Impacts of Energy Shocks on US Agricultural Productivity Growth and Food Prices

—A Structural VAR Analysis[1]

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Abstract

This study proposes to use a structural VAR model, using annual percentage change series on U.S. gasoline prices, agricultural productivity, real GDP, agricultural exports, and agricultural commodity prices, to assess the impact of energy shocks on U.S. agricultural productivity growth and food price variations. These data span the period 1948 to 2009. Study results indicate that in the short-run (1 year) an energy shock and a productivity shock each accounts equally for 10 percent of the food price volatility. However, the impact from an energy shock overweighs the contribution of a productivity shock in the intermediate term (3 years), where an energy shock's contribution increases to twice as much as a productivity shock's contribution (16 percent compared to 8 percent). Besides the specific food market shock, the global demand shock in U.S. agricultural exports is the major factor in explaining the volatility in U.S. food prices, and accounts for one-third of the food price fluctuations.

Key words: Energy shock, Total Factor Productivity (TFP), U.S. agriculture, food price, Structural VAR model

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I. Introduction

According to the Food and Agriculture Organization (FAO) of the United Nations (2012), the annual global food price index spiked to a post-1996 high in 2008. That year, the global food price index was more than double than its earlier lowest level in 2002. While the price index briefly declined in 2009, it continued to grow and reached 2.5 times its 2002 level in 2011. According to the U.S. Department of Agriculture (USDA), Economic Research Service (ERS), the U.S. food grain price measure increased to 2.3 times of its 2002 level in 2008, and the feed grain price increased to 2 times of its 2000 level in 2008. Some researchers have pointed to a decline in the growth rate of crop yields (World Bank (2007), Alston, Beddow, and Pardey (2009)) as a factor behind the rise in food prices. In recent years soaring food prices have also generated concern about a slowdown in global agricultural productivity growth (Alston et al. (2010)). Slower productivity growth which fails to keep pace with increasing global food demand may not only lead to food price increases but could also cause environmental problems as farmers tend to use more chemicals to boost their production to a higher level. While there is no consistent conclusion regarding the productivity slowdown issue among studies focusing on either a single country (James, et al (2009), Alston et al. (2010), Veeman and Gray, (2009), Jin, et al. (2009), Gasques et. al (2012), Wang (2010), Gasques et. al (2012)) or a region (Alston et al. (2010), Nin-Pratt and Yu(2012), Wang, Schimmelpfennig, and Fuglie (2012), Ball et al. (2010)), Fuglie (2008), in examining whether slowing productivity growth led to the rise in commodity prices, found no evidence of a sector-wide agricultural productivity slowdown.

While food prices may be affected by agricultural productivity, food prices and agricultural productivity may both be influenced by energy price shocks and substantial increases in the crude petroleum price. Many studies in discussing the impact of energy prices on US productivity or economic growth have asserted that energy price shocks were a critical determinant of the slowdown in the U.S. economic growth or the manufacturing productivity growth during the 1973-1980 period (Jorgenson and Wilcoxen (1993)). However, Berndt (1980) found energy prices had no significant role in the labor productivity slowdown in the U.S. manufacturing sector. From the perspective of agriculture and food production, we suspect that high energy prices can contribute to an escalation in food prices due to higher production costs. In addition, short term inefficiency in agricultural input use may result in greater volatility in the rate of agricultural productivity growth. Higher crude petroleum prices can cause not only an increase in fertilizer and pesticide costs but can also affect production costs directly through farm energy use, including fuel for farm machinery used in tillage, cultivating and harvesting operations, and cooling and heating systems for livestock. Skyrocketing energy prices have also increased ethanol production (Banse et al. (2011)). The emergence of large scale biofuel production and the increased use of agricultural commodities to produce energy, has increased the linkage between agriculture and energy (Zhang et al. (2009), Ciaian and Kancs (2011), McPhail (2011), Du and McPhail (2012)). The induced demand for corn in ethanol production has also boosted corn prices and thus pushed-up sector-wide food grain and feed grain prices in recent years.

Nevertheless, the size of the impacts of energy prices on U.S. agricultural productivity growth and increases in food prices are still uncertain. How much of the increase in food prices can be attributed to the productivity changes and energy price shocks? Are there other factors

that are contributing to the volatility in food prices? The purpose of this paper is two-fold: first, to evaluate the impacts of energy price shocks on agricultural productivity growth and food price changes; second, to disentangle demand and supply shocks in the U.S. food market and to quantify the contribution of each individual shock, with a special focus on energy shocks and productivity shocks.

Many studies in assessing the impact of energy price shocks on economic growth or agricultural production have employed general equilibrium modeling techniques (Jorgenson and Wilcoxen (1993), Gehlhar et al. (2010), Bans et al. (2011)). The robustness of the results from these studies depends heavily on the numerous assumptions used, such as elasticities. This study relies on historical data and limited assumptions and employs a structural VAR (SVAR) model to analyze the impact of energy prices on agricultural productivity and food prices. The model incorporates U.S. GDP and agricultural exports to control for demand side impacts. Impulse response is used to examine the response of food prices to demand or supply shocks. Variance decomposition is used to measure the importance of each shock, particularly an energy price shock, to explain fluctuations in total factor of productivity (TFP) and food prices. We propose that food prices are driven by the following factors: (1) energy shocks; (2) agricultural productivity shocks; (3) domestic demand shocks measured by US GDP; (4) global supply and demand shocks measured by US agricultural export; and (5) other shocks in the U.S. food market that are not captured by the shocks listed above. While there may exist many causal forces (Heady and Fan (2008), Peters, Langley, and Westcott (2009), Farm Foundation (2011)) that affect the global food trade or domestic agricultural commodity demand, we assume the volatility in food prices caused by those factors will be captured by the global demand shock, domestic demand shock, and other specific shocks in the model.

2. Decomposition of the food price and the structural VAR model

Many studies have investigated the response of food prices (or individual farm commodity prices) to either an energy shock or to a productivity shock individually. This study proposes a more comprehensive model which takes into account shocks from both supply and demand sides in the food market. Shocks are conceptually defined as changes from individual sources that are not anticipated by the SVAR model. For example, an energy shock can be an unexpected change in gasoline prices.

This study uses a SVAR model with five variables to capture the impacts of an energy shock on U.S. agricultural productivity growth as well as on fluctuations in food prices. By doing so, it can also identify the contributions of each shock from the demand side and supply side to food price changes. The five annual variables are defined as a vector $x_t = (\Delta P_{Et}, \Delta TFP_t, \Delta X_{At}, \Delta GDP_t, \Delta P_{Ft})'$ where P_E is the US gasoline price index, which is assumed to be affected by demand and supply in the global oil market; TFP is the US agricultural total factor productivity index; X_A is the real US agricultural export index, which represents foreign demand for U.S. agricultural commodities; GDP is the US real gross domestic product, which is a proxy for U.S. domestic food demand; P_F is the food price index, which is measured by U.S. farm commodity prices; and t is the time script. Δ denotes the percentage change rate in each series. The structural VAR model is represented as:

$$A_0 x_t = \alpha + \sum_{i=1}^{p} A_i x_{t-i} + \varepsilon_t \qquad (1)$$

where p is the order of lags, ε_t is the vector of serially and mutually uncorrelated structural innovations, A_0, A_i, and α are unknown coefficients matrixes and the vector to be estimated. The reduced form of the VAR representation is:

$$x_t = A_0^{-1}\alpha + \sum_{i=1}^{p} A_0^{-1}A_i x_{t-i} + e_t \tag{2}$$

Where e_t is the vector of estimated residuals in the reduced form and can be expressed as

$$e_t = A_0^{-1}\varepsilon_t. \tag{3}$$

Following Killian (2009) we impose theoretical restrictions to the recursive structure on A_0^{-1} assuming that variables will not respond to all contemporaneous shocks from variables other than those being specified. It is similar to putting restrictions on a demand or supply curve in the short run. For example, in this study, we assume that US oil refiners are price takers who set the retail price based on their import cost and a specific amount of mark-up in the short-run. Therefore, the US gasoline price shock in the model is not affected by any contemporaneous shocks other than the one from the specific energy price shock which is not explained by the model, such as the supply shift in global oil market. A US agricultural productivity shock is assumed to respond only to contemporaneous energy shocks and specific agricultural productivity shocks, such as unexpected input or output changes due to unfavorable weather, animal disease, or other factors. A US agricultural export shock is assumed to respond to contemporaneous energy shocks and US agricultural productivity shocks. Other innovations are assumed to take more than a year to affect US agricultural exports. US domestic food demand is assumed to respond to contemporaneous shocks from US agricultural exports, US agricultural productivity, and domestic energy prices. Finally, a US food price shock responds to domestic food demand shocks, foreign demand in US agricultural export shocks, US agricultural

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productivity shocks, and energy shocks. Accordingly, the reduced form errors e_t can be decomposed into the following components:

$$
e_t \equiv \begin{bmatrix} e_t^{\Delta P_E} \\ e_t^{\Delta TFP} \\ e_t^{\Delta X_A} \\ e_t^{\Delta GDP} \\ e_t^{\Delta P_F} \end{bmatrix} =
$$

$$
\begin{bmatrix} \alpha_{11} & 0 & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & 0 \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & \alpha_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{global\ energy\ market\ shock} \\ \varepsilon_t^{US\ agricultural\ productivity\ shock} \\ \varepsilon_t^{Foreign\ demand\ on\ US\ agricultural\ export\ shock} \\ \varepsilon_t^{US\ domestic\ food\ demand\ shock} \\ \varepsilon_t^{US\ food\ commodity\ specific\ demand\ shock} \end{bmatrix} \quad (4)
$$

We impose restrictions by making the components in the A_0^{-1} matrix equal to zero when there is not an expected immediate impact from the specific contemporaneous shock. For example, all values on the top row of the A_0^{-1} matrix are set to zero except for α_{11} allowing that $e_t^{\Delta P_E}$ only responds to the contemporaneous shock from $\varepsilon_t^{global\ energy\ market\ shock}$. By making all values on the last row of the A_0^{-1} matrix nonzero, food prices are assumed to be driven by the following shocks: (1) energy shocks; (2) agricultural productivity shocks; (3) foreign demand on US agricultural export shocks; (4) domestic food demand shocks; and (5) other food market shocks.

Impulse response is used to examine the response of food prices to demand or supply shocks. Variance decomposition is used to measure the importance of each shock, particularly a positive energy shock or a negative TFP shock, in explaining food price fluctuations.

3. Data

Our data consists of five annual series—energy prices, US total factor productivity (TFP), US agricultural exports, US GDP, and US food prices. The study period is 1948 to 2009. Definitions for each variable as well as their data sources are addressed below.

Energy prices

Studies in identifying the determination of domestic gasoline prices tend to include global crude oil supply and demand shocks in the model. In this study, since our focus is to assess the impact of energy shocks on productivity growth and food price changes, we assume the U.S. energy price shocks is affected by global oil market shocks and will be captured as unexpected energy price shocks in our system. We choose the gasoline price index from Bureau of Labor Statistics (BLS) at U.S. Department of Labor (USDOL, 2012) as the measure of energy price. One reason is because gasoline refiners are small and act as price takers in the global oil market. The trend and percentage change of this series can reflect shifts in global demand and supply in oil market. In addition, gasoline prices have strong links to ethanol prices while ethanol prices are thought to have a significant influence on food prices by many studies in recent years (Ciaina and Kancs (2011)).

U.S. agricultural productivity

Many studies use partial productivity, such as crop yield or labor productivity, to address the productivity slowdown issue or link it to surging food prices. Yet, agriculture is a joint production process. Partial productivity can be boosted by adding more of other inputs, for instance agricultural chemicals, while the overall productivity level is not improved. In this study, we propose to employ a total factor productivity (TFP) index developed by the Economic

Research Service (ERS) at the U.S. Department of Agriculture (USDA, 2012). TFP takes into account all outputs produced at the farm and all inputs used in the production process. Productivity therefore measures changes in the efficiency with which inputs are transformed into outputs. The ERS's TFP estimates are based on the translog transformation frontier which relates the growth rates of multiple outputs to the growth rates of multiple inputs. As a result, the TFP growth rate measures the difference between output growth and input growth. Therefore, the TFP series is a better measure to assess the impact of an energy shock on productivity growth in the U.S. farm sector as a whole. A complete data description and methodology can be found in Ball, Wang and Nehring (2012), and Ball et al. (1999).

U.S. agricultural exports

To capture shocks in foreign demand for U.S. agricultural exports we use a U.S. agricultural export series in real terms or in terms of implicit quantity. U.S. trade data are collected by U.S. Department of Homeland Security, U.S. Customs and Border Protection. The data are compiled and distributed by the U.S. Department of Commerce, U.S. Census Bureau using the United States' Harmonized Tariff Schedule (HTS) of 10-digit codes. ERS publishes Foreign Agricultural Trade of the United States (FATUS) based on standard USDA aggregation of several thousand HTS codes into 213 agricultural groups most used by the public. Yet, this dataset is in nominal value, which needs to be deflated into the real value. The most appropriate deflator for this series is BLS's agricultural export price index. However, the earliest year of this series is 1983. Bureau of Economic Analysis (BEA) at U.S. Department of Commerce, on the other hand, publishes a Food, Feed, and Beverage export price index starting in 1967.   BEA also publishes an overall export price index back to earlier years. We compare these three price indices in figure 1. The comparison shows that BLS's agricultural export price index and BEA's Food, Feed, and

Beverage export index move closely for the period 1983 to 2009 while the BEA's export GDP deflator moves distantly from these two series in that period. Nevertheless, if we compare the BEA's export GDP deflator and its Food, Feed, and Beverage export price index in the pre-1973 period, or the pre oil shock period, we can see that these two series move amazingly close to each other during the 1967 (the earliest year in Food, Feed, and Beverage export price series) to 1973 period. It seems that the oil shock contributes differently to the prices of agricultural export and manufacturing exports in the post-oil shock era. Due to the lack of a long series of agricultural exports deflator we decide to use the BLS's agricultural export price index as the agricultural exports deflator for the 1983 to 2009 period. This series is then chain-linked with the BEA's food, feed, and beverage export price index from 1983 to 1967, and once again chain-linked with the BEA's export GDP deflator from 1967 to 1948, the earliest year in our dataset. We employ this export price series to deflate the USDA's FATUS annual data to get the real U.S. agricultural export series.

(Insert Figure 1 here)

U.S. real GDP

Domestic food demand is affected by the average U.S. income level and number of consumers, which can be measured by the US real GDP. This series is drawn from the BEA's National Income and Production Account (NIPA).

U.S. food prices

Previous studies linking agricultural productivity growth and food prices, or energy shocks and food prices, tend to apply individual crop prices, such as prices of corn, soybean, wheat, in

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their assessment. There is lack of information regarding the impact on overall food prices. In this study, we employ an aggregate agricultural output price index from the ERS's productivity accounts as a proxy of the level U.S. Food prices. This series is constructed based on the Törnqvist-Theil index approach using price information from individual crops and livestock. This method utilizes rolling weights based on each commodity's revenue shares. Therefore, the percentage change in this series can represent a general change in food prices as it allows the commodity composition to shift from year to year in the calculation. Figure 2 presents growth rates of price indices--crops, livestock, and aggregate agricultural output from ERS's productivity accounts. While those series move attendantly with each other over time, the aggregate agricultural price index moves, in general, between the crop price and livestock price series. Over the study period, the percentage change rates in 1973, 1983, 2005, and 2007 are among the highest in the study period. The first two points coincide with two oil shocks and the later two points have been linked to global food price shocks driven by either biofuel policy, or agricultural productivity slowdown in previous studies.

(Insert Figure 2 here)

While all variables are in the form of percentage changes (growth rates) in our analysis we plot their level series in Figure 3 to get some idea on how their levels evolved over the post-war period. In general, energy prices increased dramatically and were much more volatile after the global oil shock in 1973. Real GDP moves relatively smoothly compared to the other series. The descriptive analysis for the growth rates of the five series is presented at table 1. According to the standard deviation of the growth rates, gasoline prices and US agricultural exports are much volatile than the other variables.

(Insert Figure 3 here)

(Insert Table 1 here)

4. Empirical Results and Discussions

We first conduct the Augmented Dickey-Fuller (ADF) unit root test to examine if the growth rates of the five time series are stationary. We present the results of unit root test in table 1. According to the ADF statistics all five series reject the hypothesis of nonstationarity at 1% significance level.

(Insert table 2 here)

After confirming the stationarity of five variables we estimate the SVAR model using three lags based on Akaike information criterion (AIC). We impose ten just-identifying restrictions on SVAR model specified by equation (4). The reduced form of VAR system (2) is estimated using least-squares approach. The structural shocks ε_t can be retrieved using estimated residuals from the VAR estimates and the A_0 matrix.

The time path of the estimated historical structural shocks

The historical structural shocks estimates for the five variables are exhibited in Figure 4, where a one-standard deviation above the mean is defined as a positive shock, and a one-standard deviation below the mean is defined as a negative shock. From Figure 4 we find that the energy shock series is much more volatile after year 2000, surpassing volatility exhibited during the last global oil shock in early 1980s. The oscillation in US agricultural productivity shock series was greater since 1980s. The short-term shock may also reflect the El Niňo-Southern Oscillation (ENSO) effect. Increases in air temperatures, changes in the air pressure patterns and

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shifts in the high-level winds that direct the movement of weather resulted in increasing frequency in unusual warm temperatures and excess precipitation. As a weather sensitive industry, U.S. agriculture has suffered from drought or flood in many regions more often since the 1980s. The peaks in the estimated global food market structural shock series are in year 1973 and 2008. The first is during the first global oil shock period and the second in more recent years has raised concern of a global productivity slowdown.

(Insert Figure 4 here)

We can use the Impulse Response Analysis to analyze the short-run dynamic response of dependent variables to energy shocks or other shocks of interest. On the other hand, the Generalized Forecast Error Variance Decompositions Analysis can help us to understand how much of the fluctuation can be explained by the innovations from each of the shocks estimated by the system. We present the results and their implications below.

What are the dynamic responses of food price to energy shock, productivity shock and other innovations?

Figure 5 presents the time path of the response of food prices changes to one standard deviation structural innovations of an energy shock, a productivity shock, a foreign demand (agricultural export) shock, and a domestic demand (U.S. GDP) shock, respectively, based on the impulse response analysis. The solid lines denote the mean responses of food price changes to the shocks from other factors. The dotted lines show two standard deviation impacts from the mean. The standard errors for the impulse responses are calculated based on the Monte Carlo approach (Runkle, 1987).

(Insert Figure 5 here)

The first panel in figure 5 shows that food price changes respond positively to an energy shock in year 1 and 2. These responses are statistical significant, which indicates that a positive shock from the oil market will cause higher food price growth over two years. Panel B shows that food price changes respond negatively to productivity growth in year 1. Longer than one year the response becomes insignificant and approaches to zero. Panel C shows that food price changes respond to a global food market shock positively in year 1 and year 2. It implies a price pass through effect from global food market shocks to fluctuations in U.S. food price. While the response of food price changes to a domestic food demand shock is positive, its magnitude is rather small and insignificant.

Figure 6 shows the responses of changes in TFP, U.S. agricultural exports, and U.S. GDP to an energy shock. According to panel A, TFP responds to an energy shock negatively in year 1 and is significant. It indicates that higher increases in energy prices will have a negative impact on TFP growth in the same year. Panel B shows that short-term TFP growth is affected substantially by TFP specific shocks, such as shocks from bad weather which is not explained by the system. Panel C shows that U.S. agricultural export changes respond statistically significantly to an energy shock in year 1 and year 2. The responses are all positive, which indicates that a global energy shock increases demand in U.S. agricultural exports and the impact lasts for at least two years. This is consistent with some observations during the 1970s's oil shock period. In 1970s the petroleum-related revenues and foreign exchange reserves from the major oil-exporting countries promoted global trade growth as well as global agricultural commodity imports, especially those from the U.S. As a result, real U.S. agricultural exports increased 16% in 1972, and 18% in 1973. As to the response of the real U.S. GDP growth rate to energy shocks, it is significant and positive in year 1, and then becomes significantly negative in

year 2 and year 3. This is not surprising as agricultural exports usually move positively along with oil price shocks in the short run. Thus, real GDP will temporarily increase due to the increase in exports in year 1. Over time, the negative impact from higher oil prices will eventually catch up through higher production costs and inefficient input use as the U.S. is an oil import country.

(Insert Figure 6 here)

How food price fluctuations are explained by an energy shock, a productivity shock, a global market shock, and a domestic demand shock

Through generalized forecast error variance decomposition analysis we can decompose the variation of food price changes into five components—an energy shock, a U.S. agricultural productivity shock, a global food market shock, a U.S. demand shock, and a U.S. food price specific shock According to table 3, in the short run (1 year), both an energy shock and a productivity shock explain about 10% of the food price fluctuation. One-third of the food price variation can be attributed to a foreign demand shock. A domestic food demand shock seems to only have a very trivial and insignificant impact on the U.S. food price volatility. In the intermediate term (3 years), a foreign demand shock still accounts for one-third of the food price variation. However, an energy shock's impact increases through time as it explains about 16% of the food price changes while a productivity shock's contribution declines to account for only 8% of the food price variation. Its impact falls to half of the impact from an energy price shock by year 3. In the long run (7 years), the variance decomposition is rather close to the results from the intermediate term. These results imply that an energy shock seems to play a more crucial role in explaining the soaring food prices than agricultural productivity growth in both short-run and long-run.

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In summary, future U.S. food price variation is expected to rely most on foreign demand as measured by U.S. agricultural export shocks, besides the specific food price shock. Energy shocks play the second most important role in accounting for U.S. food price variation. Productivity shocks can only explain less than 10% of food price variation in the long-run. The increasing U.S. food price volatility in recent years is mainly driven by the specific food market shock, global food market shock and global energy shock.

Conclusion

The surging food prices in the last decade have raised concern about the linkage between energy prices and food prices along with the increasing demand for ethanol in recent years, especially after the blending mandates in the Energy Policy Act of 2005. On the other hand, some researchers are also concerned about a global slowing in agriculture productivity growth due to sluggish investment in public agricultural research funding around the world. While researchers have tried to tackle this issue by using individual crop prices and alternative models, it is not clear how much of the overall food price volatility can be attributed to global energy shocks or slowing agricultural productivity growth. This is especially important for its policy implication. To address this issue, we propose to use a structural VAR model, based on annual data on U.S. gasoline prices, agricultural productivity, real GDP, real agricultural exports, and agricultural commodity prices, to assess the impacts of energy shocks on U.S. agricultural productivity growth and food price variations. The data span the period 1948 to 2009. The SVAR model is estimated by restricting the impacts from each of the contemporaneous structural shock. Impulse response is used to examine the response of food prices to demand or supply shocks. Variance decomposition is used to measure the importance of each shock, particularly an energy price shock, in explaining TFP and food price fluctuations.

According to the impulse response analysis, energy shocks contribute negatively to TFP growth in the first year. Still, 95% of TFP volatility is attributable to its own specific shock in the short run based on the variance decomposition analysis. It seems that any short-term deviation from the long-run trend in productivity growth is quick "corrected" as TFP growth moves back to its long-run growth path. According to the variance decomposition analysis, in the short run, energy shocks and productivity shocks each account equally for 10% of food price volatility. Yet, the impact from energy shocks overweighs the contribution of productivity shocks in the intermediate term (3 years), where an energy shock's contribution increases to twice the size of a productivity shock's contribution (16% over 8%). It implies that energy shocks are more important in explaining the rapid increase in food prices than productivity shocks when allowing for a delayed passing through effect from high energy prices. In general, global demand shocks in U.S. agricultural exports still dominate the contributions to the U.S. food price variations, besides the specific food market shock, and accounts for one-third of the volatility in food price changes.

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Table 1. Results of unit root test

Variables	lag lengths	ADF test statistics	
ΔP_E	0	-5.26	***
ΔTFP	2	-8.08	***
ΔX_A	0	-6.33	***
ΔGDP	0	-6.36	***
ΔP_F	1	-7.07	***

Note: 1. The ADF test is based on the model with constant and trend.

2. *** denotes statistical significance at 1% level.

3. Δ denotes percentage change variables.

4. lag lengths are chosen based on the Schwarz Info Criterion.

Table2. Descriptive analysis of the variables

	ΔP_E	ΔTFP	ΔX_A	ΔGDP	ΔP_F
Mean	0.0427	0.0152	0.0548	0.0316	0.0175
Median	0.0208	0.0147	0.0464	0.0332	0.0113
Maximum	0.4727	0.1586	0.6316	0.0838	0.3008
Minimum	-0.4206	-0.1357	-0.2637	-0.0354	-0.1353
Std. Dev.	0.1577	0.0476	0.1478	0.0245	0.0753
Skewness	0.0198	-0.1332	0.7604	-0.3675	0.8685
Kurtosis	4.9788	4.4457	5.5603	2.9768	4.9801

Table 3. Contribution of each shock to the variability of US food price

Period	Energy shock		productivity shock		foreign demand shock		domestic demand shock	specific food market shock	
1	10.10		10.30	*	33.63	***	0.07	45.90	***
	(1.25)		(1.59)		(3.76)		(0.07)	(5.69)	
2	16.73	**	8.27		36.49	***	0.61	37.90	***
	(1.73)		(1.35)	*	(3.43)		(0.30)	(4.83)	
3	15.60	**	7.69		32.39	***	1.10	43.22	***
	(1.78)		(1.24)		(3.24)		(0.34)	(4.90)	
4	15.58	**	8.54		32.07	***	1.51	42.29	***
	(1.82)		(1.35)	*	(3.30)		(0.45)	(4.63)	
5	14.72	**	7.81		29.77	***	2.32	45.38	***
	(1.69)		(1.29)		(3.27)		(0.54)	(4.81)	
6	14.61	**	8.18		30.10	***	2.40	44.71	***
	(1.70)		(1.34)	*	(3.23)		(0.55)	(4.59)	
7	14.33	**	8.02		29.47	***	2.40	45.78	***
	(1.64)		(1.24)		(3.19)		(0.50)	(4.59)	

Note: The numbers in the parentheses are t statistics. Standard errors of for the variance decompositions are calculated using

the Monte Carlo approach (Runkle, 1987).

* indicates one-side statistical significance at 10% level.

** indicates one-side statistical significance at 5% level.

*** indicates one-side statistical significance at 1% level.

Figure 1

Comparison of alternative export price indices

2005=100

Legend:
- – – – BEA export GDP deflator
- ——— BLS agricultural export price index
- ········ BEA food_feed_berage export price index

x-axis: year (1948, 1954, 1960, 1966, 1972, 1978, 1984, 1990, 1996, 2002, 2008)

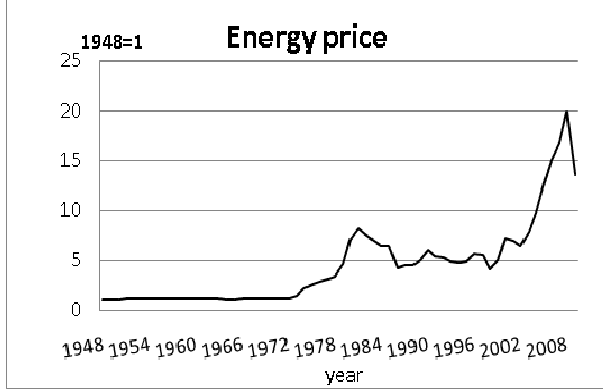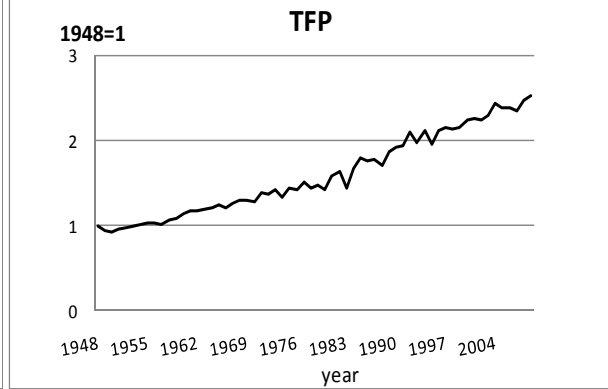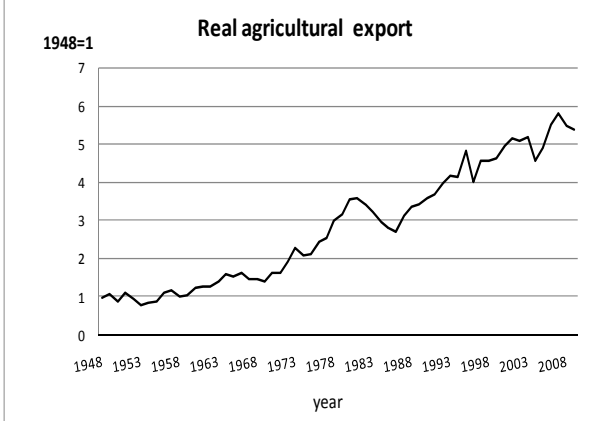y-axis: 0, 20, 40, 60, 80, 100, 120, 140, 160, 180
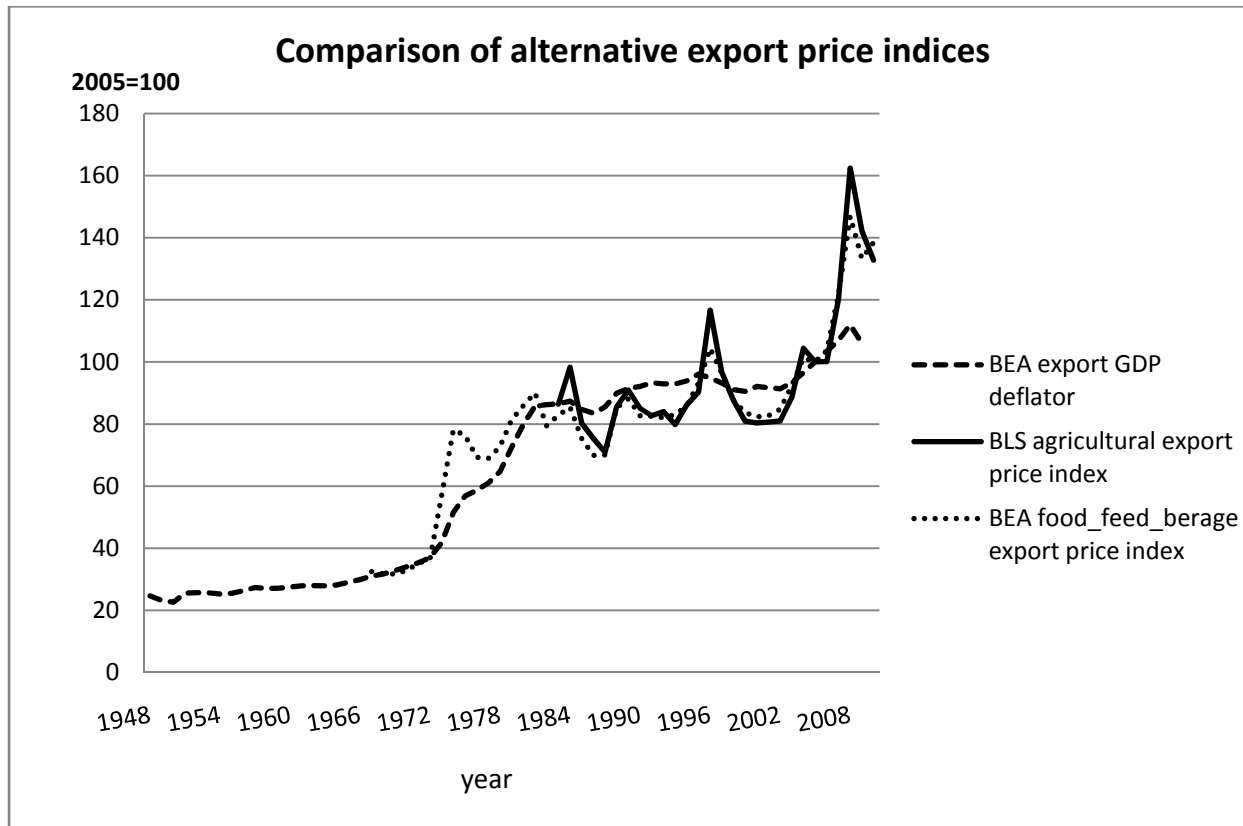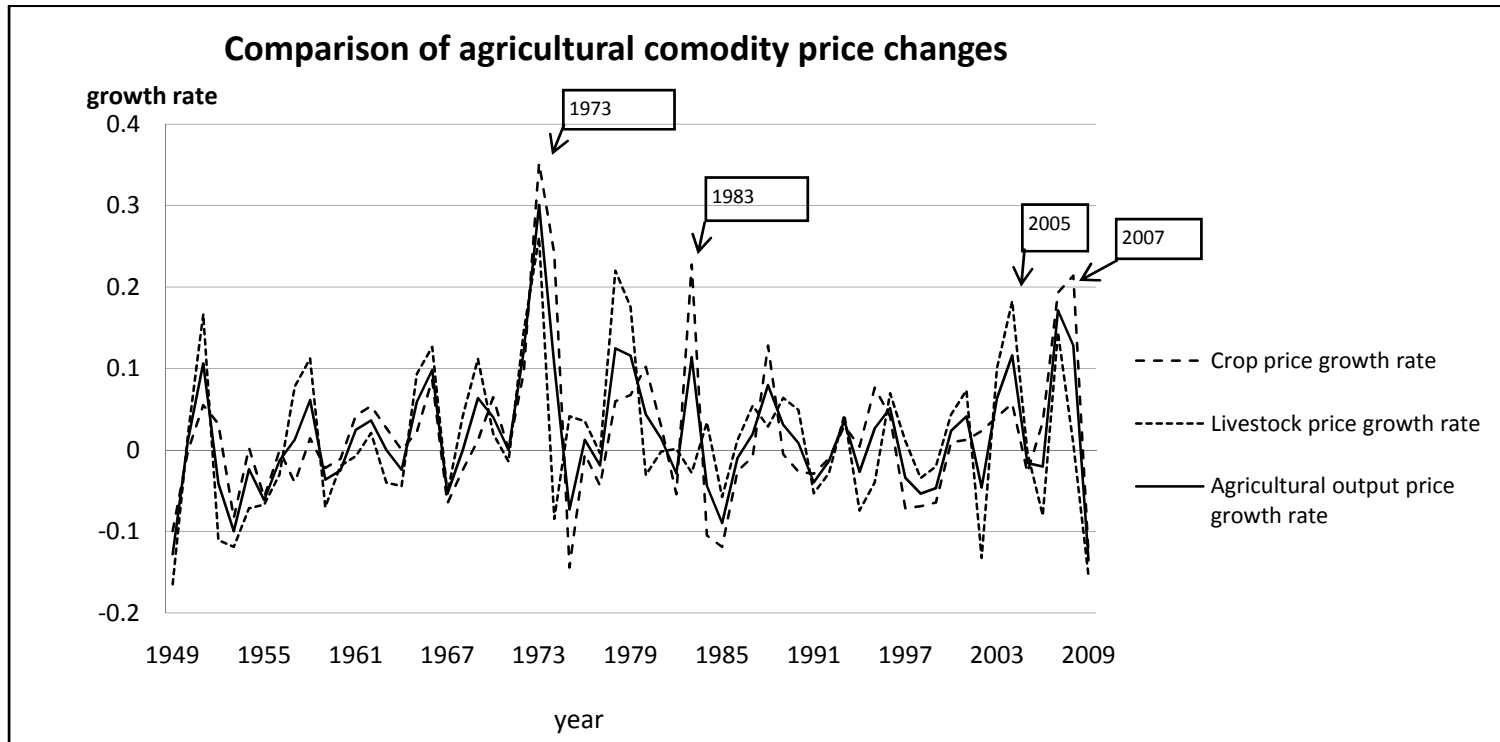
Figure 2

Figure 3 Trends of level variables
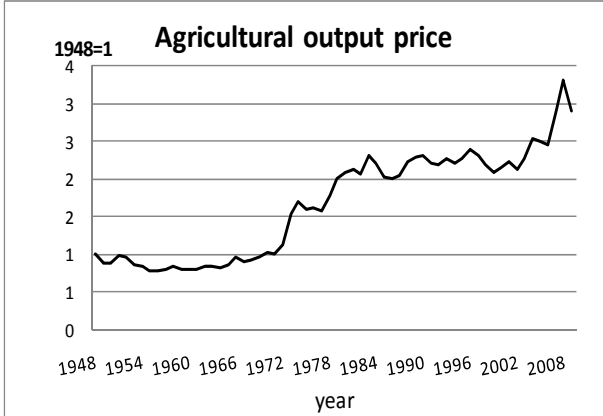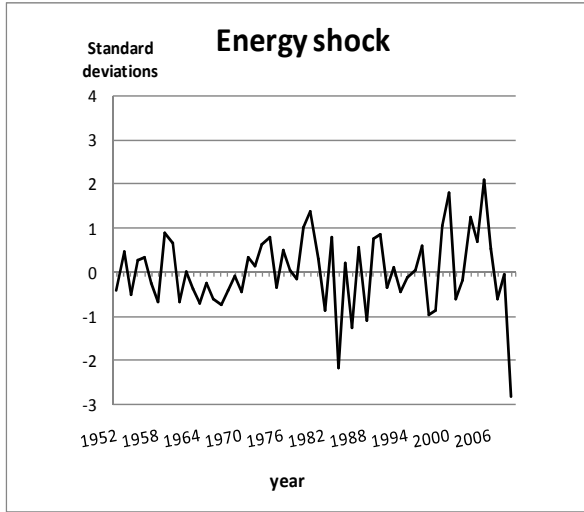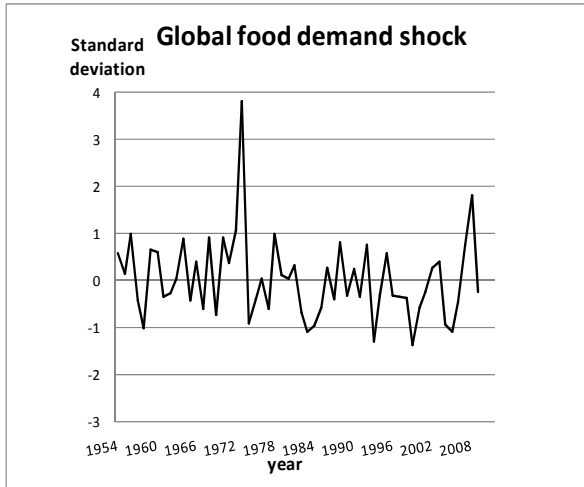
Panel A

Panel B

Panel C
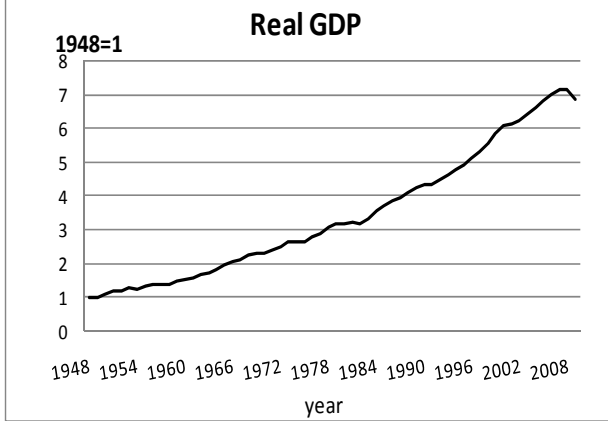
Panel D

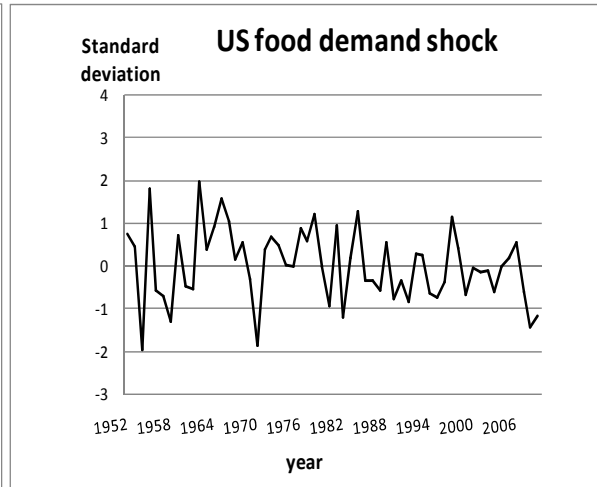Panel E

Figure 4 Estimated historical structural shocks

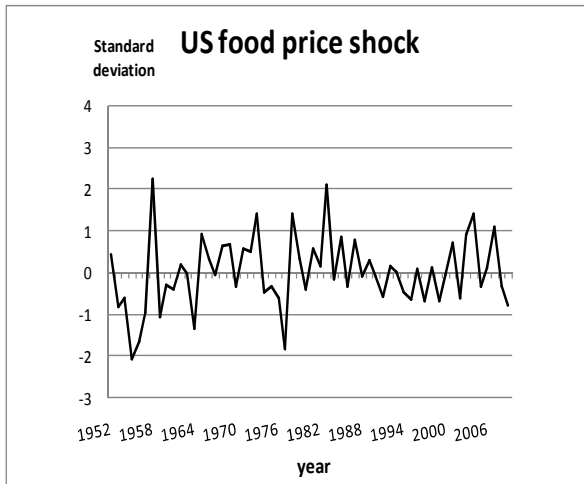Panel A.

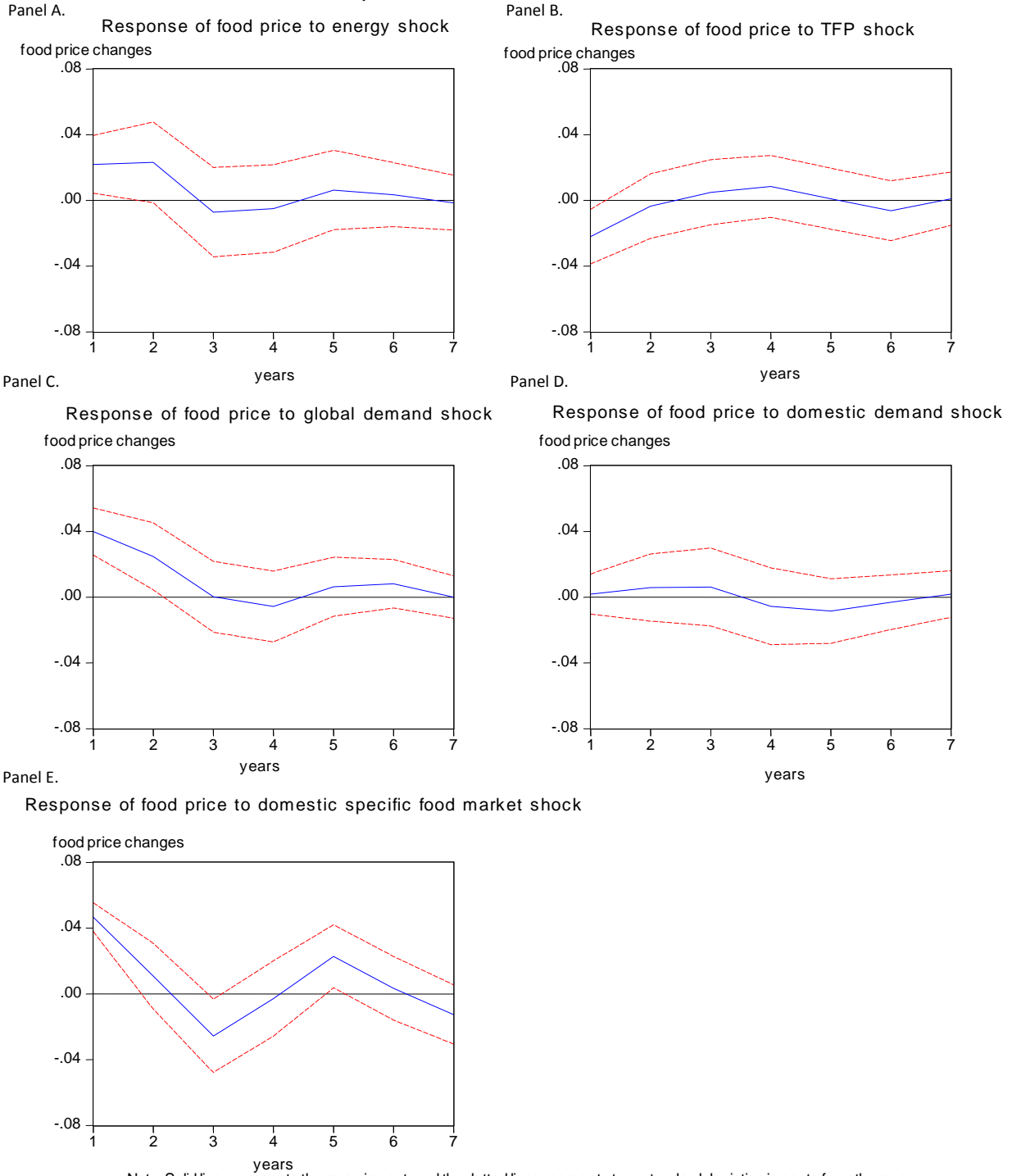Panel B.
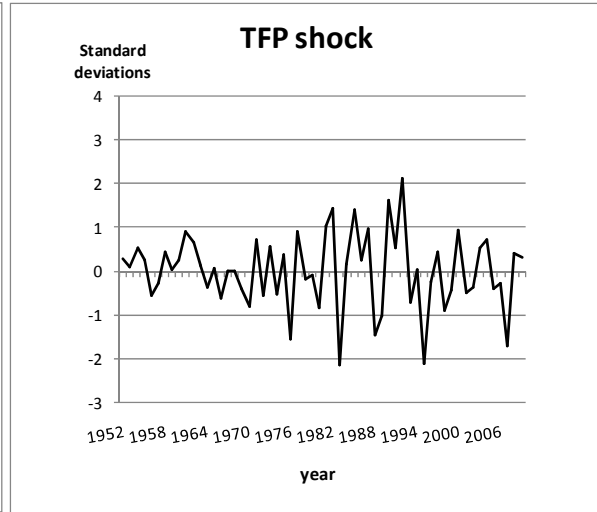
Panel C.

Panel D.

Panel E.

Figure 5

US Food Price's Response to Structural One S.D. Innovations . .

Panel A.
Response of food price to energy shock

Panel B.
Response of food price to TFP shock

Panel C.
Response of food price to global demand shock

Panel D.
Response of food price to domestic demand shock

Panel E.
Response of food price to domestic specific food market shock

Note: Solid line represents the mean impact, and the dotted lines represetn tw o standard deviation impacts from the mean.
Standard errors for the impulse responses are calculated using the Monte Carlo approach (Runkle,1987).

Figure 6. Alternative Variables' Responses to Structural One S.D. Innovations

Response of TFP growth rate to energy price shock

Panel A

Response of TFP growth rate to TFP specific shock

Panel B
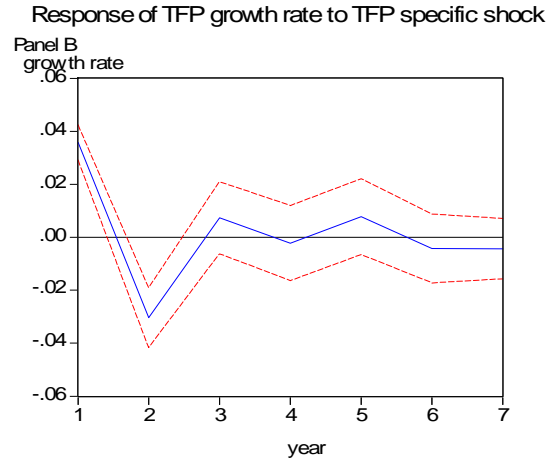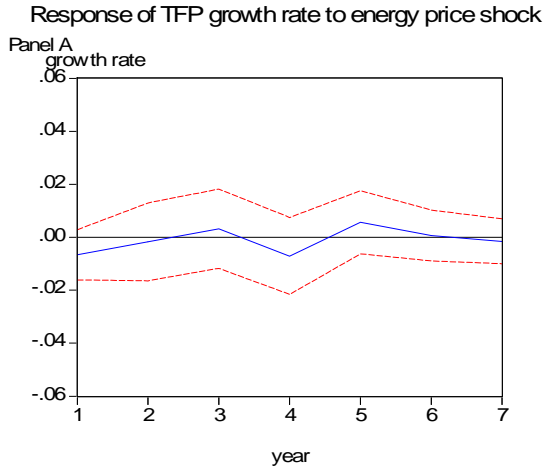
Response of agricultural export growth rate to energy price shock

Panel C
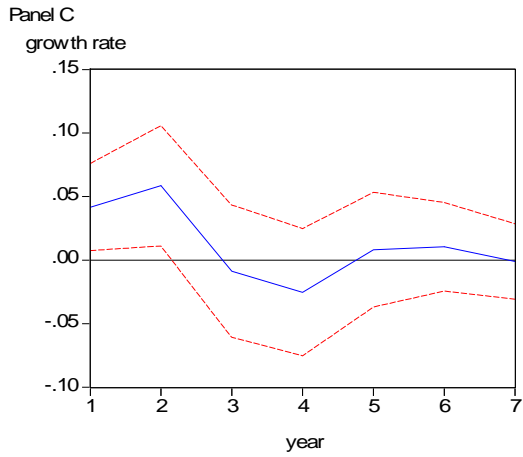
Response of GDP growth rate to energy price shock

Panel D