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Communication

Assessing the effect of oil price on world food prices: Application of principal component analysis

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ABSTRACT

The objective of this paper is to investigate the co-movement of food prices and the macroeconomic index, especially the oil price, by principal component analysis to further understand the influence of the macroeconomic index on food prices. We examined the food prices of seven major products: eggs, meat, milk, oilseeds, rice, sugar and wheat. The macroeconomic variables studied were crude oil prices, consumer price indexes, food production indexes and GDP around the world between 1961 and 2005. We use the Scree test and the proportion of variance method for determining the optimal number of common factors. The correlation coefficient between the extracted principal component and the macroeconomic index varies between 0.87 for the world GDP and 0.36 for the consumer price index. We find the food production index has the greatest influence on the macroeconomic index and that the oil price index has an influence on the food production index. Consequently, crude oil prices have an indirect effect on food prices.

1. Introduction

In the economic development process, food provision and security are vital issues. Food prices are an important effective variable of food supply and demand. Increasing food prices and incidents of food riots across the globe have increased concerns about world food supply and security. World food prices of the main arable crops (cereals, oilseed products), dairy products, sugar, wheat and most food products have increased in volatility during recent years.

World prices of crude oil and oil products in general have also increased in volatility during recent years. This contemporaneous increase in food and oil prices has reinforced attitudes towards the effect of oil prices on food prices. Raising the oil price, limited supplies of fossil fuel and increased concerns about global warming have created a growing demand for renewable energy sources (Srinivasan, 2009). The production of these fuels is highly dependent on the availability of agricultural products. However, it is possible that bio-diesel production could in fact cushion consumers from the negative effects of increasing world oil prices, but could result in increasing food prices.

Energy intensive farming is vulnerable to oil price shocks because prices paid by farmers for oil products or direct energy mirror the national energy markets. In addition, most agricultural producers purchase energy indirectly in other inputs, such as commercial nitrogen fertilizers, fuel and electricity costs for field operations, irrigation and drying. Combined with fertilizer costs, these costs account for a significant proportion of the cost of production of many crops. Recent price increases are similar to the large energy price shocks of the mid-1970s and early 1980s, which stimulated economic research on energy use in the agricultural sector (Musser et al., 2006).

There are several studies on the relationship between food and crude oil prices. Gohin and Chantret (2010) investigate the long-run relationship between world prices of some food and energy products using a world computable general equilibrium model. They find a positive relationship due to the cost-push effect. Zhang et al. (2010), using time series prices on fuels and agricultural commodities, investigate the long-run co-integration of these prices. They find no direct long-run price relationships between fuel and agricultural commodity prices. Chen et al. (2010) investigate the relationships between the crude oil price and the global grain prices of corn, soybean and wheat. The empirical results show that the change in each grain price is significantly influenced by the changes in crude oil price and other grain prices during the period extending from the 3rd week in 2005 to the 20th week in 2008, which implies that grain commodities are competing with the derived demand for bio-fuels using soybean or corn to produce ethanol or bio-diesel during the period of higher crude oil prices in these recent years. Conventional agriculture production systems in developed countries rely heavily on fossil energy (Cruse et al., 2010). Xiaodong and Hayes (2009) find evidence of volatility spillover among crude oil, corn and wheat markets, which could be largely explained by tightened interdependence between these markets induced by ethanol production. Abdel and Arshad (2008) show that there is a log-run causality from petroleum to cereal

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prices and that vegetable oil prices are affected by petroleum prices. Tokgoz (2009) shows that the impact of energy prices on the European Union agricultural sector is increasing with the emergence of the bio-fuels sector, illustrating the importance of trade policy in responding to higher crude oil and grain prices.

The objective of this paper is to investigate the co-movement of food prices and the macroeconomic index by principal component analysis (PCA) to further understand the influence of the macroeconomic index on food prices. The food prices we studied are for eggs, meat, milk, oilseeds, rice, sugar and wheat. The macroeconomic variables include the crude oil price, consumer price index (CPI) and food production index (FPI).

2. Empirical model

2.1. Principal component analysis

The analysis in this paper is based on the PCA model. The general purpose of factor analytic techniques is to find a way of condensing the information contained in a number of original variables into a smaller set of new composite factors with minimum loss of information. PCA is the most successful method under the factor analysis approach (Rao, 1964).

Given a data set with P numeric variables, one can compute P principal components. Each principal component is a linear combination of the original variables, with coefficients equal to the eigenvectors of the correlation or covariance matrixes. Principal components have a variety of useful properties (Rao, 1964; Kshirsagar, 1972).

The general form for computing the first principal component (PC1) is

$$C_1 = b_{11}(x_1) + b_{12}(x_2) + \cdots + b_{1p}(x_p) \tag{1}$$

where C_1 is PC1, b_{1p} is the regression coefficient for the Pth variable that is the eigenvector of the covariance matrix between the variables and X_p is the value of the Pth variable.

There are various methods for determining the optimum number of factors, such as the Scree test, proportion of variance, analysis of residuals and a priori hypotheses. In this paper, we use the Kaiser–Guttman rule, which has been most commonly used due to its simplicity and availability in various computer packages (Kaiser, 1960). The Kaiser–Guttman rule states that the number of factors to be extracted should equal the number of factors having an eigenvalue greater than one. The rationale for choosing this particular value is that a factor must have variance at least as large as that of a single standardized original variable.

2.2. Granger causality test

According to Engle and Granger (1987), a linear combination of two or more non-stationary series (with the same order of integration) may be stationary. If such a stationary linear combination exists, the series is considered to be co-integrated and a long-run equilibrium relationship exists. The linear combination can be written as follows: $z_t = x_t - a_0 - a_1 y_t$, where a_0 and a_1 are constant terms such that z_t is stationary. This relation is the long-run equilibrium relationship and z_t measures the deviation with respect to the equilibrium value.

Incorporating these co-integrated properties, a vector error correction model (VECM) can be constructed to test for Granger causation of the series in at least one direction. In this paper, a VECM is specifically adopted to examine the Granger causality between the extracted principal component and the macroeconomic index.

2.3. Data

The world food prices we studied are for eggs, meat, milk, oilseeds, rice, sugar and wheat. We take the world food price of seven major products for the period of 1961–2005 from FAO and macroeconomic variables from World Bank (2010) and Nation Master Sites. Representative international prices for each of the commodities or commodity groups appearing in the balance sheet are weighted by their contribution to total calorific intake.

Food price and other reports are available on the internet as a part of the FAO worldwide web (www.fao.org). The FAO food price index is a measure of the monthly change in the international prices of a food basket composed of cereals, oilseeds, dairy, meat and sugar.

3. Results and discussion

We took world food prices of seven major products (eggs, meat, milk, oilseeds, rice, sugar and wheat) for the period 1961–2005 from the websites of Food and Agriculture Organization (2010) and United Nations. Then we used PCA on the product prices and selected a number of factors, after which correlation among the common factors, crude oil price, FPI and CPI was examined.

3.1. Principal component analysis

At first, the number of components was obtained by the Kaiser–Guttman rule. Table 1 presents the eigenvalue proportions of variance for selecting the optimal number of components. In PCA, the total eigenvalues of the correlation matrix were equal to the total number of variables being analyzed because each variable contributed one unit of variance to the data set. According to the Kaiser–Guttman rule, only one factor can be retained because only the first factor has an eigenvalue of greater than one (Table 2).

Table 2 shows the calculated eigenvectors for the seven agricultural products.

By these eigenvectors, PC1 is obtained by Eq. (1).

3.2. Correlation and causality test

Prior to performing regression analysis, we first examine the correlation between the variables and then test for causality.

Table 1
Eigenvalues of reduced correlation matrix.

Number of factors	Eigenvalue	Difference	Proportion	Cumulative
1	5.983589	5.269293	0.8548	0.8548
2	0.714296	0.614783	0.102	0.9568
3	0.099513	0.020185	0.0142	0.9711
4	0.079328	0.020176	0.0113	0.9824
5	0.059151	0.019877	0.0085	0.9908
6	0.039275	0.014426	0.0056	0.9965
7	0.024849	0.0035	0.0035	1

Table 2
Eigenvectors for food products.

Variable	Factor 1
Egg	0.96058
Milk	0.79700
Oilseed	0.96192
Rice	0.95023
Sugar	0.87210
Meat	0.95767
Wheat	0.95903