1.183		1	I(1)
log (P_Rice)	-3.463	*	1	I(0)	-2.841	*	1	I(0)	-1.724		1	I(1)	-1.371		1	I(1)	-1.617		1	I(1)	-1.148		1	I(1)
log (P_Fruit)	-1.912		1	I(1)	-0.271		1	I(1)	-2.229		1	I(1)	-0.157		1	I(1)	-1.452		1	I(1)	-0.873		1	I(1)
log (P_Vegetable)	-2.919		1	I(1)	-1.164		2	I(1)	-1.570		1	I(1)	-0.281		1	I(1)	-1.532		1	I(1)	-0.959		1	I(1)
log (P_Oilseeds)	-								-1.962		1	I(1)	-1.712		1	I(1)	-1.544		1	I(1)	-0.997		1	I(1)
log (P_Oil)	-1.800		1	I(1)	-0.456		1	I(1)	-								-							
Price- First Differences																								
Dlog (P_Wheat)	-6.886	**	1		-6.806	**	1		-5.633	**	1		-0.632		6		-3.800	**	1		-3.744	**	1	
Dlog (P_Maize)	-2.557		1		-2.492	**	1		-5.476	**	1		-2.424	*	2		-4.328	**	1		-4.211	**	1	
Dlog (P_Rice)	-5.982	**	1		-4.786	**	1		-5.809	**	1		-5.413	**	1		-4.508	**	1		-4.336	**	0	
Dlog (P_Fruit)	-5.078	**	1		-5.599	**	1		-3.287	*	1		-2.231	*	1		-4.463	**	1		-3.987	**	1	
Dlog (P_Vegetable)	-8.211	**	1		-7.739	**	1		-3.509	*	1		-3.294	*	1		-4.304	**	1		-4.197	**	1	
Dlog (P_Oilseeds)	-								-4.229	**	1		-3.777	**	1		-4.138	**	1		-4.079	**	1	
Dlog (P_Oil)	-4.071	**	1		-4.129	**	1		-								-							
Dlog (Rainfall)	-5.535	**	1		-4.129	**	1		-5.338	**	1		-3.492	**	1		-4.265	**	1		-2.879		1	

[a.] ** = significant at 1% level. * = significant at 5% level.

[b.] Critical Values are based on Elliot et al. (1996): With trend: 1% 3.48, 5% 2.89, Without trend: 1% 2.58, 5% 1.95.

[c.] Lag length is determined by LR test statistics.

Tables 4, 5 and 6 present pairwise Johansen Cointegration Tests for global annual prices, and for India and China. Recall that a pair of price series is cointegrated if in the first row the the null hypothesis that r = 0 is rejected, against the alternative that r is at most 1 (i.e. the test statistic is significant), and the second does not reject the null hypothesis that r = 1, against the alternative that r is at most 2 (i.e. the test statistic is not significant). In Table 4, for most world commodity prices, the test statistic exceeds the critical values, implying the rejection of no cointegrating relationship. That is, two sets of price series are cointegrated. For Model 2 without a constant, all the pairs are cointegrated. There are a few exceptions where the null hypothesis cannot be rejected in the results based on Model 1 (with a constant in cointegration equation) and Model 3 (with a linear trend in levels), that is, the pairs of 'wheat-oil' (Model 1), 'maize-oil' (Model 2), 'rice-oil' (Model 1, only for λ_{trace}), 'fruit-oil' (Models 1 and 3), 'fruit-rainfall' (Model 3), and 'vegetable-rainfall' (Model 3).

In Table 5, pairwise cointegration tests of annual commodity prices in India confirm that most of the pairs are cointegrated. Model 2 without a constant suggests that all the pairs are cointegrated. Several exceptions are found, however, in the first and the last columns (for Model 1 with a constant in cointegration equation and Model 3 with a linear trend in levels): 'wheat-fruit' (Model 1), 'maize-fruit' (Models 1 and 3), 'maize-vegetable' (Model 1), 'wheat-fruit' (Model 1), 'wheat-rainfall' (Model 3, only for λ_{trace}), 'rice-oil' (Model 1, only for λ_{trace}), 'fruit-oil' (Models 1 and 3), and 'fruit-rainfall' (Model 3).

Table 4 Johansen Cointegration Tests for World Annual Price Variables (1966- 2005)

World (Annual)

		H_0 : r <=	Model 1: [a, b]	With Constant (in CE (Cointegration Equation))				Model 2: [a, b]	Without Constant				Model 3: [a, b]	With Linear Trend in levels			
			Lags[c]	λ_{trace}		λ_{max}		Lags[c]	λ_{trace}		λ_{max}		Lags[c]	λ_{trace}		λ_{max}	
Pairwise Cointegration Tests for Commodity Prices																	
log(P_Wheat)	log(P_Maize)	0	1	23.95		24.15	**	1	59.26	**	59.26	**	1	23.55	**	23.72	**
		1	1	0.21		0.21		1	0.00004		0.00004		1	0.17		0.17	
log(P_Wheat)	log(P_Rice)	0	1	17.41	**	17.97	**	1	52.37	**	52.5	**	1	29.12	**	29.64	**
		1	1	0.57		0.57		1	0.13		0.13		1	0.52		0.52	
log(P_Wheat)	log(P_Fruit)	0	2	17.03	**	19.57	**	1	109.12	**	109.36	**	2	18.65	**	22.89	**
		1	2	2.54	**	2.54	**	1	0.24		0.24		2	4.24		4.24	
log(P_Wheat)	log(P_Vegetable)	0	2	33.08	**	33.88	**	1	76.81	**	76.81	**	1	31.5	**	32.39	**
		1	2	0.81		0.81		1	0.003		0.003		1	0.89		0.89	
log(P_Wheat)	log(P_Oil)	0	1	9.56		10.58		1	25.29	**	25.33	**	1	14.2		15.12	
		1	1	1.01		1.01		1	0.04		0.04		1	0.92		0.92	
log(P_Wheat)	log(Rainfall)	0	3	24.33	**	35.93	**	1	62.96	**	63.2	**	6	11.04		18.56	
		1	3	11.6	**	11.6	**	1	0.24		0.24		6	7.52	**	7.52	**
log(P_Maize)	log(P_Rice)	0	2	14.77	**	18.52	**	1	43.21	**	43.23	**	1	19.11	**	20.3	**
		1	2	3.75		3.75		1	0.01		0.01		1	1.19		1.19	
log(P_Maize)	log(P_Fruit)	0	5	14.77	**	63.66	**	1	54.49	**	54.54	**	1	11.52	**	16.63	**
		1	5	11.17		11.17		1	0.05		0.05		1	5.11		5.11	
log(P_Maize)	log(P_Oil)	0	1	14.11	**	18	**	1	32.63	**	32.71	**	4	13.26		13.36	
		1	1	3.89		3.89		1	0.08		0.08		4	0.095		0.095	
log(P_Maize)	log(Rainfall)	0	3	24.33	**	35.93	**	1	62.96	**	63.2	**	6	11.04		18.56	**
		1	3	11.6	**	11.6	**	1	0.24		0.24		6	7.52	**	7.52	**
log(P_Maize)	log(P_Vegetable)	0	1	16.97	**	18.48	**	1	61.82	**	61.83	**	5	43.72	**	49.57	**
		1	1	1.5		1.5		1	0.007		0.007		5	5.85	*	5.85	*

Table 4 Johansen Cointegration Tests for World Annual Price Variables (1966- 2005) (Cont.)

		H_0 : r <=	Model 1: [a, b] With Constant (in CE (Cointegration Equation)) Lags[c]					Model 2: [a, b] Without Constant Lags[c]					Model 3: [a, b] With Linear Trend in levels Lags[c]				
				λ_{trace}		λ_{max}			λ_{trace}		λ_{max}			λ_{trace}		λ_{max}	
log(P_Rice)	log(P_Fruit)	0	2	17	**	18.92	**	1	73.73	**	73.73	**	2	22.51	**	26.55	**
		1	2	1.92		1.92		1	0.0009		0.0009		2	4.04		4.04	
log(P_Rice)	log(P_Vegetable)	0	1	21.25	**	22.22	**	1	18.32	**	18.32	**	1	22.51	**	26.41	**
		1	1	0.96		0.96		1	0.0013		0.0013		1	4.04		4.04	
log(P_rice)	log(P_Oil)	0	2	13.99		16.84	**	1	15.33	**	15.34	**	5	20.9	**	26.23	**
		1	2	2.85		2.85		1	0.008		0.008		5	5.33	**	5.33	**
log(P_rice)	log(Rainfall)	0	3	24.12	**	35.52	**	1	40.15	**	40.19	**	6	20.39	**	26.71	**
		1	3	11.4	**	11.4	**	1	0.04		0.04		6	6.31	**	6.31	**
log(P_Fruit)	log(P_Vegetable)	0	2	15.27	**	18.42	**	1	91.96	**	91.24	**	2	17.77	**	21.74	**
		1	2	3.15		3.15		1	0.28		0.28		2	3.98	**	3.98	**
log(P_fruit)	log(P_Oil)	0	3	6.85		9.63		1	52.92	**	53	**	1	11.59		13.43	
		1	3	2.78		2.78		1	0.08		0.08		1	1.84		1.84	
log(P_fruit)	log(Rainfall)	0	6	13.14	**	17.65	**	1	71.2	**	71.4	**	6	8.97		13.2	
		1	6	4.51	**	4.51	**	1	0.18		0.18		6	4.23		4.23	**
log(P_vegetable)	log(P_Oil)	0	1	11.92	**	13.61	**	1	20.1	**	20.14	**	1	15.05		16.68	
		1	1	1.68		1.68		1	0.04		0.04		1	1.63		1.63	
log(P_vegetable)	log(Rainfall)	0	3	18.5	**	26.02	**	1	46.98	**	47.01	**	6	11.88		14.72	
		1	3	7.52	**	7.52	**	1	0.03		0.03		6	2.85		2.84	

a. ** = significant at 1% level. * = significant at 5% level.
b. Critical Vaues are based on Johansen and Juselius (1990).
c. Lag length is determined by LR test statistics.

Table 5 Johansen Cointegration Tests for Indian Annual Price Variables (1966- 2005)

India (Annual)

		H_0 : r <=	Model 1: [a, b] With Constant (in CE (Cointegration Equation)) Lags[c]					Model 2: [a, b] Without Constant Lags[c]					Model 3: [a, b] With Linear Trend in levels Lags[c]				
				λ_{trace}		λ_{max}			λ_{trace}		λ_{max}			λ_{trace}		λ_{max}	
Pairwise Cointegration Tests for Commodity Prices																	
log(P_Wheat)	log(P_Maize)	0	1	40.79	**	41.78	**	1	122.32	**	122.45	**	1	45.96	**	46.92	**
		1	1	0.99		0.99		1	0.12		0.12		1	0.96		0.96	
log(P_Wheat)	log(P_Rice)	0	1	18.37	**	18.65	**	1	78.48	**	78.48	**	1	25.43	**	25.88	**
		1	1	0.28		0.28		1	0.00009		0.00009		1	0.45		0.45	
log(P_Wheat)	log(P_Fruit)	0	1	11.33		11.46		1	125.31	**	125.38	**	1	17.74	**	20.62	**
		1	1	0.13		0.13		1	0.07		0.07		1	2.89		2.89	
log(P_Wheat)	log(P_Vegetable)	0	1	21.85	**	23.45	**	1	41.42	**	41.52	**	1	28.27	**	29.96	**
		1	1	1.6		1.6		1	0.1		0.1		1	1.69		1.69	
log(P_Wheat)	log(P_Oil)	0	1	14.77	**	16.08	**	1	19.1	**	19.14	**	1	24.72	**	26.01	*
		1	1	1.31		1.31		1	0.04		0.04		1	1.28		1.28	
log(P_Wheat)	log(Rainfall)	0	3	24.33	**	35.93	**	1	62.96	**	63.2	**	6	11.04		18.56	**
		1	3	11.6	**	11.6	**	1	0.24		0.24		6	7.52	**	7.52	**
log(P_Maize)	log(P_Rice)	0	1	34.38	**	35.24	**	1	82.71	**	82.78	**	1	38.17	**	39	**
		1	1	0.85		0.86		1	0.08		0.08		1	0.83		0.83	
log(P_Maize)	log(P_Fruit)	0	1	8.09		8.19		1	112.13	**	112.44	**	1	14.87		16.83	
		1	1	0.1		0.99		1	0.3		0.31		1	1.97		1.97	
log(P_Maize)	log(P_Vegetable)	0	1	11.6		13.64		1	39.27	**	39.27	**	3	28.95	**	33.82	**
		1	1	2.04		2.04		1	0.0002		0.0002		3	4.87		4.87	**
log(P_Maize)	log(P_Oil)	0	1	15.99	**	17.72	**	1	15.31	**	15.31	**	2	20.93	**	24.59	**
		1	1	1.73		1.73		1	0.002		0.002		2	3.66		3.66	
log(P_Maize)	log(Rainfall)	0	6	13.77	**	20.27	**	6	9.8	**	9.9	**	6	16.91	**	24.23	**
		1	6	6.5		6.5		6	0.099		0.099		6	7.32	**	7.32	**

Table 5 Johansen Cointegration Tests for Indian Annual Price Variables (1966- 2005) (Cont.)

		H_0 : r <=	Model 1: [a, b]					Model 2: [a, b]					Model 3: [a, b]				
				With Constant (in CE (Cointegration Equation))					Without Constant					With Linear Trend in levels			
			Lags[c]	λ_{trace}		λ_{max}		Lags[c]	λ_{trace}		λ_{max}		Lags[c]	λ_{trace}		λ_{max}	
log(P_Rice)	log(P_Fruit)	0	2	17	**	18.92	**	1	73.73	**	73.73	**	2	22.51	**	26.55	**
		1	2	1.92		1.92		1	0.0009		0.0009		2	4.04		4.04	
log(P_Rice)	log(P_Vegetable)	0	1	21.25	**	22.22	**	1	18.32	**	18.32	**	1	22.51	**	26.41	**
		1	1	0.96		0.96		1	0.0013		0.0013		1	4.04		4.04	
log(P_rice)	log(P_Oil)	0	2	13.99		16.84	**	1	15.33	**	15.34	**	5	20.9	**	26.23	**
		1	2	2.85		2.85		1	0.008		0.008		5	5.33	**	5.33	**
log(P_rice)	log(Rainfall)	0	3	24.12	**	35.52	**	1	40.15	**	40.19	**	6	20.39	**	26.71	**
		1	3	11.4	**	11.4	**	1	0.04		0.04		6	6.31	**	6.31	**
log(P_Fruit)	log(P_Vegetable)	0	2	15.27	**	18.42	**	1	91.96	**	91.24	**	2	17.77	**	21.74	**
		1	2	3.15		3.15		1	0.28		0.28		2	3.98	**	3.98	**
log(P_fruit)	log(P_Oil)	0	3	6.85		9.63		1	52.92	**	53	**	1	11.59		13.43	
		1	3	2.78		2.78		1	0.08		0.08		1	1.84		1.84	
log(P_fruit)	log(Rainfall)	0	6	13.14	**	17.65	**	1	71.2	**	71.4	**	6	8.97		13.2	
		1	6	4.51	**	4.51	**	1	0.18		0.18		6	4.23		4.23	**
log(P_vegetable)	log(P_Oil)	0	1	11.92	**	13.61	**	1	20.1	**	20.14	**	1	15.05		16.68	
		1	1	1.68		1.68		1	0.04		0.04		1	1.63		1.63	
log(P_vegetable)	log(Rainfall)	0	3	18.5	**	26.02	**	1	46.98	**	47.01	**	6	11.88		14.72	
		1	3	7.52	**	7.52	**	1	0.03		0.03		6	2.85		2.84	

a. ** = significant at 1% level. * = significant at 5% level.
b. Critical Vaues are based on Johansen and Juselius (1990).
c. Lag length is determined by LR test statistics.

Table 6 Johansen Cointegration Tests for Chinese Annual Price Variables (1970- 2000)

China
(Annual)

			Model 1:[a, b]					Model 2:[a, b]					Model 3:[a, b]				
		H_0 :	With Constant					Without Constant					With Linear Trend				
		r <=	Lags[c]	(in CE (Cointegration Equation))				Lags[c]					Lags[c]	in levels			
				λ_{trace}		λ_{max}			λ_{trace}		λ_{max}			λ_{trace}		λ_{max}	
Pairwise Cointegration Tests for Commodity Prices																	
log(P_Wheat)	log(P_Maize)	0	6	13.83		14.91		1	3.95		3.97		1	10.53		12.91	
		1	6	1.08		1.08		1	0.016		0.016		1	2.4		2.4	
log(P_Wheat)	log(P_Rice)	0	6	13.00		13.56		1	10.72		10.73		1	8.9		10.91	**
		1	6	0.56		0.56		1	0.02		0.02		1	2.02		2.02	
log(P_Wheat)	log(P_Fruit)	0	6	12.55		12.94		1	12.06	**	12.08		1	8.5		10.91	
		1	6	0.38		0.38		1	0.01		0.01		1	2.4		2.4	
log(P_Wheat)	log(P_Vegetable)	0	6	13.52		14		1	15.26		15.27		1	9.97		11.17	
		1	6	0.47		0.47		1	0.009		0.009		1	1.66		1.7	
log(P_Wheat)	log(P_Oil)	0	1	6.75		7.85		1	25.78	**	25.88	**	1	13.41		14.68	
		1	1	1.10		1.1		1	0.1		0.1		1	1.27		1.27	
log(P_Wheat)	log(Rainfall)	0	6	21.00	**	26.25	**	1	26.63	**	26.64	**	3	21.15	**	26.83	**
		1	6	5.25	**	5.25	**	1	0.014		0.014		3	5.68	**	5.68	**
log(P_Maize)	log(P_Rice)	0	3	101.61		102.31	**	1	51.38	**	51.82	**	1	107.03	**	35.28	**
		1	3	0.71		0.71		1	0.44		0.44		1	7.22		0.1	
log(P_Maize)	log(P_Fruit)	0	3	46.43	**	46.96	**	1	43.09	**	43.21	**	1	36.08	**	36.12	**
		1	3	0.47		0.47		1	0.12		0.12		1	0.05		0.05	
log(P_Maize)	log(P_Vegetable)	0	3	62.39	**	63.23	**	1	49.79	**	50.02		1	34.09		34.09	**
		1	3	0.84		0.84		1	0.23		0.23		1	0.0002		0.0002	
log(P_Maize)	log(P_Oil)	0	1	5.64		6.64		1	11.36		11.46		1	14.17		15.64	
		1	1	1.00		1		1	0.11		0.11		1	1.47		1.47	
log(P_Maize)	log(Rainfall)	0	2	13.74		14.32		1	12.64	**	12.64	**	3	17.98	**	21.82	**
		1	2	0.58		0.58		1	0.014		0.014		3	5.68	*	5.68	*

Table 6 Johansen Cointegration Tests for Chinese Annual Price Variables (1970- 2000) (Cont.)

			Model 1: [a, b] With Constant (in CE (Cointegration Equation))					Model 2: [a, b] Without Constant					Model 3: [a, b] With Linear Trend in levels				
		H_0 : r <=	Lags[c]	λ_{trace}		λ_{max}		Lags[c]	λ_{trace}		λ_{max}		Lags[c]	λ_{trace}		λ_{max}	
Pairwise Cointegration Tests for Commodity Prices & Other Variables																	
log(P_Rice)	log(P_Fruit)	0	1	25.49	**	25.57	**	1	35.88	**	35.88	**	1	43.11	**	43.28	**
		1	1	0.09		0.09		1	3E-05		3E-05		1	0.16		0.16	
log(P_Rice)	log(P_Vegetable)	0	1	26.64	**	26.64	**	1	60.83	**	60.83	**	1	38.15	**	38.16	**
		1	1	0.00		0.0009		1	0.13		0.13		1	0.008		0.008	
log(P_rice)	log(P_Oil)	0	6	17.07	**	17.36	**	1	20.27	**	20.5	**	5	17.06	**	22.48	**
		1	6	0.22		0.29		1	0.02		0.23		5	5.43	**	5.43	**
log(P_rice)	log(Rainfall)	0	2	13.77		14.32	**	1	13.63	**	13.63	**	3	17.93	**	21.46	**
		1	2	0.55		0.55		1	0.0014		0.0014		3	3.53		3.53	
log(P_Fruit)	log(P_Vegetable)	0	1	31.50	**	31.74	**	1	36.19	**	36.19	**	1	38.22	**	38.23	**
		1	1	0.24		0.24		1	0.0007		7E-05		1	0.008		0.008	
log(P_fruit)	log(P_Oil)	0	1	3.65		4.08		1	20.56	**	20.89	**	5	18.91	**	25.02	**
		1	1	0.43		0.43		1	0.34		0.34		5	6.12	**	6.12	**
log(P_fruit)	log(Rainfall)	0	6	32.15	**	33.45	**	1	12.85	**	12.85	**	3	17.09	**	20.53	**
		1	6	1.30		1.30		1	0.0018		0.0018		3	3.45		3.45	
log(P_vegetable)	log(P_Oil)	0	6	18.71	**	19.07	**	1	25.28	**	25.55	**	1	14.23		14.23	
		1	6	0.35		0.35		1	0.27		0.27		1	1.22		1.22	
log(P_vegetable)	log(Rainfall)	0	3	13.74		14.30	**	1	14.00	**	14.00	**	3	20.98	**	17.07	**
		1	3	0.56		0.56		1	0.0017		0.0017		3	3.92	**	3.92	**

a. ** = significant at 1% level. * = significant at 5% level.
b. Critical Vaues are based on Johansen and Juselius (1990).
c. Lag length is determined by LR test statistics.

Table 6 reports the results of cointegration tests for China. It seems difficult to determine whether the pairwise relationship between wheat price and other series are integrated except in the case of wheat and rainfall. Maize and other series are cointegrated in all cases except ‘maize-wheat’ and ‘maize-oil’. Otherwise, most of the pairwise cointegration tests confirm cointegration relationships except ‘fruit-oil’ in Model 1.

In sum, a general conclusion is that whatever pairs of food and oil prices are considered -global, Indian and Chinese or just monthly global prices- there is robust evidence of cointegration (with a few exceptions).

(3) Vector Autoregression (VAR)

Here, instead of pairs of prices, the focus is on Vector Autoregressions (VAR), designed to analyse simultaneously the interrelationships among prices of different agricultural commodities, rainfall and oil prices at the global level, and India and China. The results are presented several tables and graphs: of various agricultural commodity prices for the World, India and China (Tables 7-13 and Figures 1-7 for the World, Tables 14-20 and Figures 8-14 for India, and Tables 21-27 and Figures 15-21 for China). Also shown are the results of Granger Causality tests and Impulse Response Functions.

VAR for World Agricultural Commodity Prices

Table 7 shows the results of VAR applied to World monthly agricultural commodity prices. The lag length is determined as 3, $k + d_{max}$, where k, a lag length determined by Schwarz Information Criteria (SIC), is 2 and d_{max} , the maximal order of integration, is 1 (Toda and Yamamoto, 1995). We are interested in the significance of the off-diagonal coefficient estimates that capture the inter-relationships among these prices. Granger causality tests are also carried out to examine the causality among them, and the results are given at the bottom of Table 7. Figure 1 shows impulse responses which trace the response of current and future values of each of the variables to a one-unit increase in the current value of one of the VAR errors, assuming that this error returns to zero in subsequent periods and that all other errors are equal to zero (Stock and Watson, 2001). For example, the first row of graphs in Figure 1 shows the effect of an unexpected 1 percentage point increase in log(maize price) (or an impulse variable) on other variables (or response variables).

To avoid cluttering the text, we summarise the key results as follows.

(i) There is a strong link between monthly wheat and maize prices. The former Granger causes and *vice versa*. The Granger causality tests, however, suggest that the causality from wheat to maize is stronger than that from maize to wheat in terms of statistical significance.

(ii) Monthly rice price Granger causes monthly crude oil price, but not *vice versa*.

(iii) Monthly crude oil price Granger causes monthly wheat price, but not *vice versa*.

(iv) Impulse response function shows that an unexpected increase in monthly oil price has a positive effect on monthly wheat price (and the positive effect is gradually increasing over time). It also implies that wheat price has positive effects on maize and rice prices (and the positive effect is gradually increasing over time).

Table 7 Vector Autoregression (VAR) for Monthly World Commodity Prices (Jan 1980- Oct 2007)

	Dependent Variables											
	log(maize)			log(wheat)			log(rice)			log(oil)		
	Coef.	z value		Coef.	z value		Coef.	z value		Coef.	z value	
log(maize)												
L1	1.18	(19.44)	**	-0.03	(-0.59)		-0.03	(-0.49)		-0.14	(-1.47)	
L2	-0.36	(-3.87)	*	-0.09	(-1.06)		0.08	(0.88)		0.17	(1.17)	
L3	0.06	(0.94)		0.12	(2.09)	*	-0.05	(-0.89)		-0.05	(-0.54)	
log(wheat)												
L1	0.05	(0.86)		1.23	(20.44)	**	0.08	(1.17)		0.01	(0.11)	
L2	0.16	(1.58)		-0.17	(-1.78)	*	-0.01	(-0.07)		-0.16	(-1.07)	
L3	-0.13	(-1.97)	*	-0.10	(-1.64)		-0.04	(-0.64)		0.21	(2.06)	
log(rice)												
L1	0.06	(1.12)		0.03	(0.51)		1.28	(23.45)	**	-0.26	(-3.24)	**
L2	-0.01	(-0.08)		0.07	(0.91)		-0.45	(-5.26)	**	0.36	(2.82)	**
L3	-0.03	(-0.63)		-0.08	(-1.52)		0.13	(2.33)	*	-0.12	(-1.41)	
log(oil)												
L1	-0.05	(-1.46)		-0.01	(-0.40)		-0.02	(-0.67)		1.27	(23.43)	**
L2	0.07	(1.31)		0.07	(1.38)		0.06	(1.03)		-0.40	(-4.69)	**
L3	-0.01	(-0.39)		-0.04	(-1.19)		-0.03	(-0.86)		0.11	(2.06)	*
Constant	0.04	(0.57)		0.10	(1.42)		0.11	(1.34)		-0.06	(-0.52)	
Obs	331			331			331			331		
RMSE	0.05			0.05			0.05			0.08		
R-sq	0.94			0.95			0.96			0.97		
chi^2	5309.76			5808.5			7555.15			11193.17		
P> chi^2	0.00			0.00			0.00			0.00		

** = significant at 1% level. * = significant at 5% level.

Granger causality	Wald tests			
Equation	Excluded	chi2	df	Prob > chi2

log(P_Maize)	log(P_Wheat)	19.4785	**	3	0.0002
log(P_Maize)	log(P_rice)	3.7865		3	0.2855
log(P_Maize)	log(P_Oil)	3.4569		3	0.3264
log(P_Maize)	ALL	36.3412	**	9	0
log(P_Wheat)	log(P_Maize)	6.4326	+	3	0.0924
log(P_Wheat)	log(P_Rice)	6.0467		3	0.1094
log(P_Wheat)	log(P_Oil)	10.6121	*	3	0.014
log(P_Wheat)	ALL	23.1797	**	9	0.0058
log(P_Rice)	log(P_Maize)	0.8826		3	0.8296
log(P_Rice)	log(P_Wheat)	3.4853		3	0.3227
log(P_Rice)	log(P_Oil)	1.3304		3	0.7219
log(P_Rice)	ALL	8.7689		9	0.4589
log(P_Oil)	log(P_Maize)	2.1597		3	0.5399
log(P_Oil)	log(P_Wheat)	5.3753		3	0.1463
log(P_Oil)	log(P_Rice)	10.7467	*	3	0.0132
log(P_Oil)	ALL	21.3794	*	9	0.0111

Figure 1 Impulse Response Function for Monthly World Commodity Prices (Jan 1980- Oct 2007)

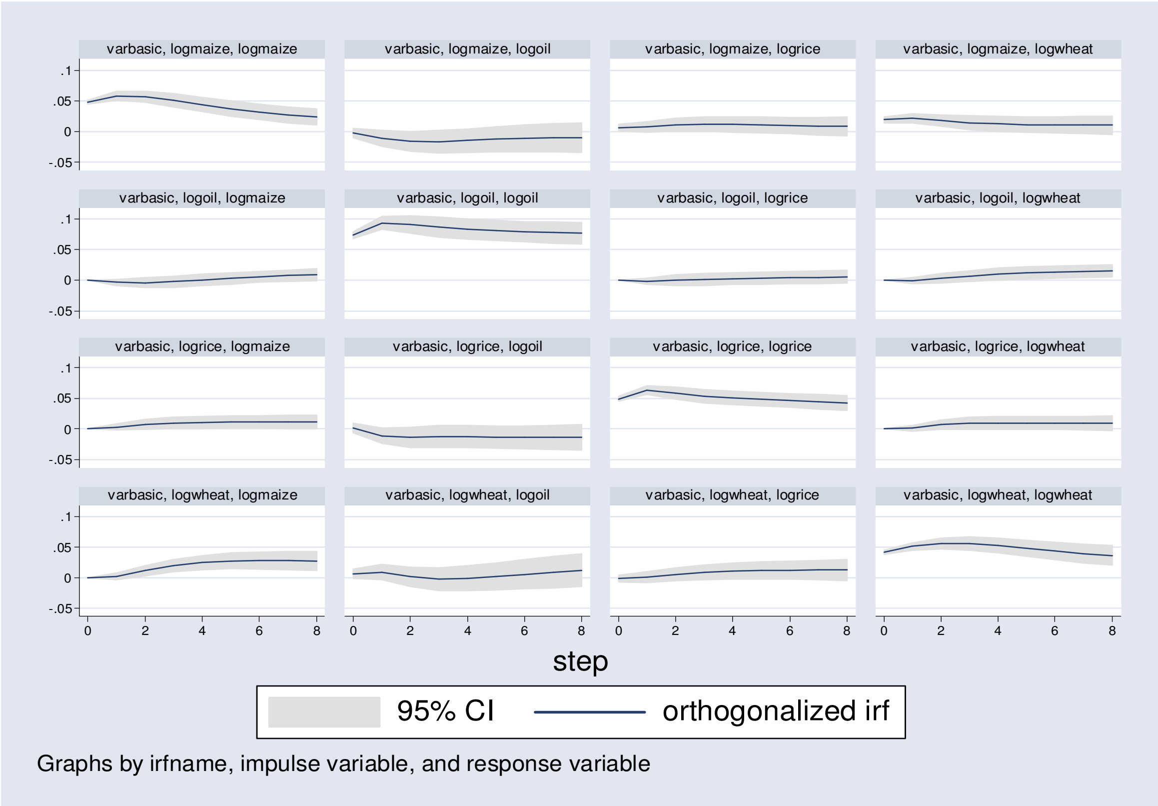


Table 8 shows the results of VAR for the interrelationships among annual World commodity prices. The lag length is determined as 2, k + d_{max} where k, a lag length determined by SIC, is 1 and d_{max} , the maximal order of integration, is 1. The lag length is taken as 2 in other cases, as SIC shows that the optimal lag length is 1 and the maximal order of integration is 1 in most cases.

Table 8 and Figure 2 show that:

(i) Annual oil price Granger causes annual fruit price, but *not* vice versa. This is consistent with the positive and significant coefficient estimate of the first lagged oil price on fruit price in the VAR results.

(ii) Annual wheat price Granger causes annual vegetable price, but *not* vice versa, which is consistent with the positive and significant coefficient estimate of the first lagged wheat price on vegetable price in the results of VAR. The impulse response function is S shaped where the positive effect of unexpected increase in wheat price on vegetable price gradually fades away.

(iii) Annual wheat price Granger causes annual oil price, but *not* vice versa. The impulse response function shows that the sharp increase in the positive effect of wheat price on oil price gradually fades away.

Table 8 Vector Autoregression (VAR) for Annual World Commodity Prices (1966- 2005)

	log(P_Wheat)			log(P_Rice)			log(P_Fruit)			log(P_vegetable)			log(P_Oil)		
	Coef.	z value		Coef.	z value		Coef.	z value		Coef.	z value		Coef.	z value	
log(P_Wheat)															
L1	0.91	(4.19)	**	0.32	(1.08)		0.12	(0.75)		0.50	(1.85)	+	0.35	(1.18)	
L2	-0.46	(-2.00)	*	0.10	(0.33)		0.04	(0.22)		0.20	(0.70)		-0.65	(-2.12)	*
log(P_Rice)															
L1	0.05	(0.30)		0.77	(3.59)	**	0.02	(0.20)		-0.13	(-0.64)		0.07	(0.31)	
L2	-0.19	(-1.19)		-0.55	(-2.60)	*	-0.09	(-0.80)		-0.11	(-0.54)		-0.04	(-0.19)	
log(P_fruit)															
L1	0.28	(1.38)		0.01	(0.05)		0.64	(4.46)	**	0.04	(0.14)		0.06	(0.22)	
L2	-0.09	(-0.51)		-0.15	(-0.60)		0.22	(1.72)	+	-0.16	(-0.70)		-0.08	(-0.33)	
log(P_vegetable)															
L1	0.18	(1.11)		-0.01	(-0.06)		-0.10	(-0.84)		0.66	(3.26)	**	0.30	(1.35)	
L2	0.06	(0.35)		0.04	(0.19)		0.15	(1.33)		-0.44	(-2.21)	*	0.15	(0.72)	
log(P_Oil)															
L1	0.05	(0.44)		0.06	(0.34)		0.29	(3.39)	**	-0.10	(-0.62)		0.82	(4.97)	**
L2	0.01	(0.10)		0.00	(0.02)		-0.29	(-3.65)	**	0.16	(1.18)		-0.01	(-0.04)	
_cons	1.08	(2.60)		2.11	(3.75)		-0.02	(-0.07)		1.91	(3.67)		-0.11	(-0.20)	
Obs	38			38			38			38			38		
RMSE	0.1635			0.2214			0.1160			0.2048			0.2206		
R-sq	0.8233			0.6507			0.9459			0.6973			0.8385		
chi^2	177.0585			70.7956			664.3191			87.5509			197.3600		
P>chi2	0			0			0			0			0		

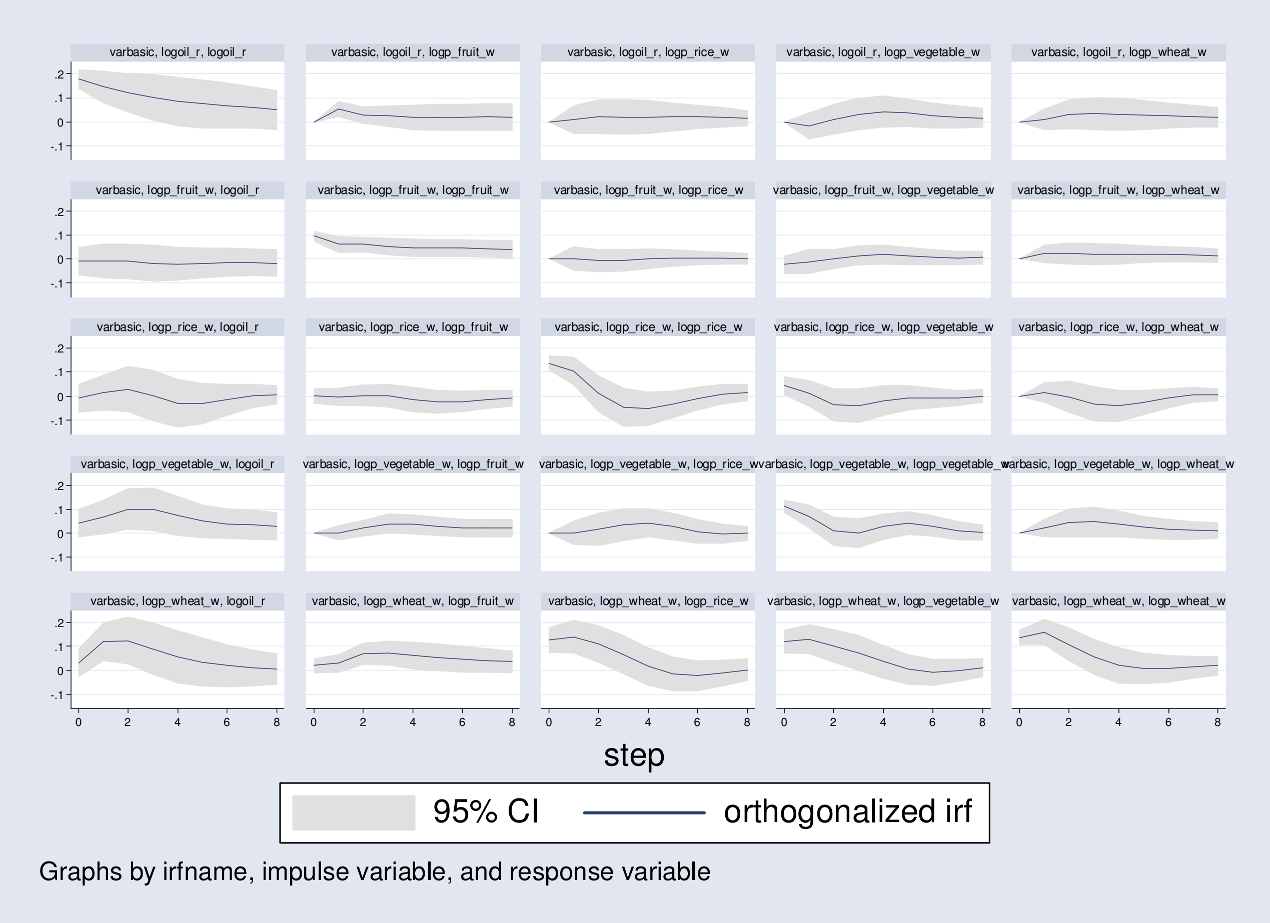
a. ** = significant at 1% level. * = significant at 5% level.

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
log(P_Wheat)	log(P_Rice)	1.6775	2	0.4322
log(P_Wheat)	log(P_fruit)	3.3336	2	0.1888
log(P_Wheat)	log(P_vegetable)	2.0146	2	0.3652

log(P_Wheat)	log(P_Oil)	0.8977		2	0.6384
log(P_Wheat)	ALL	8.9233		8	0.3488
log(P_Rice)	log(P_Wheat)	1.895		2	0.3877
log(P_Rice)	log(P_fruit)	1.0708		2	0.5854
log(P_Rice)	log(P_vegetable)	0.0376		2	0.9814
log(P_Rice)	log(P_Oil)	0.4078		2	0.8155
log(P_Rice)	ALL	6.3636		8	0.6066
log(P_fruit)	log(P_Wheat)	0.9057		2	0.6358
log(P_fruit)	log(P_Rice)	0.7445		2	0.6892
log(P_fruit)	log(P_vegetable)	1.8738		2	0.3918
log(P_fruit)	log(P_Oil)	13.69	**	2	0.0011
log(P_fruit)	ALL	28.3118	**	8	0.0004
log(P_vegetable)	log(P_Wheat)	5.9953	*	2	0.0499
log(P_vegetable)	log(P_Rice)	1.713		2	0.4246
log(P_vegetable)	log(P_fruit)	1.1729		2	0.5563
log(P_vegetable)	log(P_Oil)	1.8498		2	0.3966
log(P_vegetable)	ALL	10.8133		8	0.2125
log(P_Oil)	log(P_Wheat)	4.6117	+	2	0.0997
log(P_Oil)	log(P_Rice)	0.0964		2	0.9529
log(P_Oil)	log(P_fruit)	0.1207		2	0.9414
log(P_Oil)	log(P_vegetable)	3.8107		2	0.1488
log(P_Oil)	ALL	16.2061	*	8	0.0395

Figure 2 Impulse Response Function for Annual World Commodity Prices (1966- 2005)



The interrelationships among agricultural commodity prices, rainfall and oil prices at the global level are given in Tables 9-13 and Figures 3-7. A brief summary of the results is given below.

(i) Rainfall has a negative effect on wheat price with 2 lags in VAR results, consistent with the Granger causality test which shows that rainfall causes wheat, but not vice versa (Table 9). The negative effect of rainfall fades away gradually (Figure 3).

(ii) Wheat price has a negative effect on oil price with 2 lags in VAR results. The former Granger causes the latter, but not vice versa (Table 9). The negative effect of wheat price on oil price fades away gradually (Figure 3).

(iii) Rainfall and maize price are strongly correlated. The former Granger causes the latter and vice versa (Table 10). The negative effects of rainfall on maize price fades away gradually (Figure 4).

(iv) Rainfall has a positive effect on oil price with one year lag, consistent with the Granger causality test which shows that rainfall causes oil price, but not vice versa. Oil price has a positive effect on rice price with one year lag. The positive effect weakens gradually (Table 11 and Figure 5).

(v) Oil price Granger causes fruit price, but not vice versa, reflected in the significant coefficient estimates of oil price on fruit price in VAR. The positive effect of oil price fades away gradually. Rainfall causes oil price, but not vice versa. The coefficient estimate of rainfall on oil price is positive with one year lag.

(vi) Rainfall has a positive effect on oil price with one year lag and the former Granger causes the latter, but not vice versa. The positive effect weakens gradually.

Table 9 Vector Autoregression (VAR) for Annual World Wheat Prices (1966- 2005)

	log(P_Wheat)			log(rainfall)			log(Oil)		
log(P_Wheat)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.85	(5.44)	**	0.00	(0.04)		0.27	(1.10)	
L2	-0.43	(-3.23)	**	-0.04	(-1.23)		-0.43	(-2.05)	*
log(rainfall)									
L1	-0.18	(-0.25)		-0.03	(-0.17)		2.84	(2.45)	*
L2	-1.99	(-2.81)	**	-0.38	(-2.20)	*	-0.70	(-0.63)	
log(Oil)									
L1	0.12	(1.05)		0.05	(1.62)		0.92	(5.06)	**
L2	-0.07	(-0.62)		-0.04	(-1.53)		-0.04	(-0.22)	
Constant	17.97	(2.53)		10.19	(5.84)		-14.00	(-1.27)	
Obs	29			29			29		
RMSE	0.138704			0.033972			0.2156		
R-sq	0.6645			0.2482			0.8365		
chi^2	57.44506			9.576059			148.3926		
P>chi2	0			0.1437			0.0000		

** = significant at 1% level. * = significant at 5% level.

Granger causality Wald tests					
Equation	Excluded	chi2		df	Prob > chi2
log(P_Wheat)	log(rainfall)	8.0692	*	2	0.0177
log(P_Wheat)	log(Oil)	1.5467		2	0.4615
log(P_Wheat)	ALL	8.5887	+	4	0.0722
log(rainfall)	log(P_Wheat)	3.5813		2	0.1669
log(rainfall)	log(Oil)	2.6715		2	0.263
log(rainfall)	ALL	7.1427		4	0.1285
log(Oil)	log(P_Wheat)	4.8029	+	2	0.0906
log(Oil)	log(rainfall)	6.2653	*	2	0.0436
log(Oil)	ALL	16.252	**	4	0.0027

Figure 3 Impulse Response Function for Annual World Wheat Prices (1966- 2005)

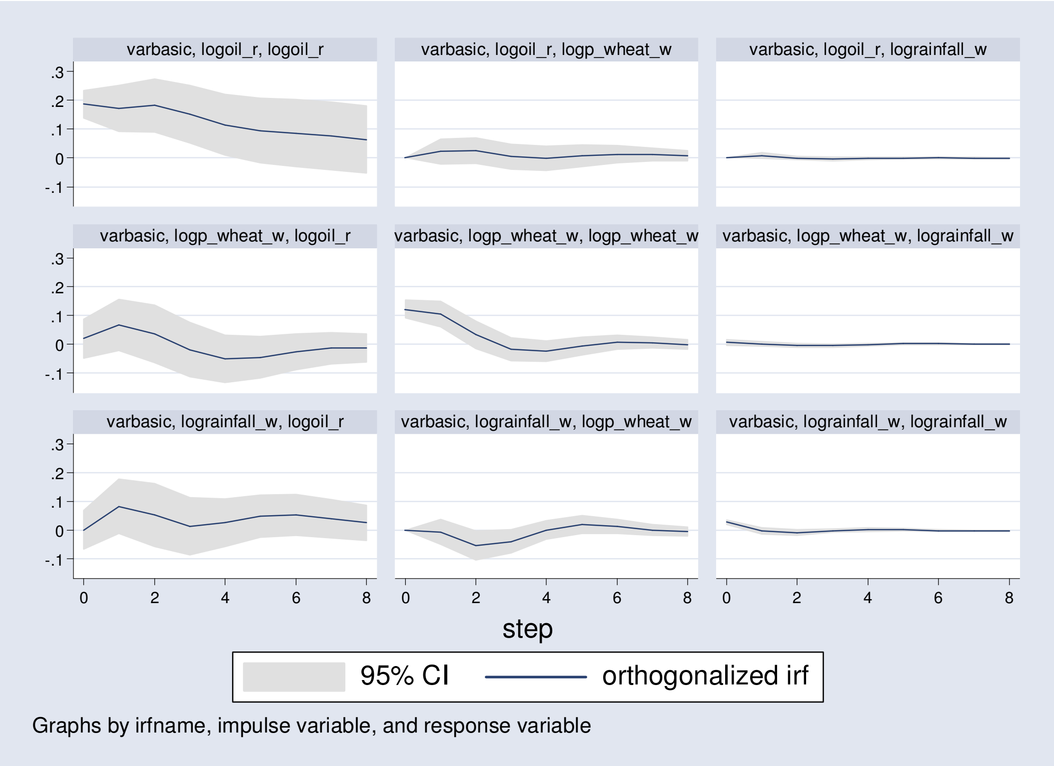


Table 10 Vector Autoregression (VAR) for Annual World Maize Prices (1985- 2005)

	log(P_Maize)			log(rainfall)			log(Oil)	
log(P_Maize)	Coef.	z value		Coef.	z value		Coef.	z value
L1	1.19	(4.22)	**	0.00	(-0.01)		-0.05	(-0.12)
L2	-1.14	(-3.29)	**	-0.19	(-1.90)	+	-0.44	(-0.83)
log(rainfall)								
L1	-3.59	(-2.64)	**	-0.68	(-1.72)	+	1.81	(0.87)
L2	0.70	(0.72)		0.17	(0.59)		1.12	(0.75)
log(Oil)								
L1	-0.27	(-1.24)		-0.16	(-2.47)	*	0.49	(1.47)
L2	-0.20	(-1.15)		0.01	(0.13)		-0.21	(-0.78)
Constant	26.54	(2.69)		12.14	(4.21)		-16.07	(-1.07)
Obs	13			13			13	
RMSE	0.1315			0.038408			0.20	
R-sq	0.5938			0.578			0.63	
chi^2	19.0000			17.80422			21.67	
P>chi2	0.0042			0.0067			0.00	

Granger causality Wald tests					
Equation	Excluded	chi2		df	Prob > chi2
log(P_Maize)	log(rainfall)	7.1359	*	2	0.0282
log(P_Maize)	log(Oil)	4.4949		2	0.1057
log(P_Maize)	ALL	7.2349		4	0.124
log(rainfall)	log(P_Maize)	10.7436	**	2	0.0046

log(rainfall)	log(Oil)	6.7615	*	2	0.034
log(rainfall)	ALL	13.0516	*	4	0.011
log(Oil)	log(P_Maize)	2.577		2	0.2757
log(Oil)	log(rainfall)	2.2261		2	0.3286
log(Oil)	ALL	11.3181	*	4	0.0232

Figure 4 Impulse Response Function for Annual World Maize Prices (1985- 2005)

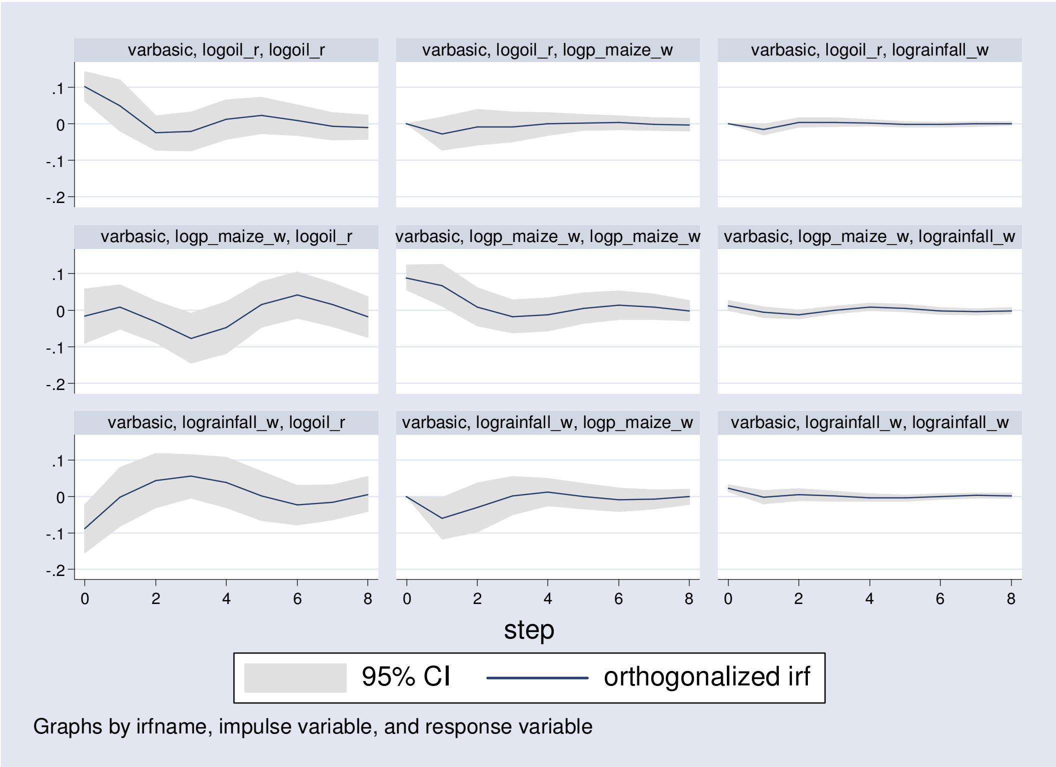


Table 11 Vector Autoregression (VAR) for Annual World Rice Prices (1966- 2005)

	log(P_Rice)			log(rainfall)			log(Oil)		
log(P_Rice)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.74	(4.62)	**	0.04	(1.35)		0.25	(1.41)	
L2	-0.49	(-3.33)	**	-0.06	(-2.31)	*	-0.22	(-1.37)	
log(rainfall)									
L1	-0.75	(-0.73)		-0.02	(-0.09)		3.25	(2.84)	**
L2	-0.66	(-0.63)		-0.29	(-1.69)	+	-0.22	(-0.19)	
log(Oil)									
L1	0.31	(1.78)	+	0.04	(1.51)		0.90	(4.68)	**
L2	-0.24	(-1.45)		-0.04	(-1.48)		-0.07	(-0.37)	
Constant	13.45	(1.34)		9.35	(5.68)		-21.08	(-1.89)	
Obs	29			29			29		
RMSE	0.20			0.033083			0.223522		
R-sq	0.54			0.2871			0.8243		
chi^2	34.60			11.6761			136.0827		
P>chi2	0.00			0.0696			0		

Granger causality Wald Test					
Equation	Excluded	chi2		df	Prob > chi2
log(P_Rice)	log(rainfall)	1.0028		2	0.6057
log(P_Rice)	log(Oil)	3.2219		2	0.1997
log(P_Rice)	ALL	3.5608		4	0.4687
log(rainfall)	log(P_Rice)	5.3549	+	2	0.0687
log(rainfall)	log(Oil)	2.3659		2	0.3064
log(rainfall)	ALL	9.1103	+	4	0.0584
log(Oil)	log(P_Rice)	2.4572		2	0.2927
log(Oil)	log(rainfall)	8.0817	*	2	0.0176
log(Oil)	ALL	13.1118	*	4	0.0107

Figure 5 Impulse Response Function for Annual World Rice Prices (1966- 2005)

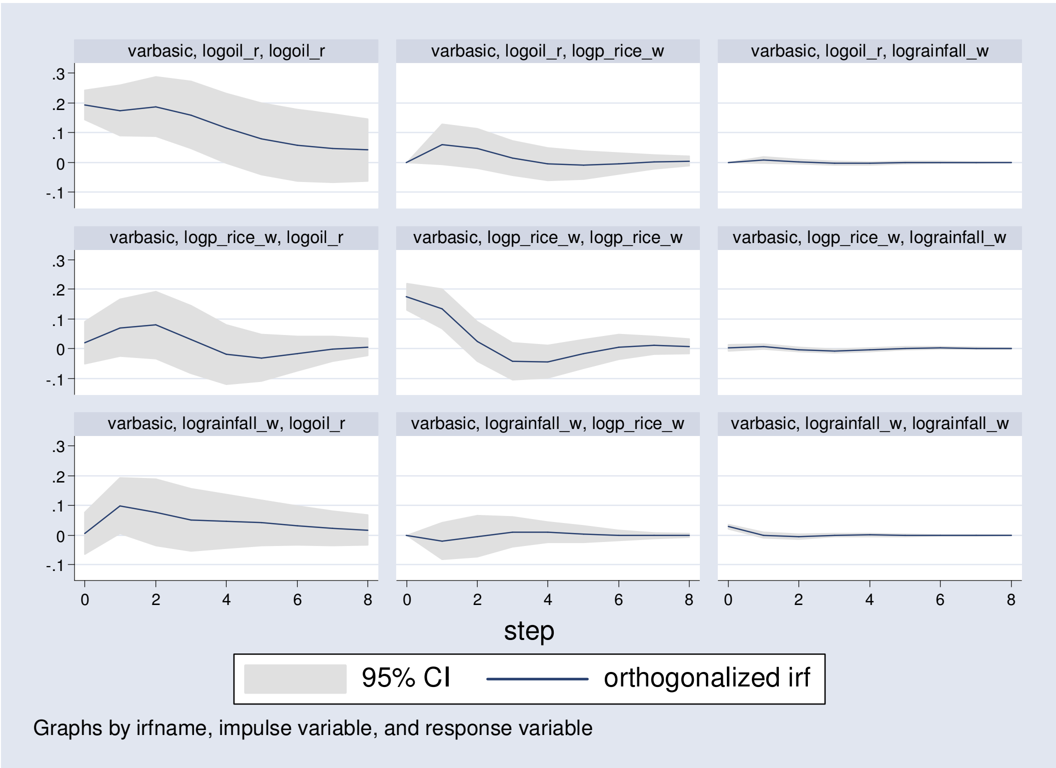


Table 12 Vector Autoregression (VAR) for Annual World Fruit Prices (1966- 2005)

	log(P_Fruit)			log(rainfall)			log(Oil)		
log(P_Fruit)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.74	(5.67)	**	0.00	(0.01)		-0.01	(-0.03)	
L2	0.17	(1.36)		-0.04	(-0.71)		-0.16	(-0.45)	
log(rainfall)									
L1	0.60	(1.49)		-0.07	(-0.42)		3.17	(2.75)	**
L2	0.34	(0.84)		-0.46	(-2.70)	**	-1.20	(-1.03)	
log(Oil)									
L1	0.20	(3.16)	**	0.03	(1.12)		0.90	(5.02)	**

L2	-0.18	(-2.87)	**	-0.04	(-1.37)		-0.08	(-0.43)
Constant	-6.28	(-1.49)		11.06	(6.19)		-12.55	(-1.04)
Obs	29			29			29	
RMSE	0.20			0.033083			0.223522	
R-sq	0.54			0.2871			0.8243	
chi^2	34.60			11.6761			136.0827	
P>chi2	0.00			0.0696			0	

Granger Causality Wald Test

Equation	Excluded	chi2		df	Prob > chi2
log(P_Fruit)	log(rainfall)	2.7763		2	0.2495
log(P_Fruit)	log(Oil)	9.9782	**	2	0.0068
log(P_Fruit)	ALL	17.8311	**	4	0.0013
log(rainfall)	log(P_Fruit)	5.7259	+	2	0.0571
log(rainfall)	log(Oil)	1.9347		2	0.3801
log(rainfall)	ALL	9.5217	*	4	0.0493
log(Oil)	log(P_Fruit)	2.6688		2	0.2633
log(Oil)	log(rainfall)	8.9991	*	2	0.0111
log(Oil)	ALL	13.395	**	4	0.0095

Figure 6 Impulse Response Function for Annual World Fruit Prices (1966- 2005)

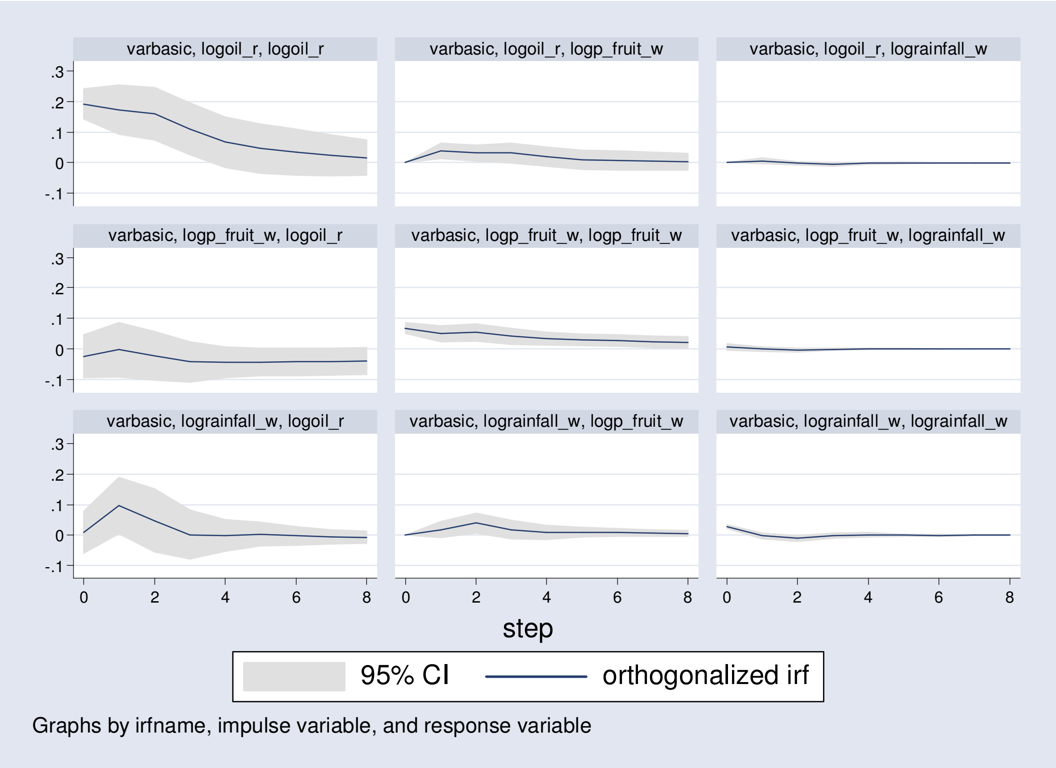


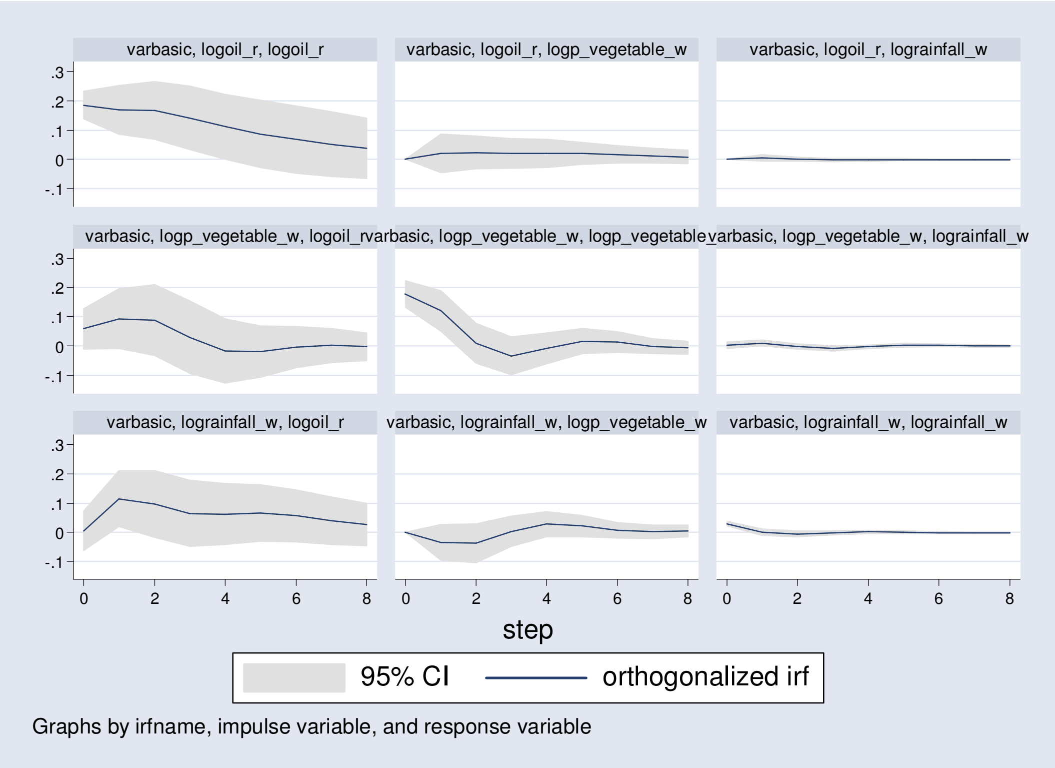
Table 13 Vector Autoregression (VAR) for Annual World Vegetable Prices (1966- 2005)

	log(P_Vegetable)			log(rainfall)			log(Oil)		
log(P_Vegetable)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.65	(3.40)	**	0.04	(1.41)		0.18	(0.87)	
L2	-0.37	(-2.21)	*	-0.05	(-1.86)	+	-0.29	(-1.55)	
log(rainfall)									
L1	-1.20	(-1.15)		0.03	(0.20)		3.74	(3.27)	**
L2	-0.86	(-0.76)		-0.23	(-1.21)		-0.20	(-0.16)	
log(Oil)									
L1	0.11	(0.59)		0.03	(0.93)		0.91	(4.63)	**
L2	0.00	(-0.03)		-0.03	(-1.06)		-0.05	(-0.26)	
Constant	17.78	(1.67)		8.52	(4.82)		-24.11	(-2.07)	
Obs	29			29			29		
RMSE	0.203991			0.033908			0.223663		
R-sq	0.4407			0.2511			0.8241		
chi^2	22.84723			9.721895			135.8746		
P>chi2	0.0008			0.1369			0		

Granger Causality Wald Test

Equation	Excluded	chi2		df	Prob > chi2
log(P_Vegetable)	log(rainfall)	2.0271		2	0.3629
log(P_Vegetable)	log(Oil)	1.5264		2	0.4662
log(P_Vegetable)	ALL	3.9793		4	0.4088
log(rainfall)	log(P_Vegetable)	3.7044		2	0.1569
log(rainfall)	log(Oil)	1.1169		2	0.5721
log(rainfall)	ALL	7.2793		4	0.1218
log(Oil)	log(P_Vegetable)	2.4175		2	0.2986
log(Oil)	log(rainfall)	10.7135	**	2	0.0047
log(Oil)	ALL	13.0587	*	4	0.011

Figure 7 Impulse Response Function for Annual World Vegetable Prices (1966- 2005)



VAR for Agricultural Commodity Prices in India

Here our focus is on agricultural commodity price series for India. First, we will comment on the interrelationship among commodity price series, based on VAR in Table 14. The main findings are summarised below.

(i) Crude oil price has positive and significant effects on prices of wheat, rice, fruit and vegetable. The former Granger causes the latter, but *not* vice versa (except for rice price that Granger causes oil price). The first row of Figure 8 suggests that the positive effects of oil price weakened over time.

(ii) Agricultural commodity prices are interlinked. Wheat price Granger causes rice price and vice versa. Likewise, wheat price Granger causes fruit price and vice versa.

We then examine the relationships among commodity prices, oil prices and rainfall (e.g. Tables 15-20 and Figures 9-14). Our comments are brief and selective.

(iii) The coefficient of second lag of wheat price is negative and significant for oil price (Table 15).

(iv) The coefficient estimate of the first lagged maize price is significant for oil price. However, oil price Granger causes maize price but not vice versa (Table 16). Positive effects of maize price or oil price fade away over time (Figure 10).

(v) Rainfall Granger causes oil price but not vice versa, which is reflected in the positive and significant coefficient estimate of rainfall on oil price (Table 17).

(vi) Rice price Granger causes oil price, but not vice versa. However, the coefficient estimate of the first lag of oil price is positive and significant for rice price (Table 17).

(vii) Rainfall Granger causes fruit price. The first lag of rainfall is negative and significant, while the second lag is positive and significant. Impulse response shows that the negative effect of rainfall gradually fades away (Table 18 and Figure 12).

(viii) Oil price Granger causes vegetable price, not vice versa. The first lag of coefficient estimate of oil price is positive and significant and the second lag is negative and significant for vegetable price (Table 19). The impulse response function suggests a gradually weakening positive effect of oil price on vegetable price (Figure 13).

(ix) Rainfall Granger causes oilseed price (but not vice versa), as reflected in the negative and significant coefficient estimate of the first lag of rainfall (Table 20). The negative effect gradually weakens and approaches 0 (Figure 14).

(x) Oil and oilseed prices are strongly interlinked. The former Granger causes the latter and vice versa. The first lag of oil price is positive and significant in the oilseeds equation, while the impulse response function suggests that the positive effect weakens over time. On the other hand, the first lag of oilseed price is negative and significant and the second lag is positive and significant. The impulse response implies that the negative effect of oilseed price fades away over time.

Table 14 Vector Autoregression (VAR) for Annual Commodity Prices in India (1966- 2005)

	log(P_Wheat)			log(P_Rice)			log(P_Fruit)			log(P_vegetable)			log(P_Oil)		
	Coef.	z value		Coef.	z value		Coef.	z value		Coef.	z value		Coef.	z value	
log(P_Wheat)															
L1	0.00	(-0.01)		-0.60	(-2.51)	*	-0.49	(-2.60)	**	0.59	(1.17)		-0.36	(-0.73)	
L2	-0.37	(-1.91)	+	-0.74	(-3.02)	**	-0.03	(-0.18)		-0.93	(-1.80)	+	0.12	(0.24)	
log(P_Rice)															
L1	0.27	(2.10)	*	0.89	(5.51)	**	0.20	(1.56)		0.07	(0.21)		1.29	(3.86)	**
L2	-0.01	(-0.05)		-0.01	(-0.06)		-0.35	(-2.45)	*	0.39	(1.01)		-1.27	(-3.38)	**
log(P_fruit)															
L1	0.18	(1.29)		-0.11	(-0.63)		0.76	(5.32)	**	-0.43	(-1.14)		-0.22	(-0.60)	
L2	0.05	(0.30)		0.27	(1.28)		0.05	(0.29)		0.46	(1.03)		-0.19	(-0.43)	
log(P_vegetable)															
L1	-0.01	(-0.23)		-0.04	(-0.59)		0.03	(0.56)		0.72	(4.82)	**	0.04	(0.25)	
L2	0.05	(1.01)		0.10	(1.44)		0.11	(1.98)	*	0.20	(1.39)		0.16	(1.15)	
log(P_Oil)															
L1	0.13	(2.13)	*	0.09	(1.18)		0.13	(2.08)	*	0.35	(2.15)	*	0.92	(5.70)	**
L2	0.03	(0.49)		0.17	(2.40)	*	0.02	(0.27)		-0.37	(-2.47)	*	-0.09	(-0.61)	
_cons	3.70	(4.40)		5.35	(4.98)		3.22	(3.81)		-0.23	(-0.10)		2.79	(1.25)	
Obs	38			38			38			38			38		
RMSE	0.0773			0.0987			0.0778			0.2086			0.2044		
R-sq	0.8217			0.834			0.9577			0.9551			0.8615		
chi^2	175.17			190.89			859.46			808.31			236.32		
P>chi2	0			0			0			0			0		

Granger causality Wald Test

Equation	Excluded	chi2		df	Prob > chi2
log(P_Wheat)	log(P_Rice)	7.2198	*	2	0.0271
log(P_Wheat)	log(P_fruit)	5.5453	+	2	0.0625
log(P_Wheat)	log(P_vegetable)	1.7466		2	0.4176
log(P_Wheat)	log(P_Oil)	7.3964	*	2	0.0248

log(P_Wheat)	ALL	46.7804	**	8	0
log(P_Rice)	log(P_Wheat)	16.7769	**	2	0.0002
log(P_Rice)	log(P_fruit)	1.9271		2	0.3815
log(P_Rice)	log(P_vegetable)	2.7137		2	0.2575
log(P_Rice)	log(P_Oil)	12.6172	**	2	0.0018
log(P_Rice)	ALL	31.0597	**	8	0.0001
log(P_fruit)	log(P_Wheat)	6.9257	*	2	0.0313
log(P_fruit)	log(P_Rice)	5.999	*	2	0.0498
log(P_fruit)	log(P_vegetable)	14.294	**	2	0.0008
log(P_fruit)	log(P_Oil)	6.3385	*	2	0.042
log(P_fruit)	ALL	32.3189	**	8	0.0001
log(P_vegetable)	log(P_Wheat)	4.2969		2	0.1167
log(P_vegetable)	log(P_Rice)	2.2554		2	0.3238
log(P_vegetable)	log(P_fruit)	1.3565		2	0.5075
log(P_vegetable)	log(P_Oil)	7.365	*	2	0.0252
log(P_vegetable)	ALL	24.1405	**	8	0.0022
log(P_Oil)	log(P_Wheat)	0.5596		2	0.7559
log(P_Oil)	log(P_Rice)	16.3195	**	2	0.0003
log(P_Oil)	log(P_fruit)	2.2221		2	0.3292
log(P_Oil)	log(P_vegetable)	4.3922		2	0.1112
log(P_Oil)	ALL	25.1788	**	8	0.0014

Figure 8 Impulse Response Function for Annual Commodity Prices in India (1966- 2005)

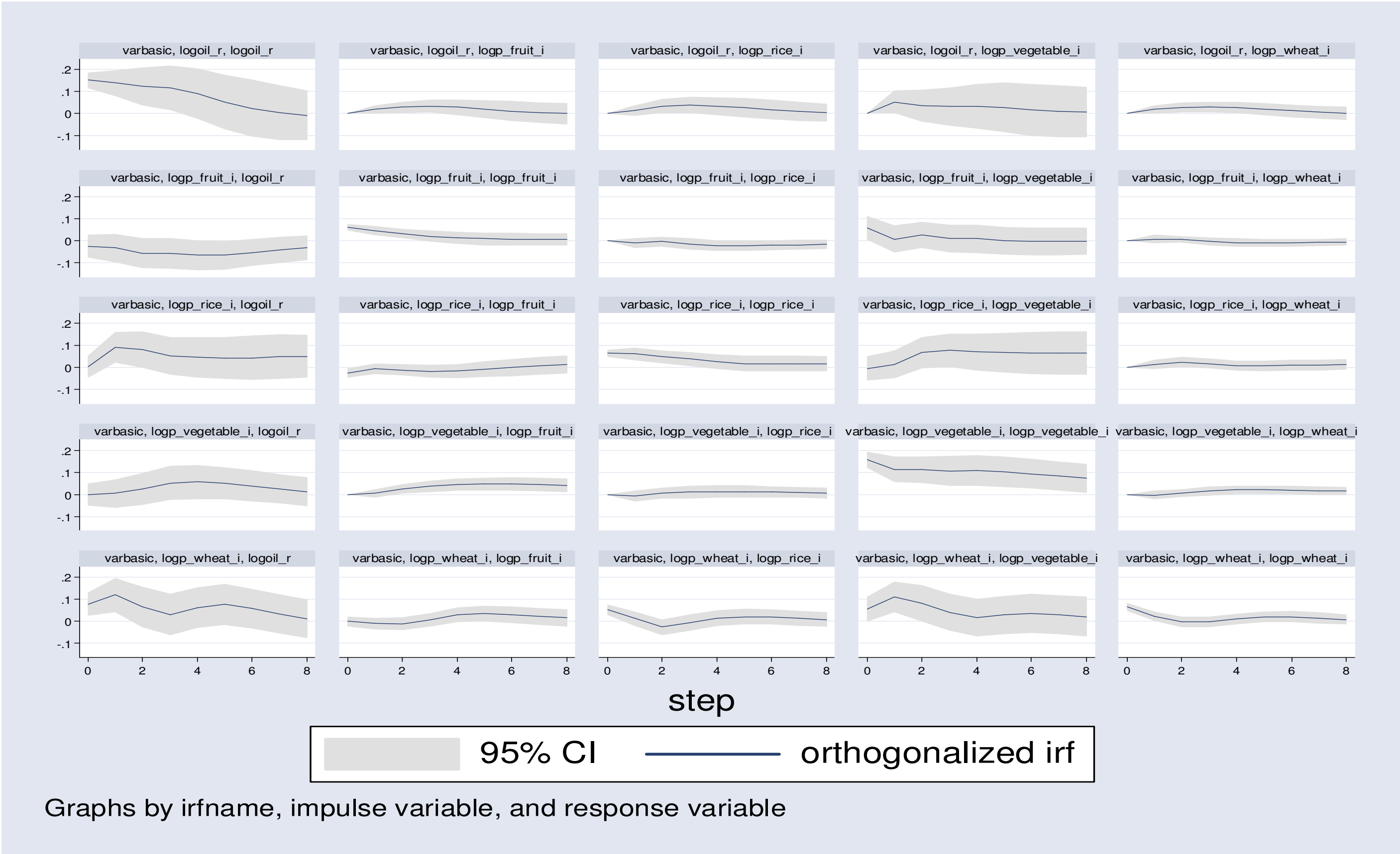


Table 15 Vector Autoregression (VAR) for Annual Wheat Prices in India (1966- 2005)

	log(P_Wheat)			log(rainfall)		log(Oil)		
log(P_Wheat)	Coef.	z value		Coef.	z value	Coef.	z value	
L1	0.62	(3.72)	**	0.03	(0.18)	0.36	(0.93)	
L2	-0.02	(-0.11)		0.08	(0.53)	-0.64	(-1.71)	+
log(rainfall)								
L1	-0.03	(-0.17)		-0.20	(-1.22)	0.20	(0.50)	
L2	-0.07	(-0.43)		0.06	(0.35)	0.24	(0.61)	
log(Oil)								
L1	0.09	(1.18)		0.07	(1.00)	0.99	(5.93)	**
L2	0.00	(0.01)		-0.10	(-1.39)	-0.08	(-0.48)	
Constant	2.37	(1.23)		7.52	(4.22)	-1.34	(-0.30)	
Obs	38			38		38		
RMSE	0.1024			0.094788		0.24		
R-sq	0.6414			0.1078		0.79		
chi^2	67.9705			4.592234		140.94		
P>chi2	0.0000			0.5971		0.00		

Granger Causality Wald Test

Equation	Excluded	chi2	df	Prob > chi2
log(P_Wheat)	log(rainfall)	0.187	2	0.9107
log(P_Wheat)	log(Oil)	3.8283	2	0.1475
log(P_Wheat)	ALL	4.1456	4	0.3867
log(rainfall)	log(P_Wheat)	0.6634	2	0.7177
log(rainfall)	log(Oil)	1.9523	2	0.3768
log(rainfall)	ALL	2.0808	4	0.7209
log(Oil)	log(P_Wheat)	2.9196	2	0.2323
log(Oil)	log(rainfall)	0.5108	2	0.7746
log(Oil)	ALL	3.2115	4	0.5231

Figure 9 Impulse Response Function for Annual Wheat Prices in India (1966- 2005)

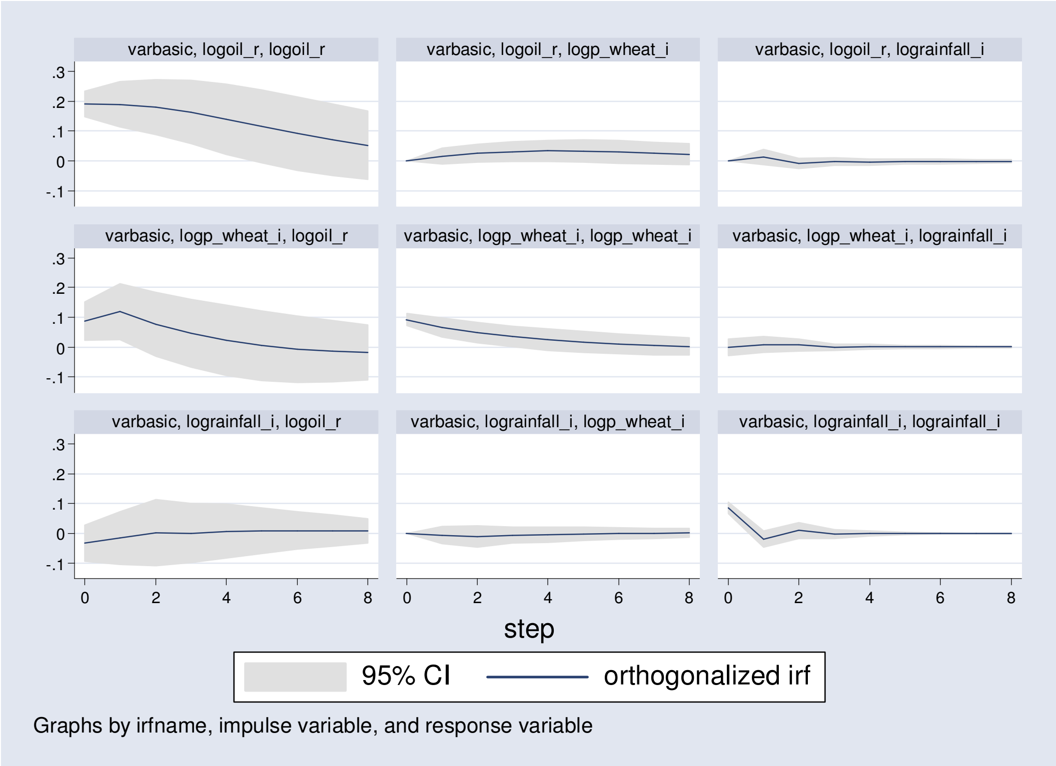


Table 16 Vector Autoregression (VAR) for Annual Maize Prices in India (1966- 2005)

	log(P_Maize)			log(rainfall)			log(Oil)		
log(P_Maize)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.71	(4.62)	**	-0.08	(-0.76)		0.46	(1.75)	+
L2	-0.36	(-2.31)	*	0.14	(1.28)		-0.10	(-0.36)	
log(rainfall)									
L1	-0.13	(-0.57)		-0.20	(-1.24)		0.26	(0.65)	
L2	-0.07	(-0.29)		0.08	(0.50)		0.22	(0.57)	
log(Oil)									
L1	0.10	(1.07)		0.07	(1.01)		0.96	(5.79)	**
L2	0.06	(0.62)		-0.09	(-1.41)		-0.22	(-1.39)	
Constant	3.94	(1.49)		7.61	(4.16)		-4.22	(-0.92)	
Obs	38			38			38		
RMSE	0.14			0.093574			0.235058		
R-sq	0.61			0.1305			0.7896		
chi^2	58.74			5.704785			142.5748		
P>chi2	0.00			0.4571			0		

Granger Causality Wald Tests

Equation	Excluded	chi2		df	Prob > chi2
log(P_Maize)	log(rainfall)	0.35		2	0.8395
log(P_Maize)	log(Oil)	6.0326	*	2	0.049
log(P_Maize)	ALL	6.2802		4	0.1792
log(rainfall)	log(P_Maize)	1.6733		2	0.4332
log(rainfall)	log(Oil)	1.9955		2	0.3687

log(rainfall)	ALL	3.1278	4	0.5367
log(Oil)	log(P_Maize)	3.2939	2	0.1926
log(Oil)	log(rainfall)	0.6145	2	0.7355
log(Oil)	ALL	3.5884	4	0.4646

Figure 10 Impulse Response Function for Annual Maize Prices in India (1966- 2005)

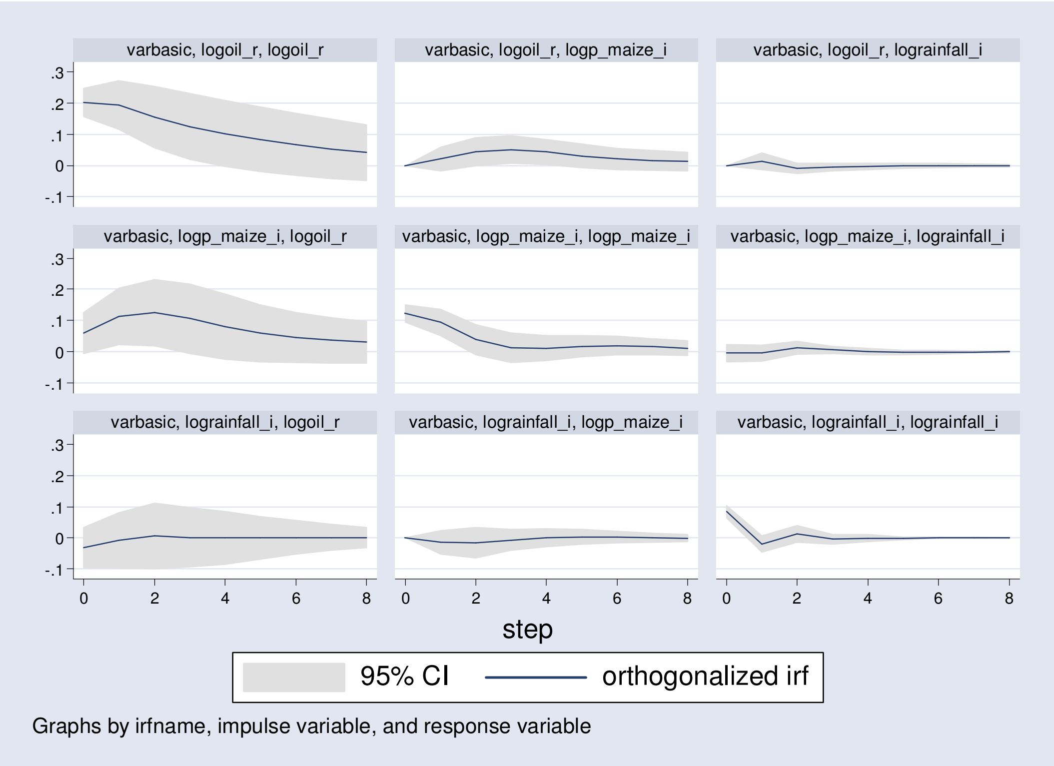


Table 17 Vector Autoregression (VAR) for Annual Rice Prices in India (1966- 2005)

	log(P_Rice)			log(rainfall)			log(Oil)		
log(P_Rice)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.74	(4.62)	**	0.04	(1.35)		0.25	(1.41)	
L2	-0.49	(-3.33)	**	-0.06	(-2.31)	*	-0.22	(-1.37)	
log(rainfall)									
L1	-0.75	(-0.73)		-0.02	(-0.09)		3.25	(2.84)	**
L2	-0.66	(-0.63)		-0.29	(-1.69)	+	-0.22	(-0.19)	
log(Oil)									
L1	0.31	(1.78)	+	0.04	(1.51)		0.90	(4.68)	**
L2	-0.24	(-1.45)		-0.04	(-1.48)		-0.07	(-0.37)	
Constant	13.45	(1.34)		9.35	(5.68)		-21.08	(-1.89)	
Obs	38			38			38		
RMSE	0.117295			0.089392			0.202296		
R-sq	0.7307			0.2065			0.8441		
chi^2	103.1223			9.888853			205.7992		
P>chi2	0			0.1294			0		

Granger causality Wald Test					
Equation	Excluded	chi2		df	Prob > chi2
log(P_Rice)	log(rainfall)	0.5737		2	0.7506
log(P_Rice)	log(Oil)	4.3878		2	0.1115
log(P_Rice)	ALL	4.5783		4	0.3334
log(rainfall)	log(P_Rice)	5.4714	+	2	0.0648
log(rainfall)	log(Oil)	5.3964	+	2	0.0673
log(rainfall)	ALL	7.0651		4	0.1325
log(Oil)	log(P_Rice)	17.7521	**	2	0.0001
log(Oil)	log(rainfall)	1.0951		2	0.5784
log(Oil)	ALL	18.1497	**	4	0.0012

Figure 11 Impulse Response Function for Annual Rice Prices in India (1966- 2005)

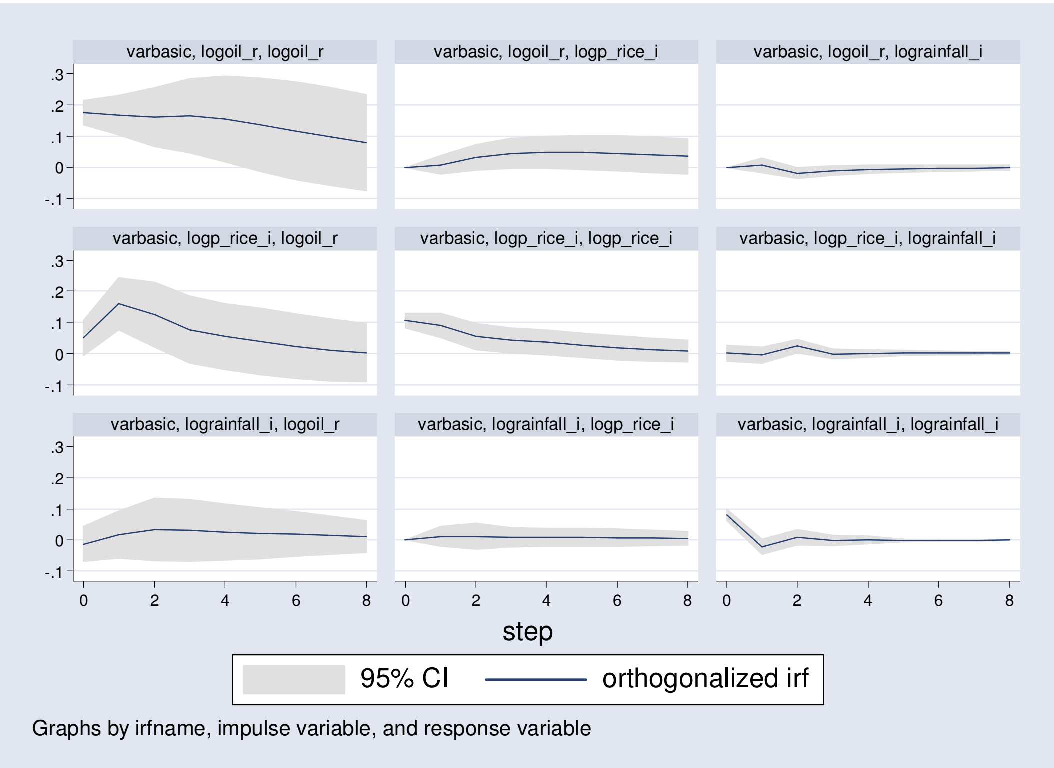


Table 18 Vector Autoregression (VAR) for Annual Vegetables Prices in India (1966-2005)

	log(P_Fruit)			log(rainfall)		log(Oil)		
log(P_Fruit)	Coef.	z value		Coef.	z value	Coef.	z value	
L1	1.13	(7.80)	**	0.08	(0.46)	0.32	(0.76)	
L2	-0.19	(-1.28)		-0.05	(-0.32)	-0.39	(-0.91)	
log(rainfall)								
L1	-0.38	(-2.64)	**	-0.18	(-1.12)	0.22	(0.54)	
L2	0.27	(1.76)	+	0.09	(0.55)	0.29	(0.67)	
log(Oil)								
L1	0.00	(0.06)		0.07	(1.04)	1.01	(6.13)	**
L2	0.02	(0.42)		-0.08	(-1.23)	-0.18	(-1.09)	

Constant	0.98	(0.61)	7.50	(4.09)	-2.67	(-0.57)
Obs	38		38		38	
RMSE	0.083992		0.095083		0.241854	
R-sq	0.9434		0.1023		0.7772	
chi^2	633.3318		4.328227		132.57	
P>chi2	0		0.6324		0	

Granger Causality Wald Tests					
Equation	Excluded	chi2		df	Prob > chi2
log(P_Fruit)	log(rainfall)	13.073	**	2	0.0014
log(P_Fruit)	log(Oil)	0.948		2	0.6225
log(P_Fruit)	ALL	14.6013	**	4	0.0056
log(rainfall)	log(P_Fruit)	0.4237		2	0.8091
log(rainfall)	log(Oil)	1.5047		2	0.4713
log(rainfall)	ALL	1.8324		4	0.7666
log(Oil)	log(P_Fruit)	1.006		2	0.6047
log(Oil)	log(rainfall)	0.6028		2	0.7398
log(Oil)	ALL	1.2842		4	0.864

Figure 12 Impulse Response Function for Annual Fruit Prices in India (1966- 2005)

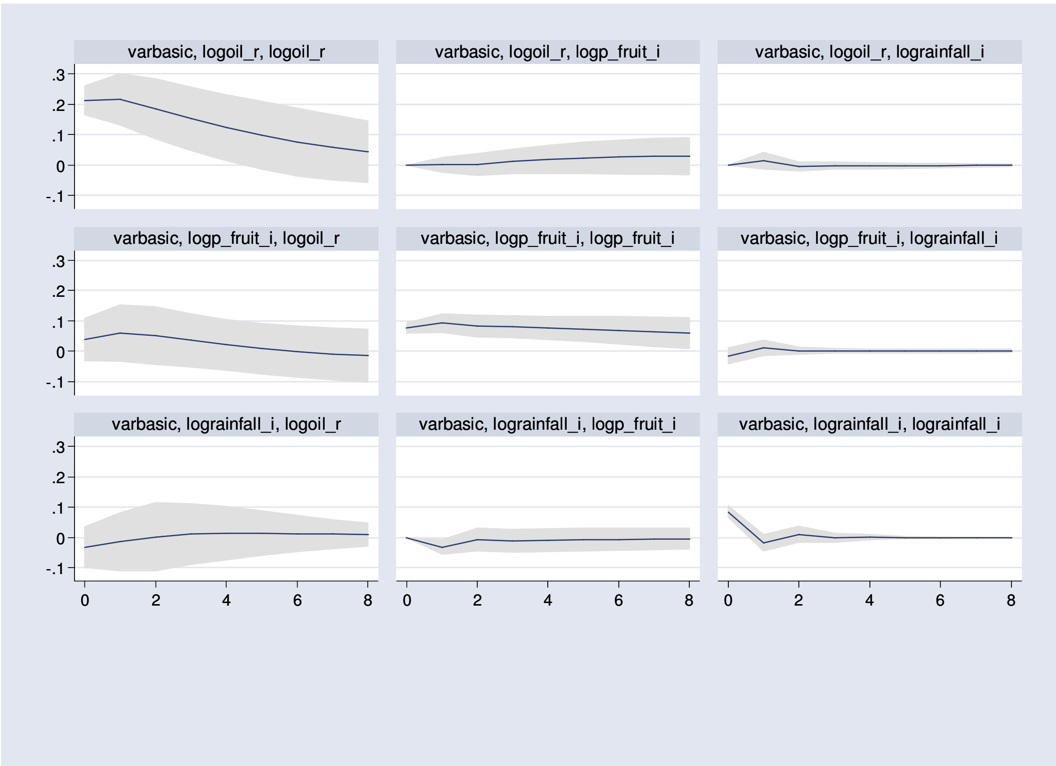


Table 19 Vector Autoregression (VAR) for Annual Vegetable Prices in India (1966- 2005)

	log(P_Vegetable)			log(rainfall)		log(Oil)	
log(P_Vegetable)	Coef.	z value		Coef.	z value	Coef.	z value
L1	0.81	(5.36)	**	0.01	(0.19)	-0.03	(-0.18)

L2	0.11	(0.79)		0.00	(-0.06)		0.02	(0.15)	
log(rainfall)									
L1	-0.37	(-1.01)		-0.20	(-1.19)		0.20	(0.48)	
L2	0.34	(0.93)		0.06	(0.39)		0.14	(0.33)	
log(Oil)									
L1	0.45	(3.08)	**	0.07	(1.05)		1.06	(6.30)	**
L2	-0.38	(-2.62)	**	-0.08	(-1.24)		-0.20	(-1.21)	
Constant	0.43	(0.11)		7.91	(4.53)		-1.83	(-0.41)	
Obs	38			38			38		
RMSE	0.211797			0.095282			0.24489		
R-sq	0.9469			0.0985			0.7716		
chi^2	677.1751			4.1512			128.3663		
P>chi2	0			0.6562			0		

Granger Causality	Wald Test				
Equation	Excluded	chi2		df	Prob > chi2
log(P_Vegetable)	log(rainfall)	2.2104		2	0.3311
log(P_Vegetable)	log(Oil)	9.5177	**	2	0.0086
log(P_Vegetable)	ALL	14.5122	**	4	0.0058
log(rainfall)	log(P_Vegetable)	0.263		2	0.8768
log(rainfall)	log(Oil)	1.546		2	0.4616
log(rainfall)	ALL	1.6658		4	0.7969
log(Oil)	log(P_Vegetable)	0.0447		2	0.9779
log(Oil)	log(rainfall)	0.2958		2	0.8625
log(Oil)	ALL	0.316		4	0.9888

Figure 13 Impulse Response Function for Annual Vegetable Prices in India (1966- 2005)

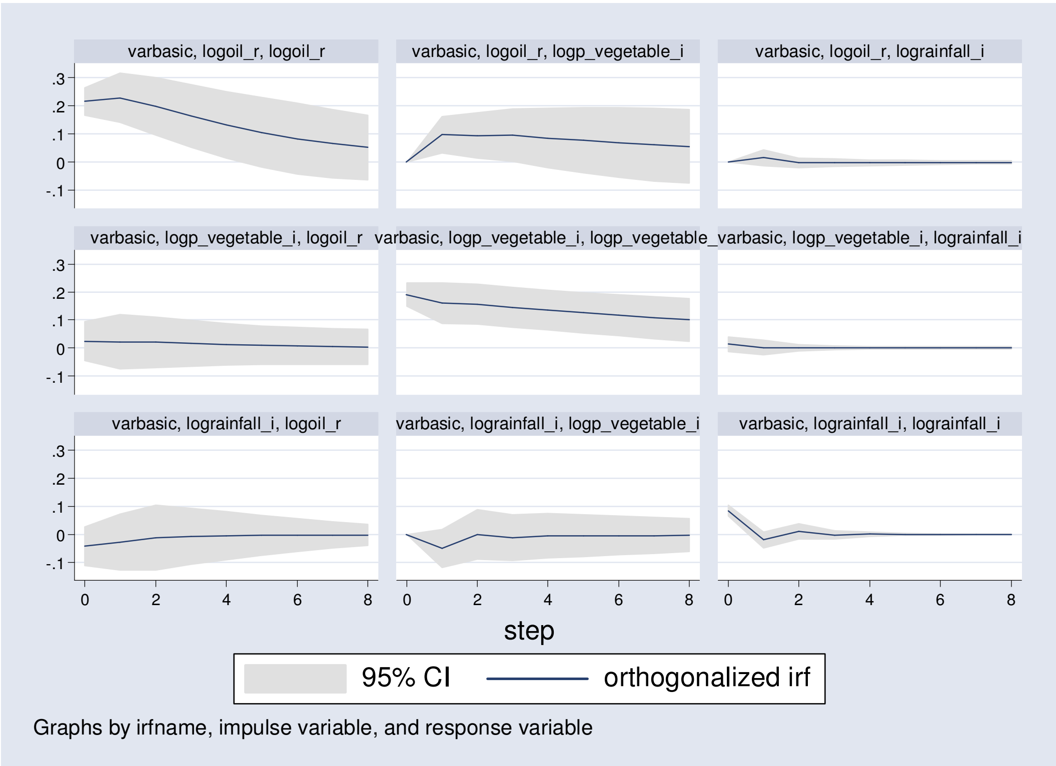
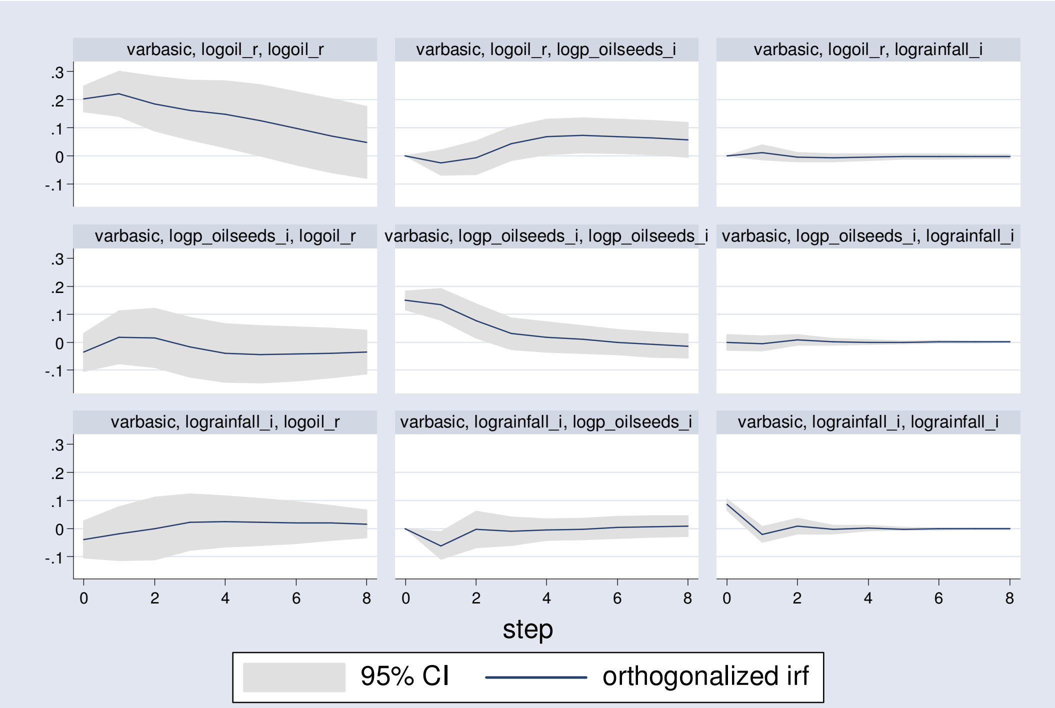


Table 20 Vector Autoregression (VAR) for Annual Oilseeds Prices in India (1966- 2005)

	log(P_Oilseeds)			log(rainfall)			log(Oil)		
log(P_Oilseeds)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.87	(5.86)	**	-0.02	(-0.18)		0.39	(1.83)	+
L2	-0.22	(-1.64)		0.04	(0.50)		-0.43	(-2.23)	*
log(rainfall)									
L1	-0.76	(-2.73)	**	-0.20	(-1.23)		0.27	(0.69)	
L2	0.50	(1.64)		0.02	(0.12)		0.45	(1.06)	
log(Oil)									
L1	-0.12	(-1.07)		0.06	(0.98)		1.08	(6.95)	**
L2	0.25	(2.20)	*	-0.08	(-1.23)		-0.23	(-1.47)	
Constant	3.47	(1.06)		8.13	(4.29)		-4.25	(-0.91)	
Obs	37			37			37		
RMSE	0.164806			0.095017			0.232926		
R-sq	0.7397			0.0995			0.7917		
chi^2	105.1351			4.09035			140.6507		
P>chi2	0			0.6645			0		

Granger Causality Wald Test					
Equation	Excluded	chi2		df	Prob > chi2
log(P_Oilseeds)	log(rainfall)	12.9705	**	2	0.0015
log(P_Oilseeds)	log(Oil)	7.4412	*	2	0.0242
log(P_Oilseeds)	ALL	19.9043	**	4	0.0005
log(rainfall)	log(P_Oilseeds)	0.3608		2	0.8349
log(rainfall)	log(Oil)	1.5302		2	0.4653
log(rainfall)	ALL	1.8427		4	0.7647
log(Oil)	log(P_Oilseeds)	5.0097	+	2	0.0817
log(Oil)	log(rainfall)	1.3289		2	0.5146
log(Oil)	ALL	5.256		4	0.262

Figure 14 Impulse Response Function for Annual Vegetable Prices in India (1966- 2005)



Graphs by irfname, impulse variable, and response variable

VAR for Agricultural Commodity Prices in China

We have carried out a similar set of VARs for agricultural commodity prices in China. First, we examine the interrelationships of agricultural commodity prices in Table 21 and Figure 15. The main difference from the results for India is that crude oil price has little impact on various agricultural commodity prices. Rather, wheat price is a leading indicator that predicts other prices.

For example, wheat price Granger causes the prices of rice, fruit, vegetable, and oil, but not vice versa. The first lag of wheat is positive and significant and the second lag is negative and significant for each price series. The impulse response shows a persistent positive effect of wheat price on other prices. On the other hand, the prices of rice, fruit, and vegetable are interlinked. Rice price Granger causes fruit price as well as vegetable price and vice versa, while fruit price Granger causes vegetable price and vice versa. The impulse response functions show, for example, the positive effects of rice on other prices but this effect fades away gradually.

Table 21 Vector Autoregression (VAR) for Annual Commodity Prices in China (1970- 2000)

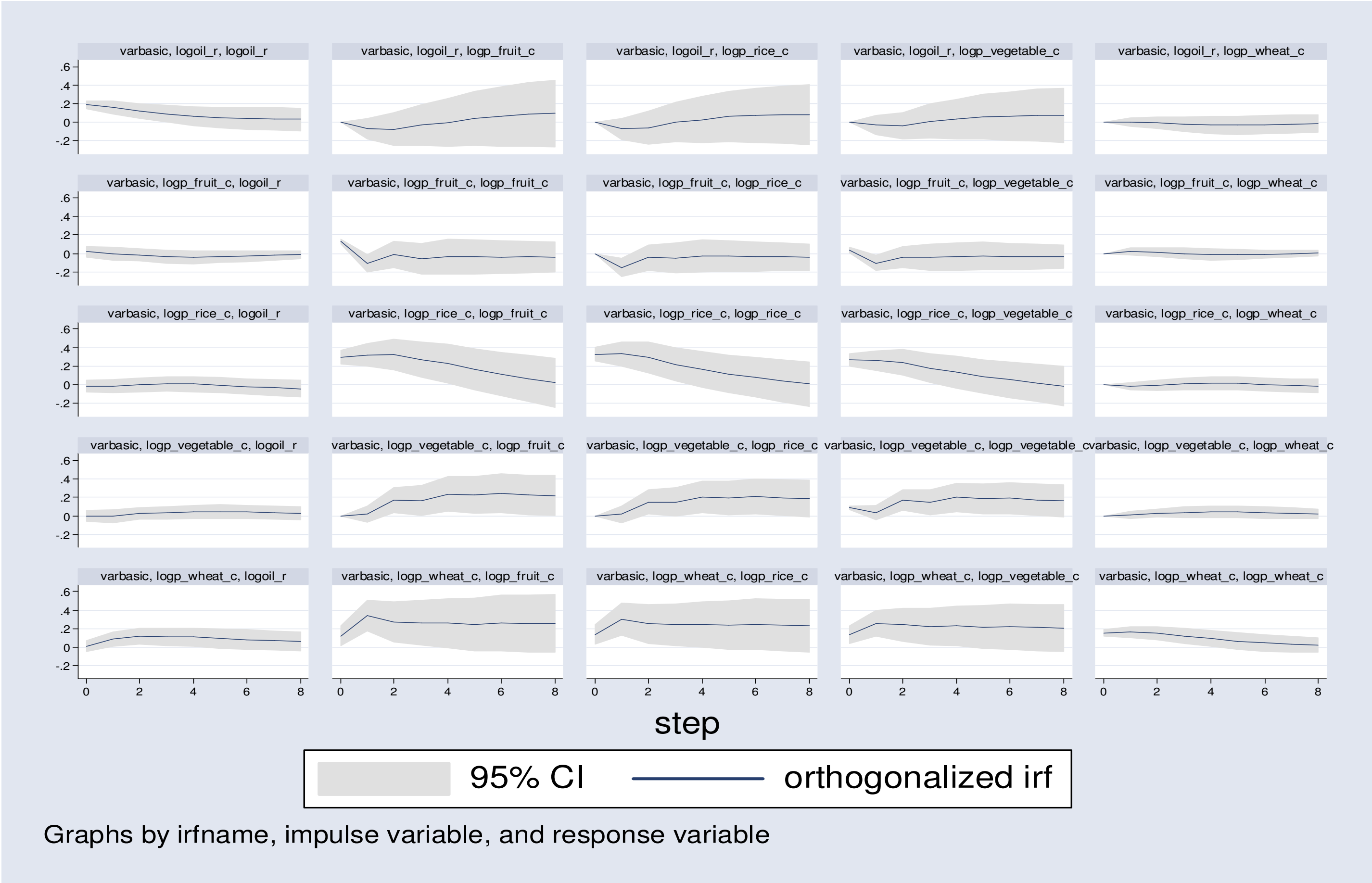
	log(P_Wheat)			log(P_Rice)			log(P_Fruit)			log(P_vegetable)			log(P_Oil)		
	Coef.	z value		Coef.	z value		Coef.	z value		Coef.	z value		Coef.	z value	
log(P_Wheat)															
L1	1.09	(6.61)	**	1.05	(2.75)	**	1.33	(3.59)	**	1.33	(3.59)	**	0.56	(2.74)	**
L2	-0.26	(-1.47)		-0.92	(-2.26)	*	-1.29	(-3.27)	**	-1.29	(-3.27)	**	-0.36	(-1.67)	+
log(P_Rice)															
L1	-0.28	(-1.36)		1.87	(3.87)	**	1.53	(3.26)	**	1.53	(3.26)	**	0.14	(0.53)	
L2	0.14	(0.70)		-1.40	(-2.95)	**	-1.47	(-3.18)	**	-1.47	(-3.18)	**	0.09	(0.34)	
log(P_fruit)															
L1	0.12	(0.73)		-1.17	(-3.01)	**	-0.86	(-2.29)	*	-0.86	(-2.29)	*	-0.15	(-0.72)	
L2	-0.22	(-1.36)		0.40	(1.08)		0.46	(1.29)		0.46	(1.29)		-0.25	(-1.28)	
log(P_vegetable)															
L1	0.16	(0.75)		0.22	(0.42)		0.25	(0.50)		0.25	(0.50)		-0.02	(-0.09)	
L2	0.14	(0.65)		1.29	(2.63)	**	1.45	(3.06)	**	1.45	(3.06)	**	0.28	(1.06)	
log(P_Oil)															
L1	0.02	(0.14)		-0.39	(-1.26)		-0.36	(-1.21)		-0.36	(-1.21)		0.86	(5.29)	**
L2	-0.11	(-0.87)		0.33	(1.14)		0.21	(0.73)		0.21	(0.73)		-0.10	(-0.67)	
_cons	0.88	(1.98)		-1.27	(-1.23)		-1.54	(-1.52)		-1.54	(-1.52)		-0.57	(-1.03)	
Obs	38			38			38			38			38		
RMSE	0.182417			0.42406			0.411549			0.373227			0.225007		
R-sq	0.8229			0.9233			0.9417			0.9241			0.8321		
chi^2	176.5759			457.5542			614.2451			462.4593			188.264		
P>chi2	0			0			0			0			0		

Granger causality Wald Test

Equation	Excluded	chi2	df	Prob > chi2
log(P_Wheat)	log(P_Rice)	1.8794	2	0.3908
log(P_Wheat)	log(P_fruit)	1.8529	2	0.396
log(P_Wheat)	log(P_vegetable)	1.7746	2	0.4118
log(P_Wheat)	log(P_Oil)	1.4558	2	0.4829

log(P_Wheat)	ALL	5.4741		8	0.7059
log(P_Rice)	log(P_Wheat)	7.6231	*	2	0.0221
log(P_Rice)	log(P_fruit)	9.4403	**	2	0.0089
log(P_Rice)	log(P_vegetable)	10.1228	**	2	0.0063
log(P_Rice)	log(P_Oil)	1.6668		2	0.4346
log(P_Rice)	ALL	33.8028	**	8	0
log(P_fruit)	log(P_Wheat)	13.619	**	2	0.0011
log(P_fruit)	log(P_Rice)	12.9189	**	2	0.0016
log(P_fruit)	log(P_vegetable)	13.7486	**	2	0.001
log(P_fruit)	log(P_Oil)	1.5652		2	0.4572
log(P_fruit)	ALL	57.7058	**	8	0
log(P_vegetable)	log(P_Wheat)	7.4649	*	2	0.0239
log(P_vegetable)	log(P_Rice)	11.7815	**	2	0.0028
log(P_vegetable)	log(P_fruit)	8.1735	*	2	0.0168
log(P_vegetable)	log(P_Oil)	0.3922		2	0.8219
log(P_vegetable)	ALL	33.3913	**	8	0.0001
log(P_Oil)	log(P_Wheat)	7.847	*	2	0.0198
log(P_Oil)	log(P_Rice)	0.9571		2	0.6197
log(P_Oil)	log(P_fruit)	4.351		2	0.1135
log(P_Oil)	log(P_vegetable)	1.3262		2	0.5153
log(P_Oil)	ALL	14.1112	+	8	0.0789

Figure 15 Impulse Response Function for Annual Commodity Prices in China (1970- 2000)



Next we examine the interrelationships among agricultural commodity prices, oil prices and rainfall in China in Tables 22-27 and Figures 16-21. The findings are briefly summarised below.

(i) Wheat price Granger causes rainfall, but not vice versa, the reason of which is unclear. The second lag of wheat price is positive and significant in rainfall equation. Wheat price Granger causes oil price[22] (Table 22).

(ii) Significant causality is not found in the Granger causality tests in Tables 23, 24 and 25. An intuitively appealing result, however, is that rainfall affects negatively maize price and fruit price with one year lag.

(iii) Vegetable price Granger causes oil price, but not vice versa. The reason is not obvious.

Table 22 Vector Autoregression (VAR) for Annual Wheat Prices in China (1970- 2000)

	log(P_Wheat)			log(rainfall)			log(Oil)		
log(P_Wheat)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	1.00	(4.96)	**	-0.05	(-1.02)		0.70	(3.35)	**
L2	-0.13	(-0.57)		0.10	(2.05)	*	-0.28	(-1.23)	
log(rainfall)									
L1	-1.06	(-1.35)		-0.26	(-1.48)		0.90	(1.12)	
L2	-0.49	(-0.63)		-0.05	(-0.31)		1.71	(2.17)	*
log(Oil)									
L1	0.09	(0.51)		-0.03	(-0.78)		0.60	(3.17)	**
L2	-0.17	(-1.09)		-0.02	(-0.55)		0.06	(0.39)	
Constant	10.90	(1.35)		8.38	(4.57)		-17.76	(-2.15)	
Obs	29			29			29		
RMSE	0.2051			0.046647			0.21		
R-sq	0.7933			0.1928			0.84		
chi^2	111.2693			6.925657			156.93		
P>chi2	0.0000			0.3278			0.00		

Granger Causality Wald Test

Equation	Excluded	chi2	df	Prob > chi2
log(P_Wheat)	log(rainfall)	1.9036	2	0.386

[22] We have avoided commenting on the Granger causality between rainfall and oil prices.

log(P_Wheat)	log(Oil)	1.6144		2	0.4461
log(P_Wheat)	ALL	2.7356		4	0.603
log(rainfall)	log(P_Wheat)	5.2597	+	2	0.0721
log(rainfall)	log(Oil)	4.8422	+	2	0.0888
log(rainfall)	ALL	5.9654		4	0.2017
log(Oil)	log(P_Wheat)	17.116	**	2	0.0002
log(Oil)	log(rainfall)	4.9928	+	2	0.0824
log(Oil)	ALL	18.429	**	4	0.001

Figure 16 Impulse Response Function for Annual Wheat Prices in China (1970- 2000)

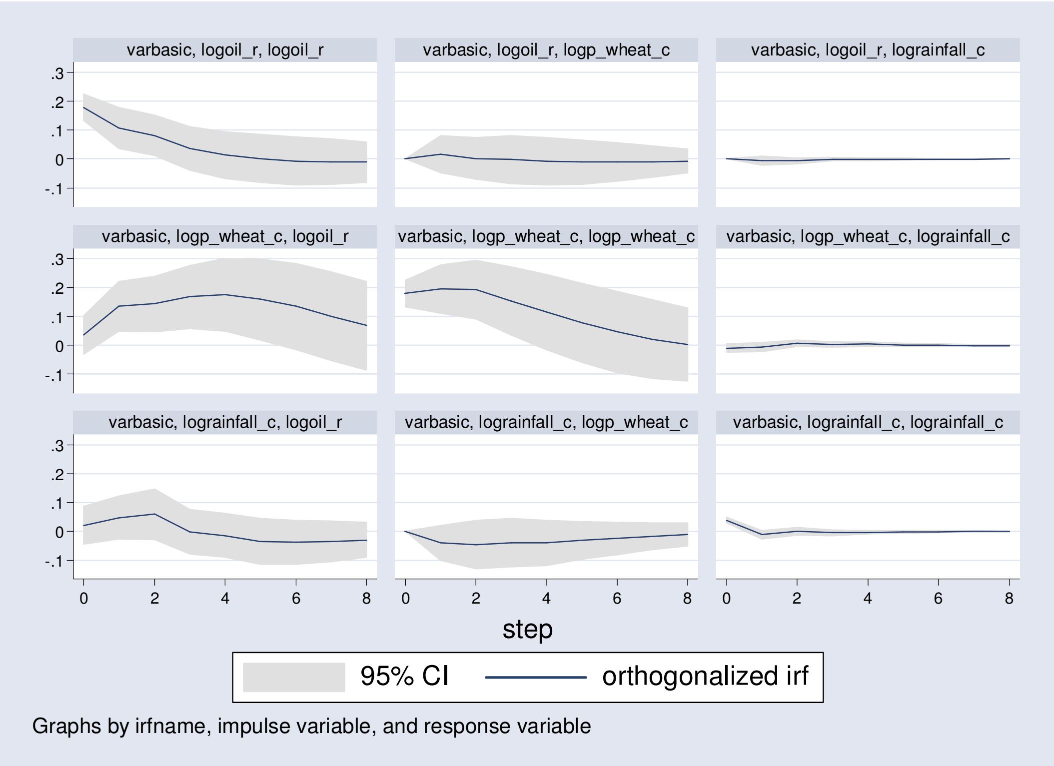


Table 23 Vector Autoregression (VAR) for Annual Maize Prices in China (1970- 2000)

	log(P_Maize)			log(rainfall)			log(Oil)		
log(P_Maize)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	1.11	(5.92)	**	0.03	(1.72)	+	0.15	(1.85)	+
L2	-0.19	(-0.96)		-0.02	(-1.29)		-0.08	(-0.97)	
log(rainfall)									
L1	-3.87	(-1.82)	+	-0.17	(-0.95)		0.18	(0.20)	
L2	-0.47	(-0.21)		0.10	(0.54)		1.29	(1.36)	
log(Oil)									
L1	-0.31	(-0.68)		-0.02	(-0.54)		0.86	(4.45)	**
L2	0.38	(0.90)		0.00	(0.01)		-0.17	(-0.92)	
Constant	28.15	(1.29)		6.91	(3.82)		-8.75	(-0.95)	
Obs	29			29			29		
RMSE	0.581748			0.048235			0.247091		
R-sq	0.8468			0.1369			0.7853		

chi^2	160.3253	4.599103	106.0919
P>chi2	**0**	0.5962	0

Granger Causality Wald Tests

Equation	Excluded	chi2	df	Prob > chi2
log(P_Maize)	log(rainfall)	3.3537	2	0.187
log(P_Maize)	log(Oil)	0.8138	2	0.6657
log(P_Maize)	ALL	4.8359	4	0.3046
log(rainfall)	log(P_Maize)	3.0411	2	0.2186
log(rainfall)	log(Oil)	0.7771	2	0.6781
log(rainfall)	ALL	3.701	4	0.448
log(Oil)	log(P_Maize)	4.5069	2	0.105
log(Oil)	log(rainfall)	1.87	2	0.3926
log(Oil)	ALL	5.4613	4	0.2432

Figure 17 Impulse Response Function for Annual Maize Prices in China (1970- 2000)

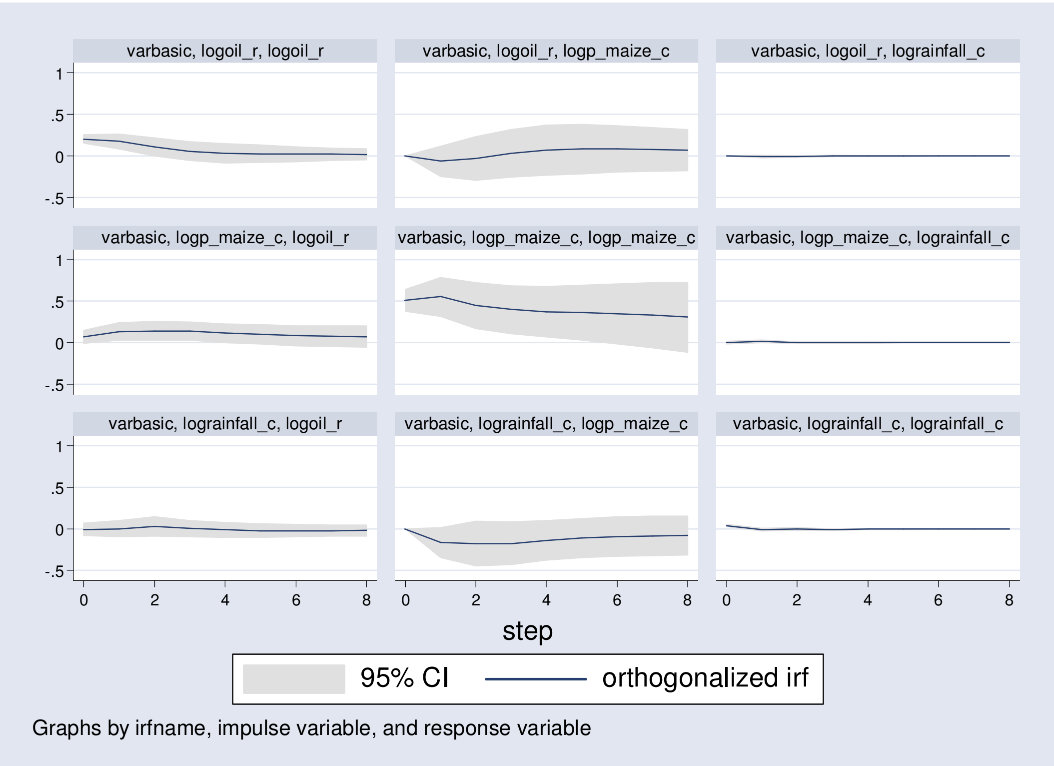


Table 24 Vector Autoregression (VAR) for Annual Rice Prices in China (1966- 2005)

	log(P_Rice)			log(rainfall)			log(Oil)		
log(P_Rice)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	1.14	(6.08)	**	0.03	(1.82)	+	0.16	(1.96)	+
L2	-0.23	(-1.12)		-0.02	(-1.38)		-0.10	(-1.17)	
log(rainfall)									
L1	-4.08	(-1.93)	+	-0.16	(-0.91)		0.23	(0.26)	
L2	-0.33	(-0.15)		0.12	(0.63)		1.41	(1.48)	
log(Oil)									

L1	-0.37	(-0.81)	-0.02	(-0.59)	0.86	(4.47)	**
L2	0.47	(1.11)	0.00	(0.05)	-0.15	(-0.85)	
Constant	28.62	(1.31)	6.77	(3.73)	-9.87	(-1.06)	
Obs	29		29		29		
RMSE	0.578449		0.047991		0.24675		
R-sq	0.8511		0.1456		0.7859		
chi^2	165.7494		4.941543		106.4652		
P>chi2	0		0.5513		0		

Granger causality Wald Test

Equation	Excluded	chi2	df	Prob > chi2
log(P_Rice)	log(rainfall)	3.8122	2	0.1487
log(P_Rice)	log(Oil)	1.2525	2	0.5346
log(P_Rice)	ALL	5.9547	4	0.2026
log(rainfall)	log(P_Rice)	3.3676	2	0.1857
log(rainfall)	log(Oil)	0.8248	2	0.6621
log(rainfall)	ALL	4.0343	4	0.4014
log(Oil)	log(P_Rice)	4.5995	2	0.1003
log(Oil)	log(rainfall)	2.1849	2	0.3354
log(Oil)	ALL	5.5565	4	0.2348

Figure 18 Impulse Response Function for Annual Rice Prices in China (1970- 2000)

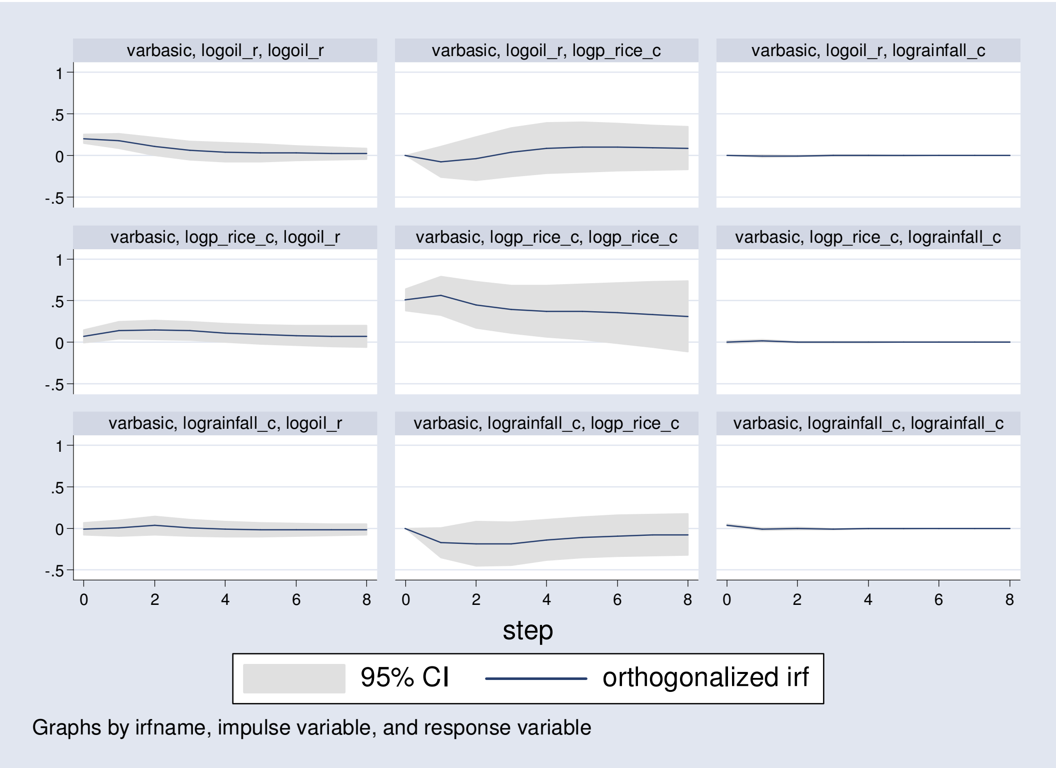


Table 25 Vector Autoregression (VAR) for Annual Vegetable Prices in China (1970-2000)

	log(P_Fruit)			log(rainfall)			log(Oil)		
log(P_Fruit)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.94	(4.75)	**	0.02	(1.71)	+	0.13	(1.81)	+
L2	0.02	(0.09)		-0.02	(-1.34)		-0.08	(-1.05)	
log(rainfall)									
L1	-4.95	(-2.03)	*	-0.15	(-0.86)		0.29	(0.31)	
L2	-1.24	(-0.48)		0.12	(0.63)		1.41	(1.47)	
log(Oil)									
L1	-0.24	(-0.45)		-0.02	(-0.64)		0.85	(4.24)	**
L2	0.23	(0.46)		0.01	(0.14)		-0.14	(-0.75)	
Constant	40.13	(1.59)		6.70	(3.67)		-10.21	(-1.08)	
Obs	29			29			29		
RMSE	0.667796			0.048318			0.249255		
R-sq	0.8333			0.1339			0.7816		
chi^2	144.9255			4.483147			103.7564		
P>chi2	0			0.6116			0		

Granger Causality Wald Tests				
Equation	Excluded	chi2	df	Prob > chi2
log(P_Fruit)	log(rainfall)	4.136	2	0.1264
log(P_Fruit)	log(Oil)	0.2261	2	0.8931
log(P_Fruit)	ALL	4.8337	4	0.3048
log(rainfall)	log(P_Fruit)	2.9305	2	0.231
log(rainfall)	log(Oil)	0.7784	2	0.6776
log(rainfall)	ALL	3.5882	4	0.4646
log(Oil)	log(P_Fruit)	3.9276	2	0.1403
log(Oil)	log(rainfall)	2.1522	2	0.3409
log(Oil)	ALL	4.8655	4	0.3014

Figure 19 Impulse Response Function for Annual Fruit Prices in China (1970- 2000)

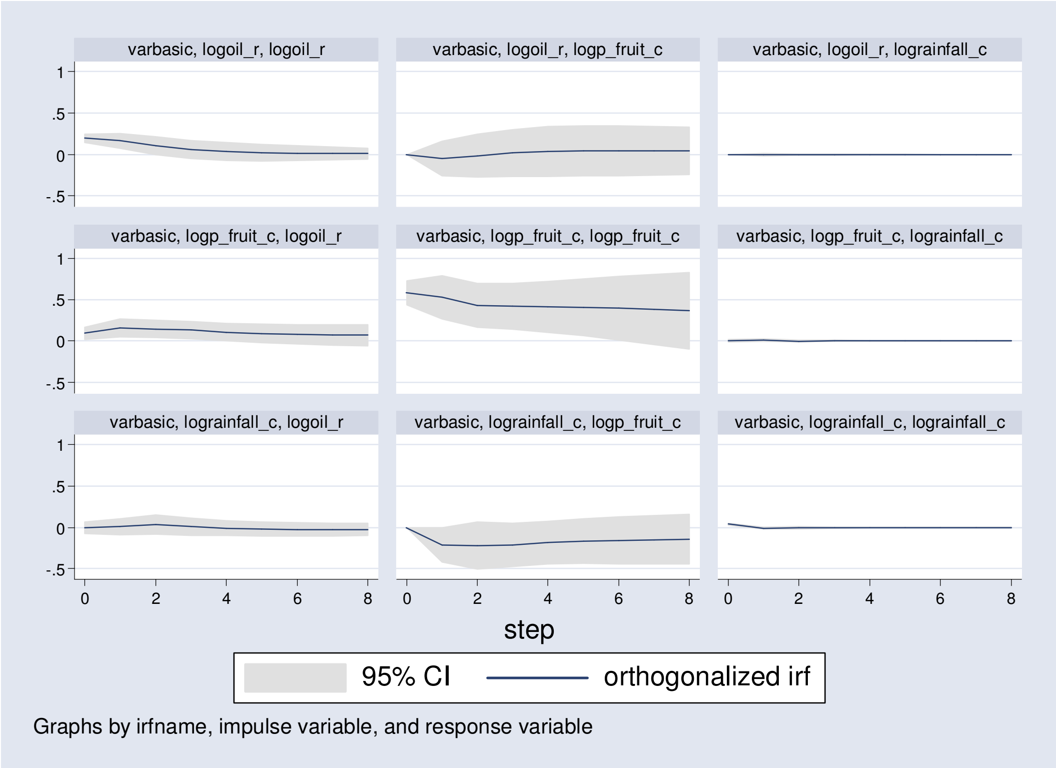


Table 26 Vector Autoregression (VAR) for Annual Vegetable Prices in China (1970-2000)

	log(P_Vegetable)			log(rainfall)			log(Oil)		
log(P_Vegetable)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	0.98	(5.08)	**	0.02	(0.97)		0.15	(1.71)	+
L2	-0.04	(-0.20)		-0.01	(-0.56)		-0.06	(-0.66)	
log(rainfall)									
L1	-3.61	(-1.88)	+	-0.17	(-0.96)		0.19	(0.21)	
L2	-0.58	(-0.29)		0.05	(0.28)		1.25	(1.34)	
log(Oil)									
L1	-0.08	(-0.19)		-0.02	(-0.41)		0.84	(4.29)	**
L2	0.10	(0.25)		-0.01	(-0.20)		-0.18	(-1.02)	
Constant	27.26	(1.38)		7.26	(3.94)		-8.55	(-0.94)	
Obs	29			29			29		
RMSE	0.531753			0.049749			0.2464		
R-sq	0.8454			0.0818			0.7865		
chi^2	158.5419			2.585244			106.85		
P>chi2	0			0.8588			0		

Granger Causality	Wald Test			
Equation	Excluded	chi2	df	Prob > chi2
log(P_Vegetable)	log(rainfall)	3.5243	2	0.1717
log(P_Vegetable)	log(Oil)	0.0626	2	0.9692
log(P_Vegetable)	ALL	3.8218	4	0.4307
log(rainfall)	log(P_Vegetable)	1.1206	2	0.571

log(rainfall)	log(Oil)	0.8554		2	0.652
log(rainfall)	ALL	1.741		4	0.7833
log(Oil)	log(P_Vegetable)	4.6949	+	2	0.0956
log(Oil)	log(rainfall)	1.7859		2	0.4094
log(Oil)	ALL	5.6547		4	0.2265

Figure 20 Impulse Response Function for Annual Vegetable Prices in China (1970- 2000)

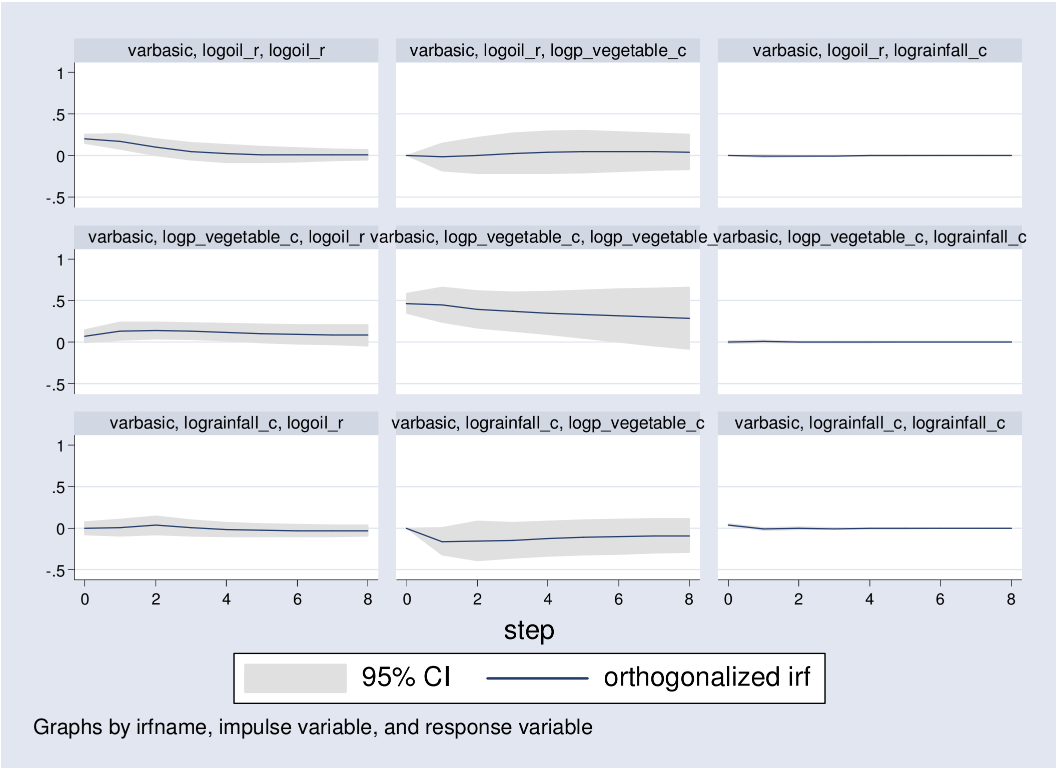


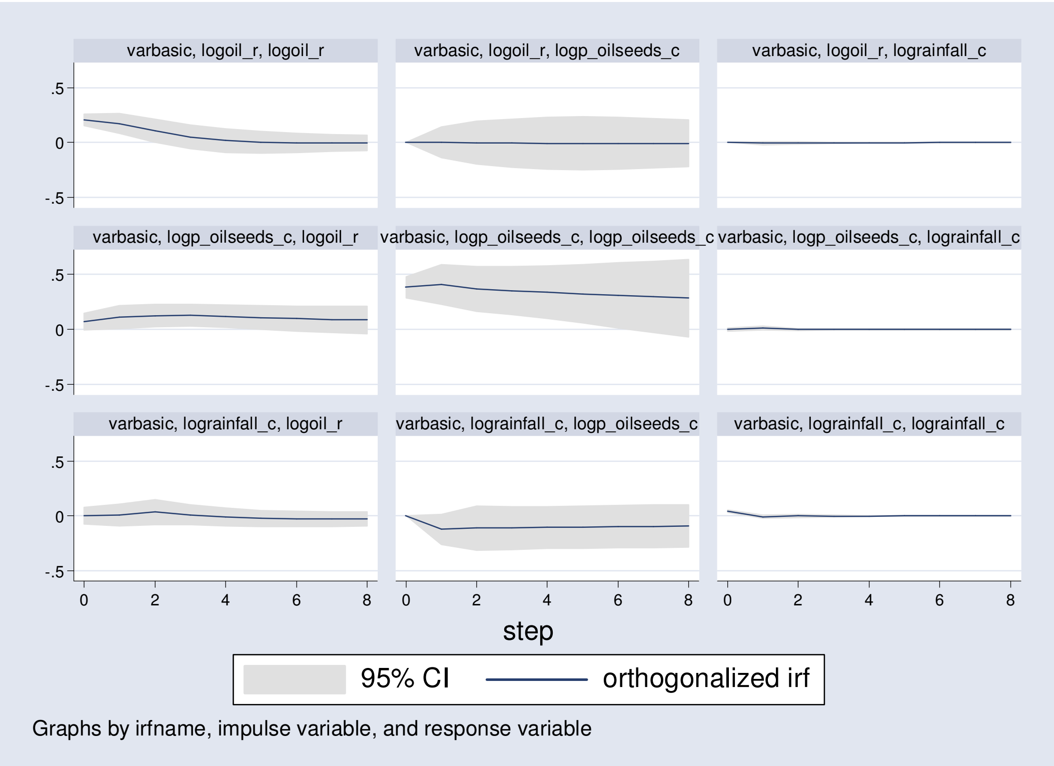
Table 27 Vector Autoregression (VAR) for Annual Oilseeds Prices in China (1970- 2000)

	log(P_Oilseeds)			log(rainfall)			log(Oil)		
log(P_Oilseeds)	Coef.	z value		Coef.	z value		Coef.	z value	
L1	1.06	(5.42)	**	0.03	(1.46)		0.14	(1.28)	
L2	-0.07	(-0.34)		-0.02	(-1.04)		-0.04	(-0.36)	
log(rainfall)									
L1	-2.86	(-1.79)	+	-0.16	(-0.93)		0.16	(0.17)	
L2	-0.08	(-0.05)		0.08	(0.43)		1.07	(1.13)	
log(Oil)									
L1	0.01	(0.02)		-0.02	(-0.60)		0.85	(4.24)	**
L2	-0.08	(-0.26)		0.00	(0.00)		-0.19	(-1.05)	
Constant	19.25	(1.18)		7.03	(3.85)		-7.28	(-0.78)	
Obs	29			29			29		
RMSE	0.437803			0.048763			0.2496		
R-sq	0.8776			0.1179			0.781		
chi^2	207.9494			3.875628			103.4281		
P>chi2	0			0.6935			0		

Granger Causality	Wald	Test		
Equation	Excluded	chi2	df	Prob >

				chi2
log(P_Oilseeds)	log(rainfall)	3.3268	2	0.1895
log(P_Oilseeds)	log(Oil)	0.1469	2	0.9292
log(P_Oilseeds)	ALL	3.3554	4	0.5002
log(rainfall)	log(P_Oilseeds)	2.3511	2	0.3086
log(rainfall)	log(Oil)	0.8933	2	0.6398
log(rainfall)	ALL	2.9969	4	0.5583
log(Oil)	log(P_Oilseeds)	3.8462	2	0.1462
log(Oil)	log(rainfall)	1.2736	2	0.529
log(Oil)	ALL	4.7818	4	0.3104

Figure 21 Impulse Response Function for Annual Oilseeds Prices in China (1970- 2000)



V. Concluding Remarks

This present study investigates the inter-relationships between food and oil prices, and an exogenous variable (rainfall). The analysis is based on monthly and annual price data for long periods at the global level. It is supplemented by similar analyses of food prices in China and India. While comovements of prices imply integration of different markets, their efficiency implications are far from obvious for familiar reasons emphasised in the recent literature.[23]

Our analysis offers useful insights. First, there is robust evidence confirming comovements of different food prices. Specifically, both monthly and annual prices (e.g. wheat, rice, fruit, vegetable and oilseeds) are strongly interlinked globally. At the country level, similar results are obtained for India and China. Second, oil price has a significant positive impact on agricultural commodity prices globally (e.g. for wheat price with monthly data and for fruit price with annual data), and for India (on wheat, rice, fruit and vegetable prices with annual data). Oil price does not have any effect on agricultural commodity prices in China where wheat price leads other prices, such as prices of rice, fruit and vegetables. Thirdly, rainfall has a negative impact on agricultural commodity price in some cases (on wheat price at the global level, and on fruit and oilseed prices in India). Finally, in some cases, the price shocks are persistent but in several others these shocks are short-lived.

[23] See, for example, two important contributions (Barrett, 2001, and Baulch, 1997). Their exposition emphasizes the importance of transfer costs. Non-random variations in transfer costs may cause the Law of One Price to reject market integration even when spatial arbitrage conditions. Other approaches such as Granger causality and cointegration also ignore transfer costs and assume a linear relationship between market prices. The latter is inconsistent with the discontinuities in trade implied by the spatial arbitrage conditions. If we do not address these concerns, it is mainly because of data constraints that we hope to overcome in a sequel to this study.

From a policy perspective, these interrelationships of food and oil prices, and rainfall warrant careful consideration in the context of the energy crisis that has erupted and likely to continue unabated in the near future. The search for alternative sources of energy (e.g. biofuel) is likely to precipitate the surge in food prices with a tightening of supply constraints (e.g., scarcity of arable land, water and stagnant productivity). While this raises serious concerns about reversal of progress in rural poverty reduction, any temptation to draw pessimistic conclusions must be resisted. Much of course will depend on what governments do in emerging economies and elsewhere to promote smallholders, technical change and easier access to credit and insurance. The desperate policy responses in the form of price and quantity restrictions have not only not worked even as short-term palliatives but, more seriously, run the risk of jeopardising any chances of protecting the poor and their livelihoods in the medium or longer-term.

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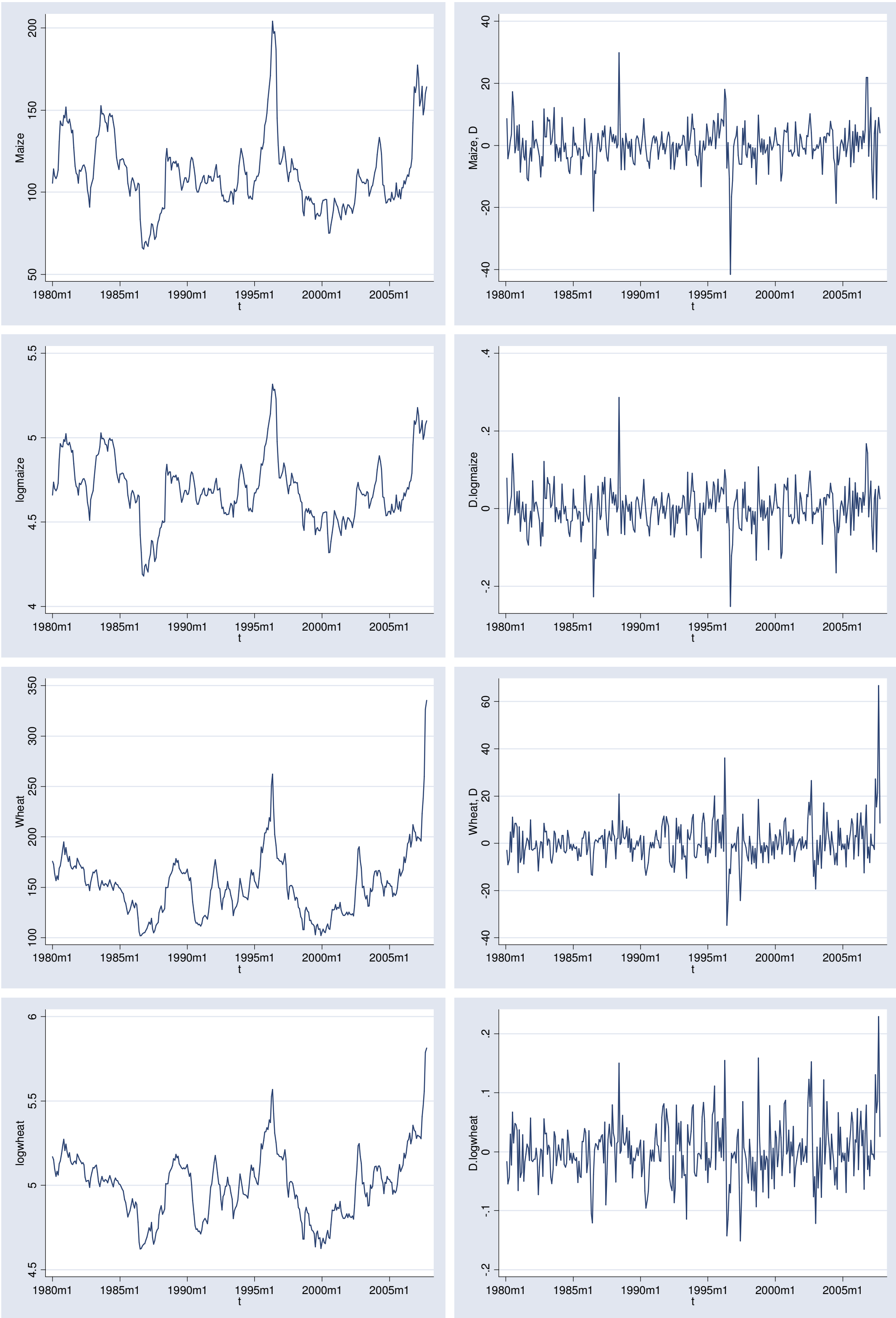
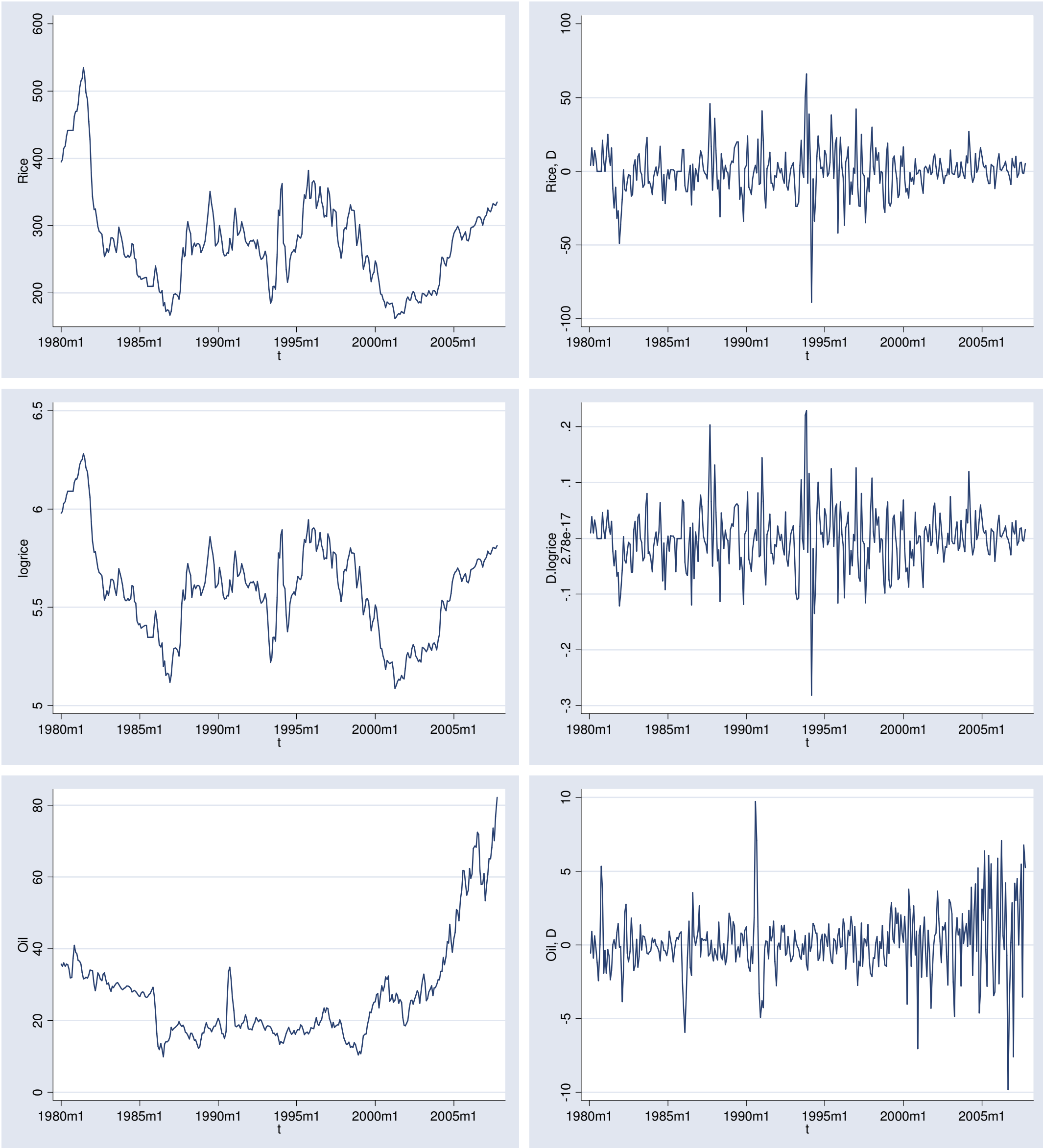
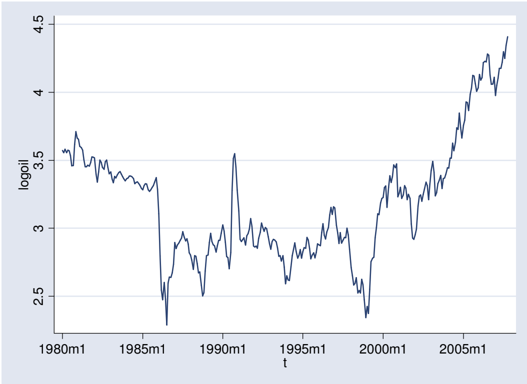
Appendix 1 Monthly Commodity Prices (for level and the first difference taking or not taking logarithm; for maize, rice, wheat, and oil, from 1980 January to 2007 October)





Rice
200
300
400
500
600
Rice, D
-100
-50
0
50
100
logrice
5
5.5
6
6.5
D.logrice
-.3
-.2
-.1
2.78e-17
.1
.2
Oil
0
20
40
60
80
Oil, D
-10
-5
0
5
10
1980m1
1985m1
1990m1
1995m1
2000m1
2005m1
t


logoil
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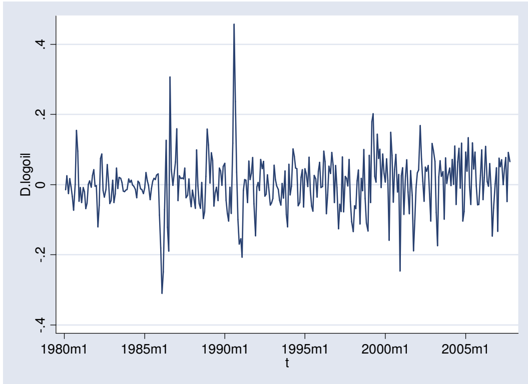
3
3.5
4
4.5
1980m1
1985m1
1990m1
1995m1
2000m1
2005m1
t


D.logoil
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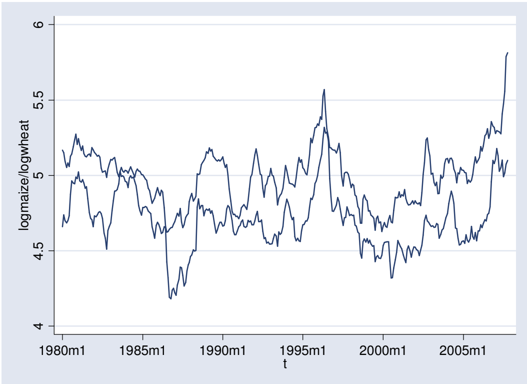
-.2
0
.2
.4
1980m1
1985m1
1990m1
1995m1
2000m1
2005m1
t


logmaize/logwheat
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4.5
5
5.5
6
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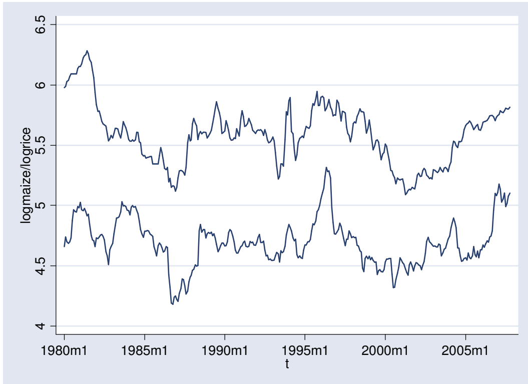
1985m1
1990m1
1995m1
2000m1
2005m1
t


logmaize/logrice
4
4.5
5
5.5
6
6.5
1980m1
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1995m1
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2005m1
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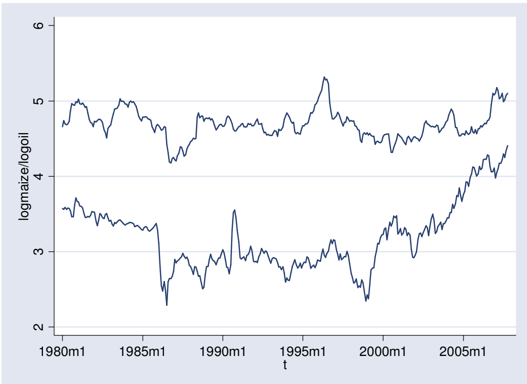
logmaize/logoil
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1990m1
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2000m1
2005m1
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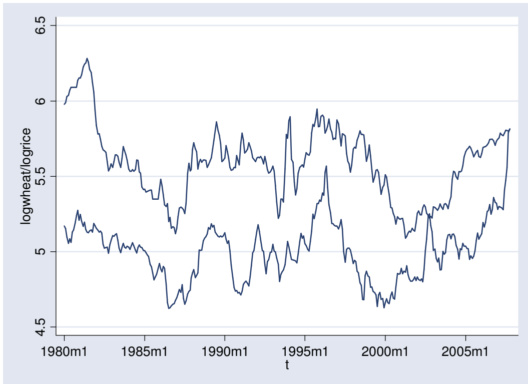
logwheat/logrice
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1980m1
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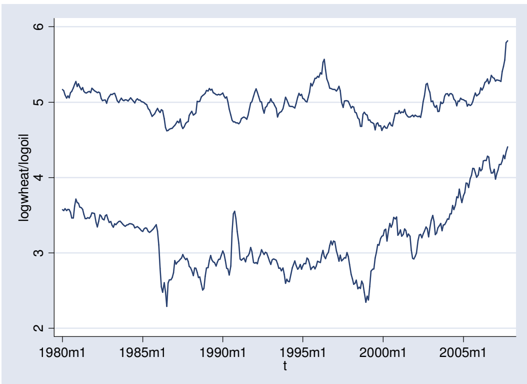
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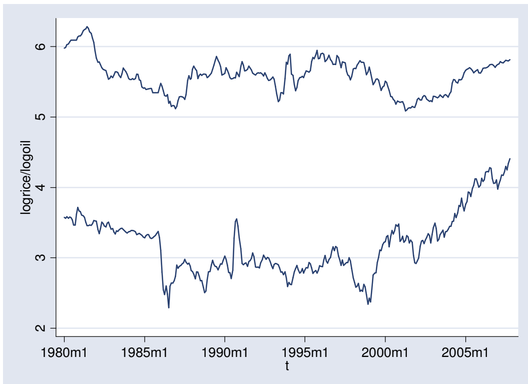
logrice/logoil
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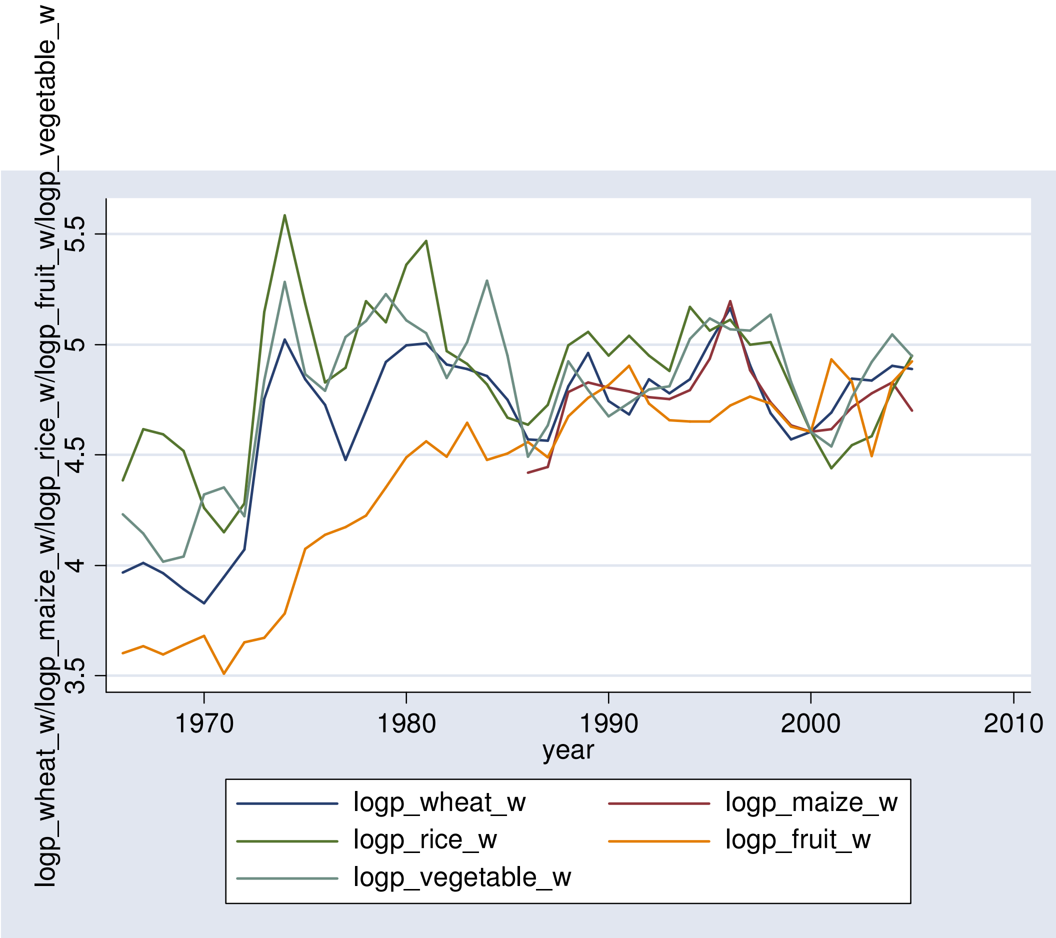
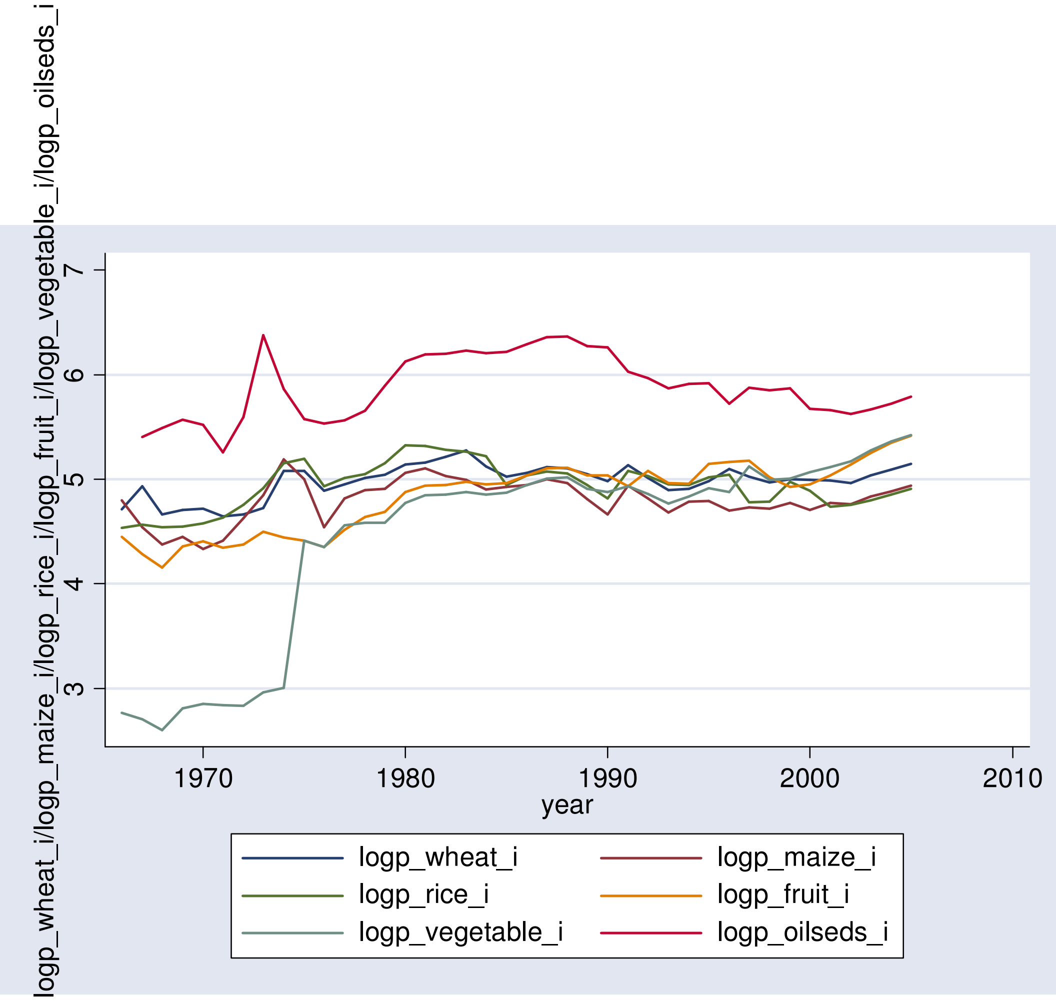
6
1980m1
1985m1
1990m1
1995m1
2000m1
2005m1
t

Appendix 2 Annual World Commodity Prices (for level, taking or not taking logarithm)



Appendix 3 Annual Commodity Prices in India (for level, taking or not taking logarithm)



Appendix 4 Annual Commodity Prices in China (for level, taking or not taking logarithm)