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Impacts of energy shocks on US agricultural productivity growth and commodity prices—A structural VAR analysis☆

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ABSTRACT

We examine the impacts of energy price shocks on U.S. agricultural productivity growth and commodity prices' volatility by developing a structural VAR model. We use historical annual data of real U.S. gasoline prices, agricultural total factor productivity (TFP), real GDP, real agricultural exports, and real agricultural commodity price from 1948 to 2011 to estimate the model. Our results indicate that an energy price shock has a negative impact on productivity growth in the short run (1 year). An energy price shock and an agricultural productivity shock each account for about 10% of U.S. agricultural commodity price volatility with the productivity shock's contribution slightly higher. However, the impact from energy prices outweighs the contribution of agricultural productivity in the medium term (3 years). With more persistent impacts, energy shocks contribute to most (about 15%) of commodity price's variation in the long run.

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1. Introduction

According to the Food and Agriculture Organization (FAO) of the United Nations (2012), the annual global food price index[1] spiked to a post-1996 high in 2008. That year, the global food price index was more than double 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 Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA), the U.S. food grain price increased to 2.5 times its 2000 level in 2008, and the feed grain price doubled its 2000 level over the same time period (USDA, 2013a). In explaining the rise of agricultural commodity prices, most of the attention has focused on demand-side factors, such as growing demand for food in emerging countries (Abbott et al., 2009; Headey and Fan, 2008), or increased use of crops in biofuel production (Zhang et al., 2009; Hertel and Beckman, 2011). However, supply-side factors, such as technical change or energy shocks, have not attracted as much attention. Although some researchers have pointed to a decline in the growth rate of crop yields or a slowing productivity growth as a causal factor behind the rise in agricultural commodity prices (World Bank, 2007; Alston et al., 2009; Abbott et al., 2009), the magnitude of the impacts of agricultural productivity on commodity prices is still unclear.

While agricultural commodity prices may be affected by productivity growth, commodity prices and agricultural productivity could both be influenced by energy prices, such as crude petroleum or gasoline prices. Energy price shocks were found to be a critical determinant of the U.S. economic growth and manufacturing sector's productivity growth during the 1973–1980 period (Jorgenson and Wilcoxen, 1993; Madisson, 1987). Sharply increased energy prices can also push up agricultural commodity prices through higher production costs. Higher crude petroleum prices not only result in higher agricultural chemicals' prices (Gellings and Parmenter, 2004[2]; Hertel and Beckman, 2011),

☆ The views expressed herein are those of the authors, and not necessarily those of the U.S. Department of Agriculture.

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[1] FAO's food price index consists of the average of five commodity group price indices, including meat price index, dairy price index, cereal price index, oil and fat price index, and sugar price index (FAO, 2012). "Food price" has been used as a general term of "agricultural commodity prices" in many studies in recent years.

[2] Gellins and Parmenter (2004) found that energy accounts for 70–80% of the total costs used to manufacture fertilizers. Therefore, the increase of energy price raises the fertilizer manufacturing cost sharply and pushes up the agricultural production cost.

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but can also increase agricultural production cost directly through the rising energy cost from using farm machinery and livestock cooling and heating systems. In addition, high energy prices could also drive farm input use away from its most efficient practice on the production frontier in the short term, and therefore result in greater volatility in the rate of agricultural productivity growth. Skyrocketing energy prices have also contributed to increased biofuel production (Banse et al., 2011). The increased use of agricultural commodities to produce energy has boosted biofuel feedstock prices and pushed up sector-wide food grain and feed grain prices in recent years (Qiu et al., 2012; Zhang et al., 2009; Trostle et al., 2011, among others). The emergence of large scale biofuel production has increased the linkage between agriculture and energy (Ciaian and d'Artis, 2011; McPhail, 2011; Du and McPhail, 2012).

Despite the many studies that have investigated the responses of agricultural commodity prices to energy shocks (Harri et al., 2009; Zhang et al., 2010; Serra, 2011) or productivity shocks (Fuglie, 2008), few have examined these relationships together. While Qiu et al. (2012) found that the fundamental market forces of demand and supply are the main drivers of food price volatility, their study only focuses on the corn market. Furthermore, the magnitude of the impacts of energy prices on U.S. agricultural productivity and commodity prices is still unknown. For example, how much of the volatility in agricultural commodity prices can be attributed to productivity or energy price shocks? Energy shocks and agricultural productivity's contribution to commodity price movement are very important and complex. Also the relationship between energy prices and agricultural productivity requires new examination due to the more integrated nature between agriculture and energy markets. We would like to introduce a new framework to understand this old topic. The purpose of this paper is two-fold: first, to evaluate the impacts of energy price shocks on agricultural productivity growth and commodity price changes; second, to disentangle demand and supply shocks in the U.S. agricultural commodity market and to quantify the contribution of each individual shock to commodity price volatility with a special focus on energy shocks and productivity shocks.

Many studies working on 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; Banse et al., 2011; Beckman 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 by employing a structural vector autoregression (VAR) model to analyze the impact of energy prices on agricultural productivity and commodity prices. We propose that commodity prices are mainly driven by the following factors: (1) energy shocks; (2) agricultural productivity shocks; (3) domestic demand shocks; (4) global supply and demand shocks; and (5) other shocks in the U.S. agricultural commodity market that are not captured by the shocks listed above. Impulse response is then used to examine the response of commodity prices to relevant demand and supply shocks. Variance decomposition is followed to measure the importance of each shock, particularly an energy price shock, to explain fluctuations in total factor of productivity (TFP) and agricultural commodity prices.

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

Studies which only focus on the demand side shock or the supply side shock may exaggerate the impact from either side. Killian (2009), in a study decomposing the real price of oil, suggests employing a structural VAR model to help decompose unpredictable changes in the real price of oil with a structural economic interpretation. Following Killian (2009), this study proposes a comprehensive structural VAR (SVAR) model to decompose unpredictable changes in agricultural commodity prices into mutually orthogonal components with economic theoretical implications that take into account shocks from both supply and demand sides in the agricultural commodity market. Shocks are conceptually defined as changes from individual sources that are not anticipated by the estimated model. For example, an energy shock can be an unexpected change in gasoline prices.

We use 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 commodity prices. By doing so, we can also identify the contributions of each shock from the demand side and supply side to commodity price changes. The five annual variables are defined as a vector $\boldsymbol{x}_t = (\Delta P_{Et}, \Delta TFP_t, \Delta X_{At}, \Delta GDP_t, \Delta P_{Ft})'$ where P_E is real U.S. gasoline price index,[3] which is assumed to be affected by demand and supply in the global oil market; *TFP* is the U.S. agricultural total factor productivity index; X_A is real U.S. agricultural export, which represents foreign demand for U.S. agricultural commodities; *GDP* is real U.S. gross domestic product, which is a proxy for U.S. domestic food demand[4]; P_F is real U.S. farm commodity price index; t is the time subscript; Δ denotes the percentage change rate in each series. The SVAR model is represented as:

$$\boldsymbol{A}_0\boldsymbol{x}_t = \boldsymbol{\alpha} + \sum_{i=1}^{p}\boldsymbol{A}_i\boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \tag{1}$$

where p is the order of lags, $\boldsymbol{\varepsilon}_t$ is the vector of serially and mutually uncorrelated structural innovations, $\boldsymbol{A}_0$, $\boldsymbol{A}_i$, and $\boldsymbol{\alpha}$ are unknown coefficient matrixes and the vector to be estimated. The reduced form of the VAR representation is:

$$\boldsymbol{x}_t = \boldsymbol{A}_0^{-1}\boldsymbol{\alpha} + \sum_{i=1}^{p}\boldsymbol{A}_0^{-1}\boldsymbol{A}_i\boldsymbol{x}_{t-i} + \boldsymbol{e}_t \tag{2}$$

where $\boldsymbol{e}_t$ is the vector of estimated residuals in the reduced form and can be expressed as

$$\boldsymbol{e}_t = \boldsymbol{A}_0^{-1}\boldsymbol{\varepsilon}_t. \tag{3}$$

Following Killian (2009), we impose theoretical restrictions to the recursive structure on $\boldsymbol{A}_0^{-1}$ 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 U.S. 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 U.S. gasoline price shock is not affected by any contemporaneous shocks from other variables in the model but only influenced by the global oil market shocks or other factors that are not included in the model. A U.S. 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

[3] Agricultural production consumes large amounts of energy, either directly through combustion of fossil fuels, or indirectly through use of energy-intensive inputs, especially fertilizer. Over 2006–10, expenses from direct energy use averaged about 5.7% of total input cost in the U.S. farm sector, while fertilizer expense represented another 5.4%. We use gasoline price as a proxy of energy price as we want to capture the global energy shock effect. U.S. gasoline price has a strong relationship with crude oil price (correlation coefficient is 0.99). In addition, U.S. gasoline refiners act as price taker in the global oil market. Therefore, the variation of U.S. gasoline price over time should capture global energy market shocks.

[4] While food preference changes could play an important role in the demand side for an individual commodity we did not include this variable in our model as this study is based on aggregate data and there is no appropriate index or variable to represent preference changes for aggregate agricultural commodity.

disease, or other factors. A U.S. agricultural export shock is assumed to respond to contemporaneous energy shocks and U.S. agricultural productivity shocks. Other innovations are assumed to take more than a year to affect U.S. agricultural exports. U.S. domestic food demand is assumed to respond to contemporaneous shocks from U.S. agricultural exports, U.S. agricultural productivity, and domestic energy prices. Finally, a U.S. commodity price shock responds to domestic food demand shocks, foreign demand in U.S. agricultural export shocks, U.S. agricultural productivity shocks, and energy shocks. Accordingly, the reduced form errors $\boldsymbol{e_t}$ can be decomposed into the following components:

$$\boldsymbol{e}_t \equiv \begin{bmatrix} \boldsymbol{e}_t^{\Delta P_E} \\ \boldsymbol{e}_t^{\Delta TFP} \\ \boldsymbol{e}_t^{\Delta X_A} \\ \boldsymbol{e}_t^{\Delta GDP} \\ \boldsymbol{e}_t^{\Delta P_F} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 & 0 \\ \alpha_{12} & \alpha_{22} & 0 & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & 0 \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & \alpha_{55} \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}_t^{\text{global energy market shock}} \\ \boldsymbol{\varepsilon}_t^{\text{US agricultural productivity shock}} \\ \boldsymbol{\varepsilon}_t^{\text{foriegn demand on US agricultural commodity shock}} \\ \boldsymbol{\varepsilon}_t^{\text{US domestic food demand shcok}} \\ \boldsymbol{\varepsilon}_t^{\text{US agricultural commodity market shock}} \end{bmatrix}. \tag{4}$$

We impose restrictions by making the components in the $\boldsymbol{A}_0^{-1}$ 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 $\boldsymbol{A}_0^{-1}$ matrix are set to zero except for α_{11} allowing that $\boldsymbol{\varepsilon}_t^{\text{global energy market shock}}$ only responds to the contemporaneous shock from $\boldsymbol{A}_0^{-1}$ By making all values on the last row of the $\boldsymbol{A}_0^{-1}$ matrix nonzero, commodity prices are assumed to be driven by the following shocks: (1) energy shocks; (2) agricultural productivity shocks; (3) foreign demand on U.S. agricultural export shocks; (4) domestic food demand shocks; and (5) other US agricultural commodity market shocks.

Impulse response is used to examine the response of commodity prices to demand or supply shocks. The reduced-form VAR can be written as the following Vector Moving Average (VMA) representation (Sims, 1980):

$$\boldsymbol{x}_t = \varphi(B)\boldsymbol{e}_t.$$

Insert $\boldsymbol{e}_t = \boldsymbol{A}^{-1}\boldsymbol{\varepsilon}_t$ into this last equation:

$$\boldsymbol{x}_t = \varphi(B)\boldsymbol{A}^{-1}\boldsymbol{\varepsilon}_t = \theta(L)\boldsymbol{\varepsilon}_t$$

where $\theta(L) = \sum_{i=0}^{\infty}\theta_i L^i$ and each θ_i is a $5 * 5$ matrix of parameters from the structural model. The above equation implies that the response of $\boldsymbol{x}_{t+i}$ to $\boldsymbol{\varepsilon}_t$ is θ_i. Hence, the sequence of θ_i from $i = 0, 1, 2, \ldots,$ illustrates the dynamic response of the variable to each of the five shocks. Standard errors for the impulse responses are calculated using the Monte Carlo approach of Runkle (1987).

A natural concern is how much of the variation in prices and quantities can be attributed to each demand and supply shocks. This question can be answered by computing forecast error variance decomposition based on the estimated VAR model. Variance decompositions allocate each variable's forecast error variance to the individual shocks, particularly a positive energy shock or a negative TFP shock in this study, in explaining commodity price fluctuations. Following Sims (1980), if $E_{t-j}\boldsymbol{x}_t$ is the expected value of $\boldsymbol{x}_t$ based on all information available at time $t-j$, the forecast error is $\boldsymbol{x}_t - E_{t-j}\boldsymbol{x}_t = \sum_{i=0}^{j-1}\theta_i\boldsymbol{\varepsilon}_{t-i}$. Since the information at time $t-j$ includes all $\boldsymbol{\varepsilon}$ occurring at or before time $t-j$ and the conditional expectation of future $\boldsymbol{\varepsilon}$ is zero because the shocks are serially uncorrelated. The forecast error variances for the individual series are the diagonal elements in the following matrix:

$$E\left(\boldsymbol{x}_t - E_{t-j}\boldsymbol{x}_t\right)\left(\boldsymbol{x}_t - E_{t-j}\boldsymbol{x}_t\right)' = \sum_{i=0}^{j-1}\theta_i\Sigma_{\boldsymbol{\varepsilon}}\theta_i'.$$

If θ_{ivs} is (v, s) element in θ_i and σ_s is the standard deviation for disturbance s $(s = 1,\ldots,n)$, the j-step-ahead forecast variance of the vth variable is easy to calculate:

$$E\left(\boldsymbol{x}_{vt} - E_{t-j}\boldsymbol{x}_{vt}\right)^2 = \sum_{i=0}^{j-1}\sum_{s=1}^{n}\theta_{ivs}^2\sigma_s^2 v = 1, 2, \ldots, n.$$

The variance decomposition function (VDF) writes the j-step-ahead percentage of forecast error variance for variable v attributable to the kth shock:

$$VDF(v, k, j) = \frac{\sum_{i=0}^{j-1}\theta_{ivk}^2\sigma_k^2}{\sum_{i=0}^{j-1}\sum_{s=1}^{n}\theta_{ivs}^2\sigma_s^2} * 100.$$

3. Data

Our data consists of five annual series—real energy prices, U.S. agricultural total factor productivity (TFP), real U.S. agricultural exports, real U.S. GDP, and real U.S. agricultural commodity prices. All variables are in their first difference of logarithmic term (percentage changes). The study period is 1948 to 2011. Definitions for each variable as well as their data sources are addressed below.

3.1. Energy prices

In this study, we choose the gasoline price index from Bureau of Labor Statistics (BLS) at U.S. Department of Labor (USDOL, 2013) as the measure of energy price.[5] One reason to use gasoline price series is because gasoline refiners are small and act as price takers in the global oil market. The trend and percentage change of gasoline price series can reflect shifts in global demand and supply in oil market. In addition, since gasoline prices are thought to have strong links to ethanol prices (Ciaian and d'Artis, 2011; Zhang et al., 2009, among others), given the lack of ethanol prices data for earlier years, the impact of ethanol prices on agricultural commodity prices could be captured by the commodity prices' responses to the gasoline price shocks as well.[6] The energy price has been deflated by U.S. CPI in the study.

3.2. 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 commodity prices. Yet, agriculture is usually in a joint production process that either a farm produces multiple products with separate production process but sharing common fixed inputs or infrastructure, or a farm produces a number of outputs from a single production process. It is hard to distinguish the contribution of one single factor from the other. Partial productivity can be boosted by adding more of other inputs, for instance agricultural chemicals, while the overall

[5] The correlation coefficient is 0.99 between crude oil price and gasoline price.

[6] Using monthly data from Jan. 1982 to Dec. 2013 we find that the correlation coefficient between ethanol prices and gasoline prices is 0.9. It is 0.7 between corn prices and ethanol prices, and is 0.8 between corn prices and gasoline prices. Therefore, we may expect that the impact of ethanol prices on agricultural commodity prices could be captured by the commodity prices' responses to the gasoline price shocks significantly.

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productivity level is not actually improved. In this study, we employ a total factor productivity (TFP) index developed by the Economic Research Service (ERS) at the U.S. Department of Agriculture (USDA, 2013a). 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, TFP growth rate measures the difference between aggregate output growth and aggregate input growth. Therefore, TFP is a more appropriate measure of productivity growth in this sector-wide study. A complete data description and methodology can be found in Ball et al. (2013).

3.3. U.S. real agricultural exports

To capture foreign demand for U.S. agricultural exports we use a U.S. agricultural export series in real terms or in terms of implicit quantity. USDA (2013b) publishes Foreign Agricultural Trade of the United States (FATUS) in current dollars based on standard USDA aggregation of several thousand HTS codes into the 213 agricultural groups most used by the public. We apply a deflator of a combination of agricultural export deflator of the U.S. Department of Commerce-Bureau of Economic Analysis (USDOC-BEA, 2013) for the period 1967 to 2011 (1967 is the earliest available data for this series) and BEA's export deflator for years between 1948 and 1967[7] to get the implicit quantity of agricultural export series for the period of 1948 to 2011.

3.4. U.S. real GDP

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

3.5. U.S. agricultural commodity prices

Previous studies linking agricultural productivity growth and commodity prices, or energy shocks and commodity prices, tend to apply individual crop prices, such as prices of corn, soybean, and wheat, in their assessment. There is lack of information regarding the impact of energy shocks on overall commodity prices. In this study, we employ an aggregate agricultural output price index from the ERS's productivity accounts (USDA, 2013a) for this variable. This series is constructed based on 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 commodity prices as it allows the commodity composition to shift from year to year in the calculation. This series has been deflated by U.S., CPI in the study. Fig. 1 presents growth rates of price indices — crops, livestock, and aggregate agricultural output from ERS's productivity accounts. While those series move in tandem 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, 2004, 2007 and 2011 are among the highest in the study period. The first two points coincide with two oil shocks and the later points have been linked to global commodity price spike driven by numerous factors including biofuel policy, or agricultural productivity shocks in previous studies.

[7] The two price series are chain-linked using 1967 as benchmark. We assume that the trend of agricultural export moved closely with an overall export price since there is lack of agricultural export price information for earlier years.

While all variables are in the form of percentage changes (growth rates) in our analysis we plot their level series in Fig. 2 to get some idea on how their levels evolved over the post-war period.[8] In general, energy prices increased dramatically and were much more volatile after the global oil shock in 1973. TFP grew faster during the 1960s, which coincides with the Green Revolution. The series then grew more smoothly before 1980s. It became more volatile after 1980s. This may reflect the increased frequencies of adverse weather events in the last few decades.[9] Real GDP moves relatively smoothly compared to other series.

4. Empirical results and discussions

The descriptive analysis for the growth rates of the five series is presented in Table 1. Coefficients of variation (CV) of the five variables suggest that gasoline price and US agricultural commodity price are much more volatile than the others. GDP, on the other hand, is rather stable compared to all other series. Before estimating the SVAR model 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 2. According to the ADF statistics all five series reject the hypothesis of unit root at 1% significance level.

After confirming the stationarity of the five variables we estimate the SVAR model using two lags based on Schwarz criterion. We impose ten restrictions on the SVAR model specified by Eq. (4) to ensure identification. The reduced form of VAR system (Eq. (2)) is estimated using least-squares approach.

4.1. The time path of the estimated historical structural shocks

The structural shocks $\boldsymbol{\varepsilon}_t$ can be retrieved using estimated residuals from the VAR estimates and the $\boldsymbol{A}_0$ matrix. The historical structural shock estimates for the five variables are exhibited in Fig. 3, 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 Fig. 3 we find that the energy shock series is much more volatile after year 2000, surpassing volatility exhibited during the global oil shock period in the 1970s. The oscillation in US agricultural productivity shocks series has been greater since the 1980s. The short-term shock may also reflect the El Niño-Southern Oscillation (ENSO) effect. Increases in air temperatures, changes in the air pressure patterns and 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 peak in the estimated global food market structural shock series is in year 1973 when U.S. agricultural export expansion was fueled by petrodollar circulation.

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 Decomposition 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[10] and their implications below.

[8] Although many of the variables are index numbers they can still be volatile from time to time in response to market shocks, and, therefore, are appropriate estimates to be used in this study.

[9] A study by Munich Re (2012) shows that North America has been most affected by weather-related extreme events in recent decades.

[10] To identify structural parameters for a structural VAR, we use economic theory as indicated in the methodology section (Section 2) to impose restrictions to exactly identify our system. While changing recursive structure may change the estimates, other identification strategy does not apply to our research purpose.

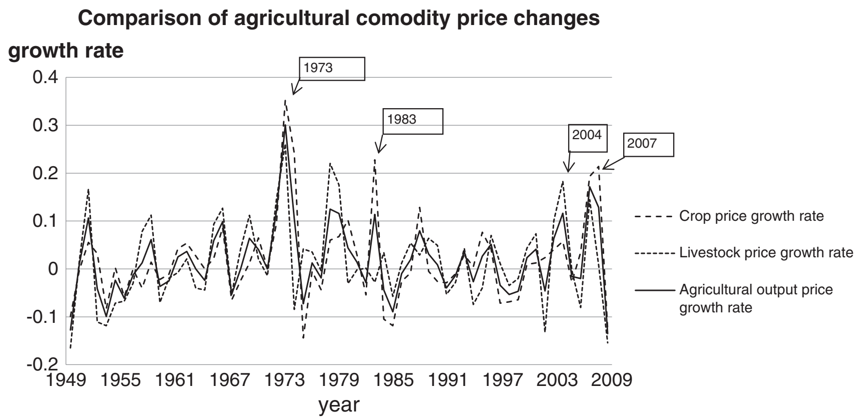

Fig. 1. Comparison of agricultural commodity price changes.

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

Fig. 4 presents the time path of the response of commodity price 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 commodity price changes to the shocks from other factors. The dotted lines show two standard deviation impacts from the mean.

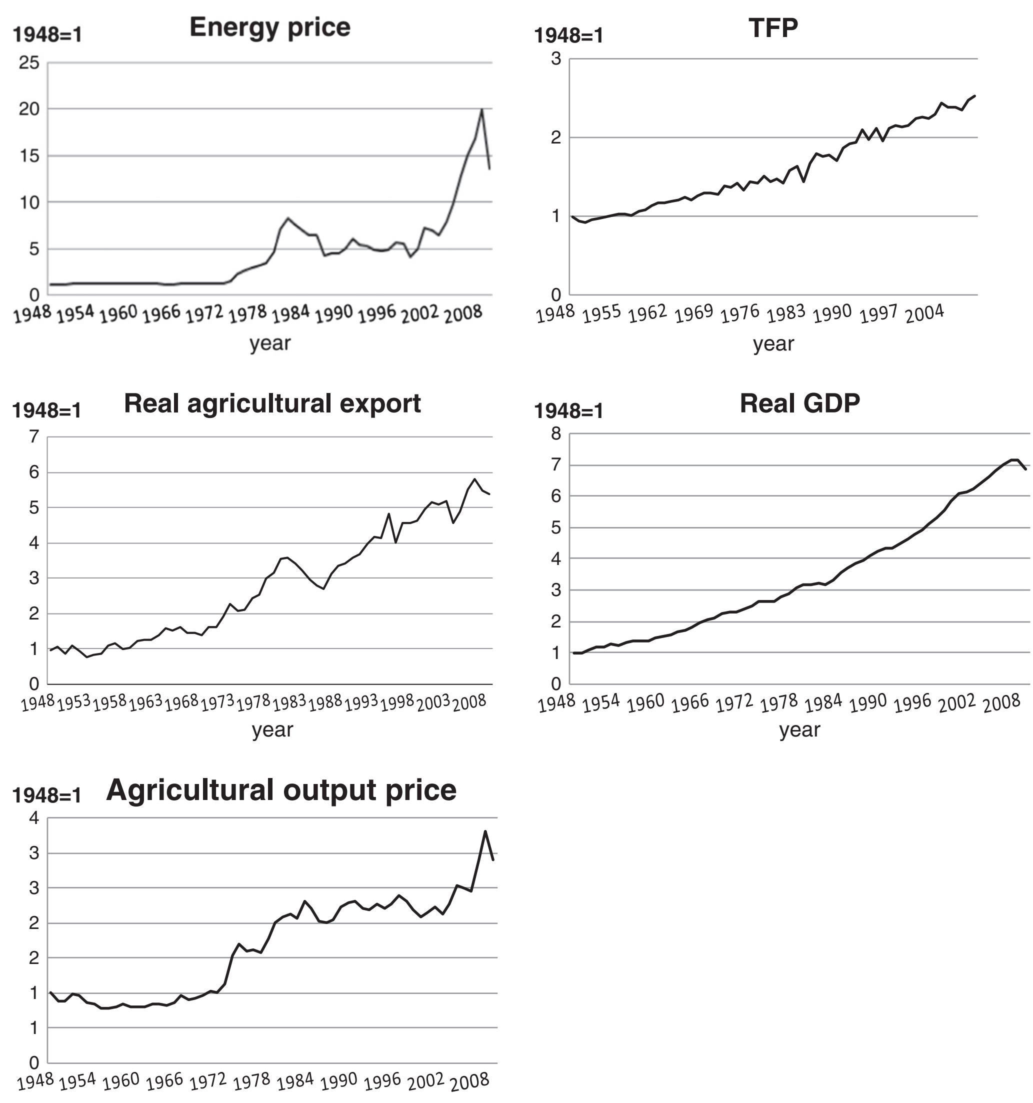

Fig. 2. Trends of level variables.

Table 1
Results of unit root test.

Variables	Lag lengths	ADF test statistics
ΔP_E	0	-6.42^{***}
ΔTFP	2	-8.30^{***}
ΔX_A	0	-9.02^{***}
ΔGDP	0	-6.82^{***}
ΔP_F	2	-4.10^{***}

Notes:
1. The ADF test is based on the model with a constant.
2. *** denotes statistical significance at 1% level.
3. Δ denotes percentage change variables.
4. Lag lengths are chosen based on the Akaike Information Criterion.

The standard errors for the impulse responses are calculated based on the Monte Carlo approach (Runkle, 1987).

The first panel in Fig. 4 shows that commodity price changes respond positively to an energy shock in year 1, negatively in year 3, and then positively in year 5. These responses are statistically significant, which indicates that a positive oil price will have persistent influences on commodity price over five years. Panel B shows that commodity price changes respond negatively to productivity growth in year 1. Longer than one year the response becomes insignificant and approaches zero. Productivity growth contributes to a lower production cost and therefore a lower commodity price. Supply led price change is not long lasting, however. Panel C shows that commodity price changes respond to a

Table 2
Descriptive analysis of the variables.

	Observations	Mean	Std. dev.	Coefficient of variation	Maximum	Minimum
ΔP_E	63	0.0139	0.1470	10.5760	0.3681	−0.4390
ΔTFP	63	0.0142	0.0479	3.3635	0.1618	−0.1404
ΔX_A	63	0.0289	0.0931	3.2221	0.2333	−0.1857
ΔGDP	63	0.0319	0.0238	0.7460	0.0836	−0.0284
ΔP_F	63	−0.0146	0.0725	−4.9777	0.2455	−0.1559

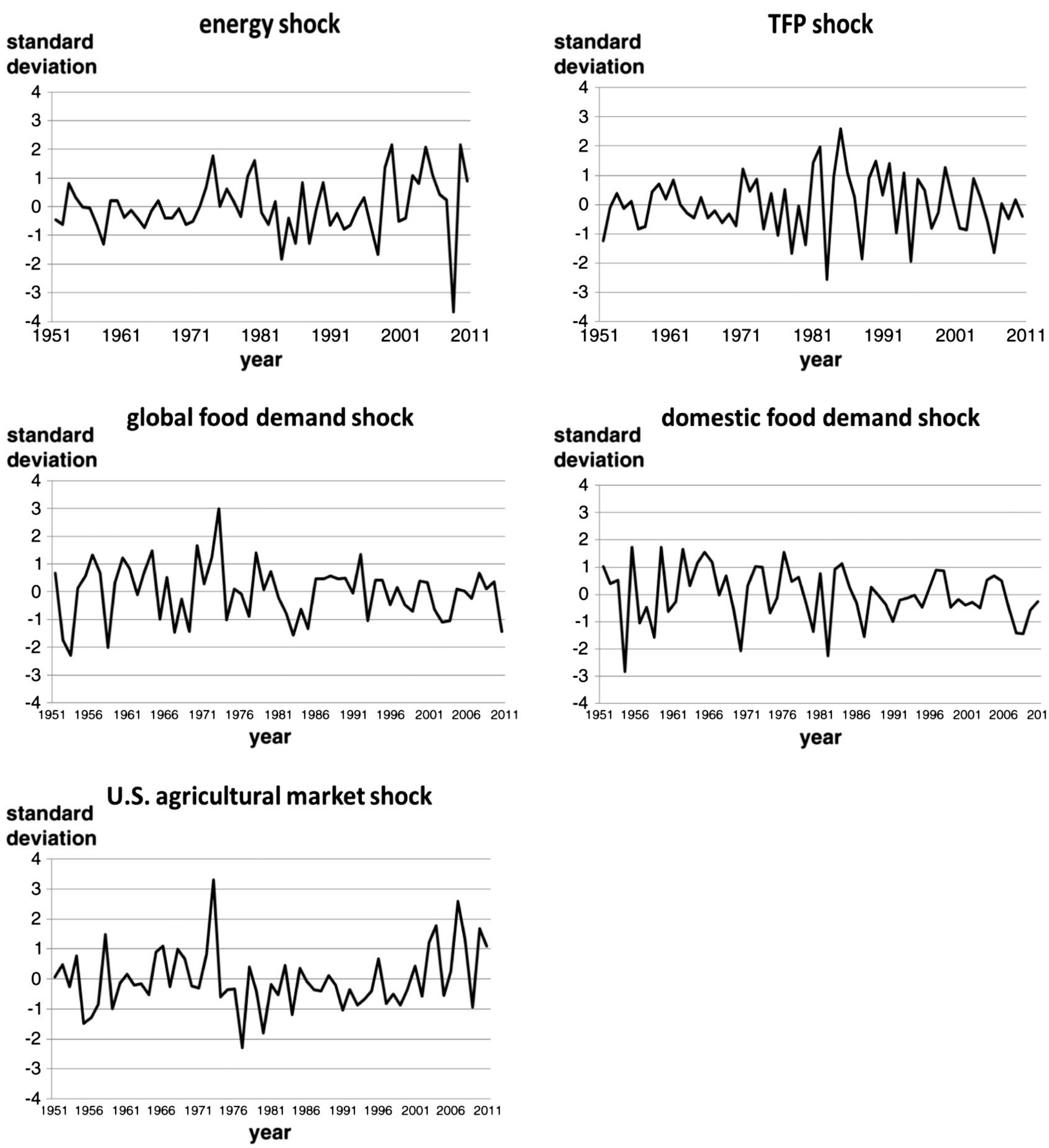

Fig. 3. Estimated historical structural shocks.

global demand shock positively in year 1 and year 2. Global demand increase for U.S. agricultural commodities leads to commodity price inflation in U.S. It implies a price pass-through effect from global commodity market shocks to the U.S. commodity market. While the response of commodity price changes to a domestic food demand shock is positive, its magnitude is rather small and less significant. The insignificance of the response might be due to the lack of variation in the data series of U.S. real GDP growth. Panel E shows the response of commodity prices to its specific commodity market shock. The impacts are strong and persist for more than five years.

Fig. 5 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 a positive energy shock negatively in year 1 with statistical significance. It indicates that higher increases in energy prices will have a negative impact on TFP growth in year 1. This is consistent with our expectation. In brief, an energy price shock affects productivity growth by shifting input use away from its most technical efficient combination. Many studies (Nishimizu and Page, 1982; Färe et al., 1994, among others) have shown that productivity growth can be decomposed into two major components — technical change and efficiency change, where the former is the shift of production frontier and the latter is the movement toward or away from the production frontier. Usually, we do not expect a deterioration in technical change as people can always use current technology instead of a worse one. Therefore, a negative productivity growth estimate may indicate inefficiency in production performance due to transitory events, such as unfavorable weather or inefficient input use due to high energy prices. A dramatic increase of energy price may trigger operators' actions on energy conservation, which may result in less capital utilization due to the energy–capital complementarity effect, and more labor use under the energy–labor substitution effect (Wood, 1990). Since the conventional TFP measurement does not adjust for capital utilization rate, the

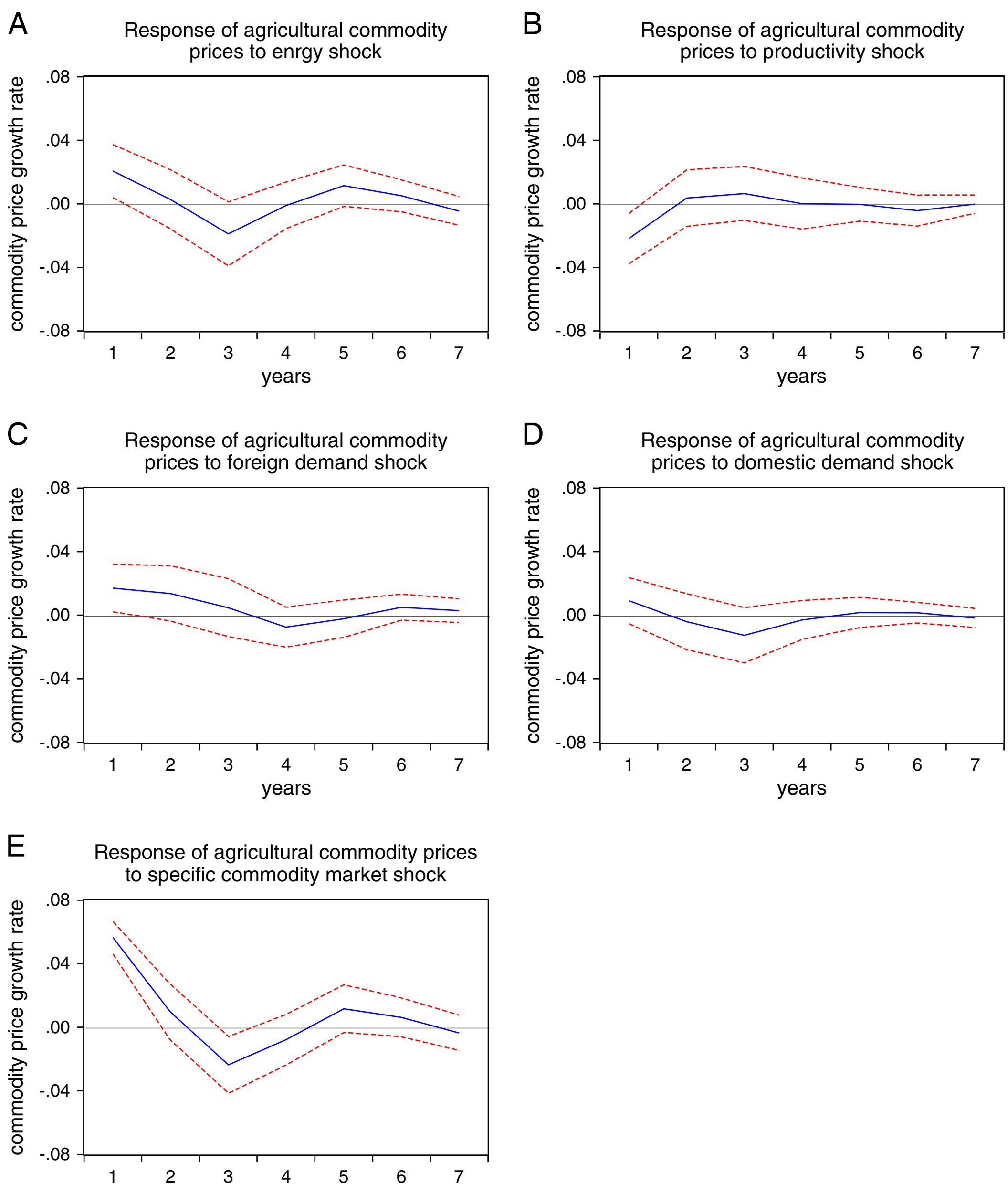

Fig. 4. Agricultural commodity prices' responses to structural one std. dev. innovations. Notes: 1. Solid line represents the mean impact, and the dotted lines represent two standard deviation impacts from the mean. Standard errors for the impulse responses are calculated using the Monte Carlo approach (Runkle, 1987). 2. The vertical axis indicates percentage change in agricultural commodities' prices.

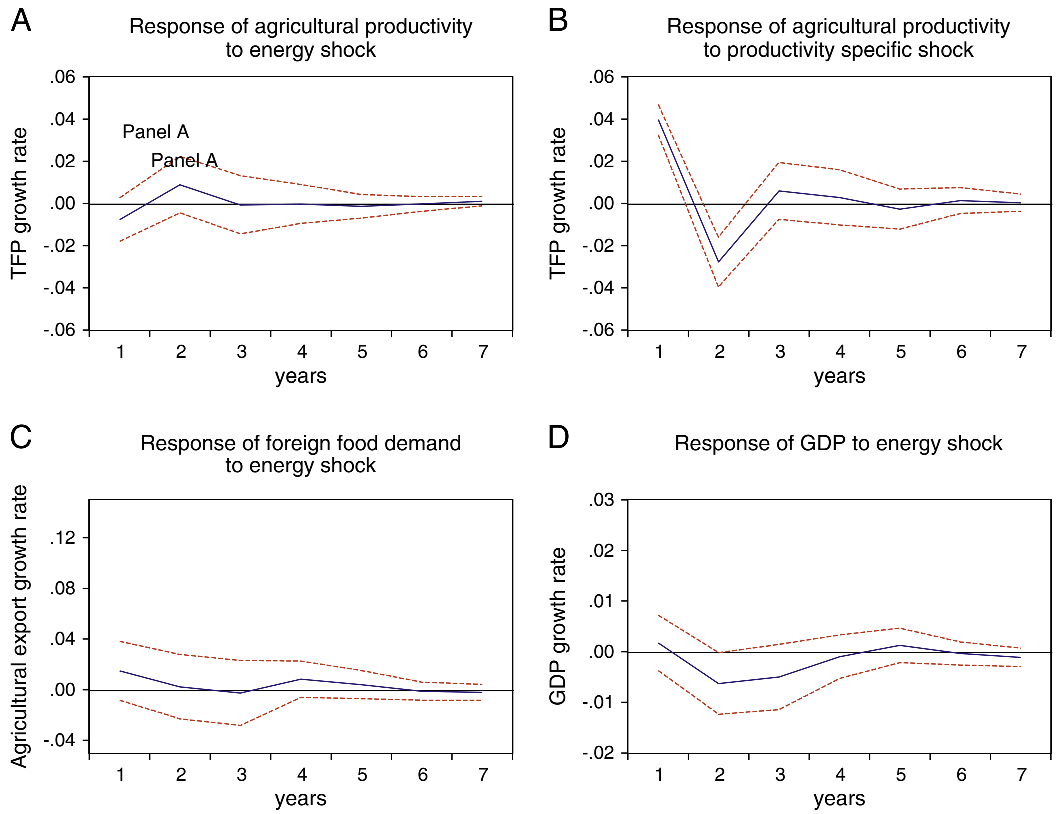

Fig. 5. Alternative variables' responses to structural one std. dev. innovations. Note: Solid line represents the mean impact, and the dotted lines represent two standard dev iation impacts f rom the mean. Standard errors f or the impulse responses are calculated using the Monte Carlo approach (Runkle, 1987).

Table 3
Percent contribution of each shock to the variability of US agricultural commodity price.

Period	Energy shock	Productivity shock	Global demand shock	Domestic demand shock	Specific commodity market shock
1	9.51	10.70	6.53	1.83	71.43
2	9.03	10.27	10.01	2.07	68.62
3	13.39	8.97	8.44	4.37	64.84
4	13.11	8.78	9.21	4.43	64.47
5	14.58	8.40	8.90	4.28	63.84
6	14.72	8.55	9.14	4.24	63.34
7	14.95	8.49	9.20	4.27	63.09
8	15.03	8.53	9.17	4.28	62.99
9	15.06	8.52	9.20	4.28	62.93
10	15.11	8.52	9.19	4.28	62.90

inefficient use of existed capital stock will cause a drop in the productivity estimate.

Panel B shows that short-term TFP growth is affected substantially by TFP specific shocks which are not explained by the system. Panel C shows that U.S. agricultural export changes respond to an energy price shock positively in year 1 and yet less significant. The positive impact was especially obvious during the 1970s' energy shock period. The large build-up of petroleum dollars induced dramatic increases in demand for U.S. agricultural commodity exports (Stallings et al., 1990). As to the response of the real U.S. GDP growth rate to energy shocks, it is significant and negative in year 2, and less significant but still negative in year 3. This is consistent with findings from the literature that an energy shock has a negative impact on economic growth.

4.3. How commodity price fluctuations are explained by an energy price shock, a productivity shock, a global demand shock, and a domestic demand shock

Through generalized forecast error variance decomposition analysis we can decompose the variation of commodity price changes into five components—an energy price shock, a U.S. agricultural productivity shock, a global demand shock, a domestic demand shock, and other shocks in U.S. agricultural commodity market. According to Table 3, in the short run (1 year), both an energy shock and a productivity shock explain about 10% of the commodity price fluctuation[11] with productivity shock's impact slightly higher (9.5% vs. 10.7%). Yet, the impact from energy shocks outweighs the contribution of productivity shocks in the intermediate term (3 years), where an energy shock's contribution increases to nearly 1.5 times of a productivity shock's contribution (13% over 9%). It implies that energy shocks have more persistent impacts in explaining the rapid increase in commodity prices than productivity shocks. In general, global demand in U.S. agricultural commodity (export) shocks accounts for about 6.5% of the commodity price volatility in year 1. This estimate is smaller than those based on single commodity studies (McPhail et al., 2012, among others). The

[11] Although energy shock influences productivity growth energy shocks and productivity shocks are exogenous to each other as productivity shock is a measure that captures the portion of productivity changes which could not be explained by energy shocks. Please refer to Eq. (4).

differences may be due to the larger fluctuation of foreign demand shock in single commodity series than in the aggregate sector. The global demand shock's contribution increases to about the same size as that of productivity growth (10%) in year 2. This is consistent with findings from McPhail et al. (2012). Domestic food demand shock has the least contribution in explaining the variability of U.S. agricultural commodity prices. Although exports of U.S. agricultural products only account for about 20% of the total agricultural production, the commodity prices' response to the foreign demand (exports) shocks is larger than that to the domestic demand shocks since exports are much more volatile than domestic food demand.

In the long run (more than 7 years), energy shocks account for about 15% of commodity price's volatility. It is about 50% more than the impact of productivity shocks and global food demand shocks in explaining commodity price's variation, while domestic demand shocks' contribution is still the least. It seems that although global food demand and productivity growth can both vary from year to year (productivity growth usually rebounds in the following year after a bad year), it is energy shocks that have more persistent and, therefore, higher impacts in explaining agricultural commodity prices' volatility in the long run.

5. Conclusion

The surging commodity prices in the last decade have raised concern about the linkage between energy prices and commodity prices. The dramatic increased use of corn to produce ethanol also contributed to tighter linkages between energy and agricultural commodity markets in recent years, especially after the origination and expansion of Renewable Fuel Standard (RFS) in the Energy Policy Act of 2005 and Energy Independence and Security Act of 2007. On the supply side, 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 commodity price volatility can be attributed to global energy shocks or slowing agricultural productivity growth. To address this issue, this study uses a structural VAR model of real U.S. gasoline prices, agricultural total factor productivity, real GDP, real agricultural exports, and real agricultural commodity prices to assess the impacts of energy shocks on U.S. agricultural productivity growth and commodity price variations based on aggregate data that has not been done before. The data span the period 1948 to 2011. The SVAR model is estimated by imposing restrictions on the feedback among the contemporaneous structural shocks based on economic theory.

According to the impulse response analysis, an energy price shock contributes negatively to TFP growth in year 1. It implies that the unexpected energy price shock could shift farmer's inputs use away from its most technical efficient combination in the short term. Operators' actions on energy conservation may result in less capital utilization and more labor use as Wood (1990) suggests. Since the conventional TFP measurement does not adjust for capital utilization rate, the inefficient use of existed capital stock will cause a drop in the productivity estimate. Growth of agricultural commodity price responds to an energy shock positively and significantly in year 1. A dramatic increase in energy price may raise fertilizer manufacturing costs and pushes up agricultural production costs. In addition, higher energy prices could also boost production costs through direct energy consumption for farm machinery or cooling or heating systems. According to the variance decomposition analysis, in the short run (1 year) productivity shocks contributed to 10.7% of commodity price volatility, which is slightly higher than the contribution of energy shocks (9.5%). In general, global demand in U.S. agricultural commodity (export) shocks account for about 6.5% of the commodity price volatility in year 1 and its impact increases to about the same size as that of productivity growth (10%) in year 2. The magnitude of its contribution in explaining the commodity price volatility is consistent with findings from single commodity studies. Domestic food demand shock has the least contribution in explaining the variability of US agricultural commodity price as the size of this shock is relatively smaller than all other shocks. In the long run (more than 7 years), energy shocks contribute to most (about 15%) commodity price variation. In summary, future U.S. commodity price volatility is expected to be affected most heavily by energy shocks in the long run. Yet, the variation explained by productivity shocks is slightly higher than energy shocks in the short term.

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