On the Economics of Commodity Price Dynamics and Price Volatility

by

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Abstract: This paper develops an economic analysis of commodity price dynamics and price volatility. The approach applies under general supply-demand conditions, including the role played by private and public inventory holders. Quantile autogression is used to estimate the evolving distribution of price. The usefulness of the method is illustrated in an application to two markets in China: a food market (rice) and a feed market (corn). Based on monthly data over the period 2000-2014, the econometric analysis shows how the price distributions (including skewness and kurtosis) vary across commodity markets. Using a Markov chain representation, the paper evaluates the dynamics of price volatility. It finds slow adjustments in the price distribution between short run and long run situations. The investigation also assesses the short run and long run effects of alternative economic policies on the price distributions. It finds that the Chinese price support programs have helped stabilize the domestic food market but not the feed market.

Keywords: price dynamics, price volatility, quantile, agricultural markets, China

JEL: C1, E3, Q1

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I. Introduction

Price volatility has been a basic characteristic of commodity markets. In general, high price volatility reflects market response to shocks under inelastic short run supply and demand. Fluctuating prices can have large effects on market participants. While price declines benefit consumers, they have negative impacts on producer income. Alternatively, while price spikes benefit producers, they have adverse effects on the welfare of consumers. At times, such adverse impacts have stimulated government interventions attempting to reduce price instability (e.g., Newberry and Stiglitz, 1981; Gouel, 2013). Much research has studied the economics of price volatility. Price volatility is part of the market response to unanticipated shocks; but it also reflects the behavior of market participants in reaction to anticipated market conditions. In particular, for storable goods, inventory holders can respond to anticipated price increases by carrying stocks forward in time, thus possibly reducing the prospects of facing future price spikes (e.g., Gustafson, 1958; Williams and Wright, 1991; Deaton and Laroque,1992, 1996; Cafiero et al., 2011). These arguments indicate that the determinants of commodity price volatility are dynamic and complex (e.g., Miao et al., 2011): they depend on supply and demand conditions, on the nature of shocks, on the information available to market participants and their dynamic response to evolving markets, and on economic policy. Such complexities make the economic analysis of commodity price dynamics challenging. Three difficulties are worth stressing. First, in the presence of unanticipated shocks, assessing price volatility must rely on the probability distribution of the market price. Second, the process generating price volatility is inherently dynamic. Thus, price volatility must involve the dynamic evolution of the price distribution. Third, the functioning of markets is typically influenced by economic policy, implying that evaluating the evolving price distribution must include the assessment of the effects of economic policy. Addressing these challenges provides the main motivations for this paper.

The objective of this paper is to develop an economic analysis of commodity price dynamics and price volatility. The investigation is presented under general supply-demand conditions, including the role played by private and public inventory holders. The approach is applied to a reduced form representation of price dynamics. We propose to use quantile regression to assess price volatility and the evolving distribution of price. Following Koenker (2005), quantile regression provides a flexible representation of the conditional price distribution. Of special interest are the skewness and kurtosis of the price distribution. For storable goods, skewness arises as storage contributes to reducing price spikes but only when stocks are positive (e.g., Deaton and Laroque, 1992, 1996). The approach also provides a basis to evaluate the occurrence of rare events located in the tails of the distribution (kurtosis and fat tails). The dynamics are captured in the context of quantile autoregression (Koenker and Xiao, 2006) which allows past prices to affect the current price distribution. In addition, the quantile analysis is conditional on policy instruments, providing a framework to investigate how economic policy affects price volatility. Using a Markov chain representation, the approach supports an analysis of how the price distribution evolves over time. This allows a distinction between short run and long run price volatility. This distinction is found to be important and provides new insights into the economics of price volatility.

The usefulness of the method is illustrated in an application to two Chinese markets: a food market (rice) and a feed market (corn).[1] China is a good case study not only for its remarkable economic growth over the last two decades, but also for its economic policy changes in agricultural markets at the beginning of the twenty-first century. In the early 2000's, China switched from taxing agriculture to subsidizing it (Anderson et al., 2013). In the process, the effects of government policy on agricultural prices became stronger. Based on monthly price data over the period 2000-2014, our econometric analysis provides new results on the determinants of price volatility during this transiting period. First, it shows how the price distributions (including skewness and kurtosis) vary across commodity markets. In our application to China, we find different results between the food market (rice) and the feed market (corn). Second, the paper documents the dynamics of price volatility. Using a Markov chain representation, it finds slow adjustments in the price distribution as price volatility differs in the short run versus the long run. Third, the investigation presents a refined assessment of the short run and long run effects of alternative economic policies. Such effects are found to vary across commodity markets. Currently, China has started a new round of agricultural policy reform, stressing the market-oriented direction towards agricultural commodity price liberalization. Our analysis provides new and useful information on the impact of economic policies on the distribution of commodity prices. We find that the Chinese price support program helped stabilize the domestic food market (rice). But we also present evidence of policy scenarios where the price support program contributed to domestic price increases and did not stabilize the Chinese feed market (corn).

The paper is organized as follows. Section 2 presents a conceptual model of price dynamics and price volatility in a commodity market. This leads to an econometric model of quantile autoregression providing a flexible way to estimate the price distribution, conditional on past prices and policy instruments. Section 3 presents an application of the approach to commodity price volatility for rice and corn in China. The econometric results are reported in section 4. Economic implications are discussed in section 5. Finally, section 6 concludes.

II. Conceptual Model

Consider the market for a commodity. At time t, let $Q_t \in \mathbb{R}_+$ be the quantity supplied, $D_t \in \mathbb{R}_+$ be the quantity demanded, and $P_t \in \mathbb{R}_+$ be the market price. And let $S_t \in \mathbb{R}_+$ be the quantity stored at the end of period t. The change in inventory is $\Delta S_t = (S_t - S_{t-1})$: when negative, ΔS_t is the reduction in stocks that become available for consumption at time t; and when positive, ΔS_t measures the quantity that is being stored during period t. It follows that the market equilibrium condition at time t is given by $D_t + \Delta S_t = Q_t$, stating that supply Q_t equals consumer demand D_t plus inventory demand ΔS_t. This shows that market equilibrium reflects supply, demand and inventory conditions.

First, consider the commodity demand. Conditional on price P_t, let $D_t(P_t, Z_{dt})$ denote aggregate demand at time t, where the vector Z_{dt} represents demand shifters (including income, the prices of other goods, and consumer preferences). In general, the aggregate demand includes domestic consumer demand as well as the demand for exports. We assume that the demand function $D_t(P_t, Z_{dt})$ is downward sloping with $\frac{\partial D_t}{\partial P_t} < 0$. The elasticity of demand $ED_t \equiv \partial \ln D_t / \partial \ln(P_t)$ affects the response of price to shocks. For example, considering the market equilibrium condition $D_t(P_t, Z_{dt}) = AS_t$ where AS_t denotes the aggregate supply at time t, we have $\frac{\partial \ln(P_t)}{\partial \ln(AS_t)} = 1/ED_t$, showing that the effect of a supply shock on market price P_t is larger (smaller) when $|ED_t|$ is smaller (larger), i.e., when the demand is more inelastic (more elastic). In other words, more inelastic demand will be associated with greater price volatility due to supply shocks.

Second, consider the commodity supply. The supply decisions are made by profit-maximizing firms in competitive markets. In the presence of production lags, production decisions are made ahead of time and depend on price expectations. In this context, the supply function is given by $Q_t\left(P_t^e, Z_{qt}\right) \in argmax_{Q_t \geq 0}\ \{P_t^e\ Q_t - C_{qt}\left(Q_t, Z_{qt}\right)\}$ where P_{qt}^e is expected market price based on the information available to firms when production decisions are made, $C_{qt}\left(Q_t, Z_{qt}\right)$ is the cost of production[2] and Z_{qt} are supply shifters. In the case where the expected price P_{qt}^e takes the form $P_{qt}^e = P_{qt}^e(P_{t-1}, P_{t-2}, \ldots)$, the supply function would become $Q_t\left(P_{t-1}, P_{t-2}, \ldots;\ Z_{qt}\right)$, where lagged prices allow for dynamics in supply decisions.

Third, consider inventory behavior. We consider two types of stocks: private stocks S_{rt} and public stocks S_{bt}, with $S_t = S_{rt} + S_{bt}$. In this context, there are two inventory demands: the demand for private stocks $\Delta S_{rt} = (S_{rt} - S_{r,t-1})$, and the demand for public stocks $\Delta S_{bt} = (S_{bt} - S_{b,t-1})$. The demand for private stocks is motivated by profit generated from anticipated price fluctuations (e.g., Gustafson, 1958; Williams and Wright, 1991; Deaton and Laroque, 1992, 1996). The choice of private stocks is given by $S_{rt}\left(P_{r,t+1}^e, Z_{rt}\right) \in argmax_{S_{rt} \geq 0}\ \{(\delta_t\ P_{t+1}^e - P_t)\ S_{rt} - C_r(S_{rt}, Z_{rt})\}$, where $\delta_t \in (0,1)$ is a discount factor, $P_{r,t+1}^e$ is the expected price for P_{t+1} based on the information available to storage firms at time t, $(\delta_t\ P_{r,t+1}^e - P_t)$ is the discounted expected price change during the t^{th} period, $C_r(S_{rt}, Z_{rt})$ is the cost of storage and Z_{rt} are private stock demand shifters. Expected price increases provide incentives for private storage. Indeed, situations where prices are high and expected to decrease are giving no incentive to carry private stocks. Alternatively, private storage firms could be active when current prices are relatively low and expected to increase, in which case they would contribute to stabilizing the market by buying (thus putting upward pressure on price) when the price is low and selling in the following period (thus putting downward pressure on price) when the price is high. In addition, the non-negativity of stocks implies that the price effects of a storage rule are necessarily nonlinear: storage can prevent price increases only when stocks are positive (Gustafson, 1958; Williams and Wright, 1991; Deaton and Laroque, 1992, 1996). In the case where the expected price $P_{r,t+1}^e$ takes the form

$P^e_{r,t+1} = P^e_{r,t+1}(P_t, P_{t-1}, P_{t-2}, \dots)$, the private stock demand function would become $\Delta S_{rt}(P_t, P_{t-1}, P_{t-2}, \dots; Z_{rt})$ where lagged prices allow for dynamics in private inventory decisions.

Fourth, consider the demand for public stocks. In the absence of public policy, then public stocks would be zero, with $\Delta S_{bt} = 0$. However, when public policy is implemented involving public stocks, then $\Delta S_{bt} \neq 0$. A common example is the case of government policy managing public buffer stocks in an attempt to stabilize market prices (e.g., Newbery and Stiglitz, 1981). We consider the generic case where the demand for public stocks is given by $\Delta S_{bt} = \Delta S_{bt}(P_t, P_{t-1}, P_{t-2}, \dots; G_t)$ where $\Delta S_{bt} + S_{b,t-1} \geq 0$ (as public stocks cannot be negative) and G_t are policy variables establishing linkages between prices $(P_t, P_{t-1}, . P_{t-2}, \dots)$ and public stocks. In general, the variables G_t reflect the nature of public buffer stock policy. A common example is a buffer stock policy associated with a price band $[p_L, p_M]$, where $p_L < p_M$. Then, the decision rule is to increase public stock when the market price is below the lower bound p_L, to release public stock when the price is higher than the upper bound p_M, and do nothing when the market price is between p_L and p_M (e.g., Newbery and Stiglitz, 1981, p. 409). In this context, the location and width of the price band $[p_L, p_M]$ determine the conditions under which public storage affects the market: a narrow price band could lead to large reductions in price volatility (by restricting price fluctuations to stay within the band); alternatively, a wide band may have little (or no) effect on market price volatility. Again, the non-negativity of stocks implies that buffer stocks can prevent price increases only when public stocks are positive (Gustafson, 1958; Newbery and Stiglitz, 1981). In general, the holding of public stocks affects other market participants and price determination, although the effects on market and price dynamics can be complex (e.g., Newbery and Stiglitz, 1981, p. 406-420). These issues are further investigated in our empirical analysis (see below).

Using $\Delta S_t = \Delta S_{rt} + \Delta S_{bt}$, it follows that the market equilibrium condition for the commodity is

$$D_t(P_t; Z_{dt}) + \Delta S_{rt}\left(P^e_{r,t+1};\ Z_{rt}\right) + \Delta S_{bt}(P_t, P_{t-1}, . P_{t-2}, \dots; G_t; Z_{bt}) = Q_t(P^e_{qt};\ Z_{qt}), \quad (1a)$$

which has for solution the market equilibrium price

$$P_t = P^0_t(P^e_{r,t+1}, P^e_{qt}, P_{t-1}, P_{t-2}, \dots;\ G_t;\ Z_t), \quad (1b)$$

where $Z_t = \left(Z_{dt}, Z_{qt}, Z_{rt}, Z_{bt}\right) \in \mathbb{R}^r$ is a r-vector of supply-demand shifters. Assume that the vector Z_t exhibits dynamics given by

$$Z_t = g_t(P_{t-1}, \dots, P_{t-n};\ Z_{t-1}, \dots, Z_{t-k}), \quad (2a)$$

where g_t is a function mapping $\mathbb{R}^n_+ \times \mathbb{R}^{kn}$ into $\mathbb{R}^r$. Equation (2a) allows for general dynamic effects of lagged P_t up to n periods and lagged Z_t up to k periods. After successive substitutions equation (2a) can be alternatively written as

$$\begin{aligned} Z_t &= g_t(P_{t-1}, P_{t-2}, \dots;\ g_{t-1}(P_{t-2}, \dots;\ Z_{t-2}, \dots), Z_{t-2}, \dots) \\ &= g_t(P_{t-1}, P_{t-2}, \dots;\ g_{t-1}(P_{t-2}, \dots;\ g_{t-2}(\dots), \dots), g_{t-2}(\dots), \dots) \\ &= \cdots \\ &= h_t(P_{t-1}, P_{t-2}, \dots), \end{aligned} \quad (2b)$$

conditional on initial conditions (Z_0, P_0) which we take as given. Assume that the lagged effects of P_{t-j} in equations (1b) and (2b) are negligible for all lags j greater than m.[3] Then, substituting equation (2b) into (1b) gives

$$P_t = P^*_t(P^e_{r,t+1}, P^e_{qt}, P_{t-1}, \dots, P_{t-m};\ G_t), \quad (3)$$

In the presence of uncertainty about market dynamics, taking the expected value of (3) gives the expected price $E[P^*_t\left(P^e_{r,t+1}, P^e_{qt}, P_{t-1}, \dots, P_{t-m};\ G_t\right)]$, where E denotes the expectation operator based on the information available to market participants. Under rationale expectation for producers and private stock holders, we would have $P^e_{qt} = E(P^*_t)$ and $P^e_{r,t+1} = E(P^*_{t+1})$, in which case expected prices take the form $P^e_{qt} = P^e_{qt}(P_{t-1}, \dots, P_{t-m};\ G_t)$ and $P^e_{r,t+1} = P^e_{r,t+1}(P_{t-1}, \dots, P_{t-m};\ G_t)$. Substituting these expressions into (3) yields

$$P_t = f_t(P_{t-1}, \dots, P_{t-m};\ G_t;\ e_t), \tag{4}$$

where e_t is a random vector representing unobservable effects (e.g., unpredictable weather shocks). We assume that e_t is identically and independently distributed with a given distribution function.[4]

Equation (4) is an m-th order stochastic difference equation representing the dynamics of market prices under general conditions. It is a "reduced form" equation that represents the net effects of past prices on current price. It has the advantage of not requiring direct measurements on the variables Z and their lagged values. In general, the Z vector includes many variables, some of them somewhat difficult to measure. On that basis, the "reduced form" specification given in (4) will be easier to use in applied work. The dynamic analysis presented in the rest of the paper will focus on equation (4).

Note that, in general, equation (4) can be alternatively written as the first-order difference equation

$$w_t \equiv \begin{bmatrix} P_t \\ \vdots \\ P_{t-m+1} \end{bmatrix} = \begin{bmatrix} f_t(P_{t-1}, \dots, P_{t-m}, G_t, e_t) \\ \vdots \\ P_{t-m+1} \end{bmatrix} \equiv H_t(w_{t-1}, G_t, e_t) \tag{5}$$

where $w_t \in \mathbb{R}^m_+$.[5] Equation (5) can be used to characterize the nature of price dynamics. Under differentiability, let $DH_t(w_{t-1}, G_t, e_t) = \partial H_t(w_{t-1}, G_t, e_t)/\partial w_{t-1}$ be a $(m \times m)$ matrix. Denote the characteristic roots of $DH_t(w_{t-1}, G_t, e_t)$ by $[\lambda_1(w_{t-1}, G_t, e_t, t), \dots, \lambda_m(w_{t-1}, G_t, e_t, t)]$ where $|\lambda_1(w_{t-1}, G_t, e_t, t)| \geq \dots \geq |\lambda_m(w_{t-1}, G_t, e_t, t)|$, $|\lambda_j|$ being the modulus of the j-th root, $j = 1, \dots, m$. The dominant root $\lambda_1(w_{t-1}, G_t, e_t, t)$ provides useful information on dynamics. In general, $|\lambda_1(w_{t-1}, G_t, e_t, t)|$ reflects the speed of dynamic adjustments in the neighborhood of point (w_{t-1}, G_t, e_t, t). Indeed, $\ln(|\lambda_1(w_{t-1}, G_t, e_t, t)|)$ measures the rate of divergence of P_t along a forward path in the neighborhood of (w_{t-1}, G_t, e_t, t). In this context, from equation (5), price dynamics is locally stable if the dominant root satisfies $|\lambda_1(w_{t-1}, G_t, e_t, t)| < 1$; and it is locally unstable if $|\lambda_1(w_{t-1}, G_t, e_t, t)| > 1$.[6]

Using equation (4), price dynamics can be alternatively written in terms of a Markov chain. This can be done by partitioning the price space $\mathbb{R}$ into K mutually exclusive intervals $(v_1, \dots, v_K)$. To illustrate, consider the case where $m = 2$. Letting $M = \{1, \dots, K\}$, we have

$$Prob(P_t \in v_i | G_t) = \sum_{j_1 \in M} \sum_{j_2 \in M} \{Prob[P_t \in v_i |\, P_t = f_t(P_{t-1}, P_{t-2}, G_t, e_t),$$

$$P_{t-1} \in v_{j1}, P_{t-2} \in v_{j2}]\; Prob[P_{t-1} \in v_{j1}, P_{t-2} \in v_{j2}]\} \tag{6a}$$

for $i \in M$. When the transition probabilities $Prob[P_t \in v_i |\, P_t = f_t(P_{t-1}, P_{t-2}, G_t, e_t), P_{t-1} \in v_{j1}, P_{t-2} \in v_{j2}]$ are time invariant (with $f_t = f$ and $G_t = G$ for all t), equation (6a) can be written as

$$p_t = A(G)\, p_{t-1} \tag{6b}$$

where $p_t = (p_{t,1}, \dots, p_{t,K^2})' = (Prob(P_t \in v_1, P_{t-1} \in v_1), \dots, Prob(P_t \in v_1, P_{t-1} \in v_K); \dots; Prob(P_t \in v_K, P_{t-1} \in v_1), \dots, Prob(P_t \in v_K, P_{t-1} \in v_K))'$ is a $(K^2 \times 1)$ vector, $A(G)$ is a $(K^2 \times K^2)$ matrix of Markov transition probabilities and $Prob(P_t \in v_i |\, G) = \sum_{j=1}^{K} p_{t,j+(i-1)K}$, $i \in M$. The matrix $A(G)$ is a Markov matrix with a dominant root equal to 1. Under time-invariant transition probabilities, when this dominant root is unique, the dynamic system (6b) has a unique stationary equilibrium given by $\lim_{t \to \infty} p_t = p^e(G)$ for all initial conditions p_0. This stationary equilibrium gives the long run equilibrium for the distribution of price P under policy G, thus providing a basis to evaluate the effects of G on the long run price distribution.

Given (4) or (5), define the conditional distribution function $F(c\,|P_{t-1}, \dots, P_{t-m};\, G_t, t) = Prob[P_t \leq c \mid P_{t-1}, \dots, P_{t-n};\, G_t, t] = Prob[f_t(P_{t-1}, \dots, P_{t-m};\, G_t, e_t) \leq c\,|P_{t-1}, \dots, P_{t-m};\, G_t,$

$t]$. The associated conditional quantile function is defined as the inverse function $q(r\,|P_{t-1},\dots,P_{t-m}\,;\;G_t,\;t) \equiv inf_c\;\{c\colon F(c\,|P_{t-1},\dots,P_{t-m};\;G_t,\;t) \geq r\}$ where r is the r^{th} quantile, $r \in (0,1)$. When $r = 0.5$, this includes as special case the conditional median $q(0.5\,|P_{t-1},\dots,P_{t-m};\;G_t,t)$. Both the distribution function $F(c\,|P_{t-1},\dots,P_{t-m};\;G_t,t)$ and the quantile function $q(r\,|P_{t-1},\dots,P_{t-m};\;G_t,t)$ are generic: they provide a complete characterization of the dynamics of P_t under a general specification of price dynamics given in equation (4). In the rest of the paper, we will make extensive use of the quantile function $q(r\,|P_{t-1},\dots,P_{t-m};\;G_t,t)$ in the analysis of the dynamics of P_t.

Relying on the conditional quantile function $q(r\,|P_{t-1},\dots,P_{t-m};\;G_t,\;t)$, we focus our attention on the case where the conditional quantile function takes the form $q(r\,|P_{t-1},\dots,P_{t-m};\;G_t,t) = X(P_{t-1},\dots,P_{t-m};\;G_t,t)\,\beta_r, r \in (0,1)$, where $X(\cdot)$ is a $(1 \times K)$ vector and $\beta_r \in \mathbb{R}^K$ is a $(K \times 1)$ vector of parameters. This restricts the analysis to situations where conditional quantiles are linear in the parameters β_r. Importantly, this specification allows the parameters β_r to vary across quantiles, thus providing a flexible representation of the underlying distribution function. This flexibility extends to the effects of the policy parameters G_t on price volatility. In addition, the functions $X(P_{t-1},\dots,P_{t-m};G_t,t)$ can possibly be nonlinear, thus allowing for the presence of nonlinear dynamics.

Below, for the r-th quantile, we will consider a quantile model specification of the form $q(r\,|P_{t-1},\dots,P_{t-m};\;G_t,t) = \beta_{0,r}(G_t,t) + \sum_{i-1}^{m}\beta_{i,r}(G_t)\,P_{t-i}, r \in (0,1)$. When $\beta_{i,r}(G_t) = \beta_i, i = 1,\dots,m$, this specification reduces to a standard autoregressive (AR) model where the autoregression parameters $(\beta_1,\dots,\beta_m)$ are treated as constants. While this AR specification still allows the policy variables G to shift the intercept, it would restrict the autoregression parameters $(\beta_1,\dots,\beta_m)$ to be constant, i.e., not to change with G or across quantiles.[7] In our quantile model, allowing the intercept $\beta_{0,r}(G_t, t)$ to vary across quantiles $r \in (0, 1)$ provides a flexible representation of the price distribution (including its moments: mean, variance, skewness and kurtosis). Perhaps more importantly, allowing the autoregression parameters $\beta_{i,r}(G_t)$ to vary across quantiles can capture flexible dynamics for any moment of the price distribution (including mean, variance and skewness, kurtosis). Finally, allowing the policy variables G to affect both the intercept $\beta_{0,r}(G_t, t)$ and the autoregression parameters $\beta_{i,r}(G_t)$ can give a flexible representation of policy effects on the dynamics of the price distribution. The usefulness of this flexible approach is illustrated in our empirical analysis below.

Consider a sample of n observations on (P, X). Denote the i^{th} observation by (P_i, X_i), $i \in N \equiv \{1, \dots, n\}$. For a given quantile $r \in (0, 1)$ and following Koenker (2005), the quantile regression estimate of β_r is

$$\beta_r^e \in argmin_\beta \{\sum_{i \in N} \rho_r(P_i - X_i\, \beta)\}, \tag{7}$$

where $\rho_r(w) = w\,[r - I(w < 0)]$ and $I(\cdot)$ is the indicator function. As discussed in Koenker (2005), the quantile estimator β_r^e in (7) is a minimum distance estimator that can be obtained by solving linear programming problems. Under some regularity conditions, β_r^e is an estimator of β with desirable statistical properties: it is consistent and asymptotically normal (Koencker, 2005). The usefulness of the quantile approach in the analysis of price dynamics and price volatility is illustrated in an application next.

III. An application to commodity price dynamics in China

This section presents an application of the approach discussed above to two agricultural markets in China: rice and corn. Using monthly data, our analysis studies the nature of price dynamics in these two markets during the period 2000-2014. As mentioned in the introduction, the sample covers a transition period exhibiting significant changes in Chinese agricultural policy. While the Chinese government has traditionally played a large role in the agricultural sector, the more direct impact of government policy on agricultural pricing has changed significantly during the sample period. Indeed, a government price support program was put in place in 2004 for rice and 2008 for corn. It means that we can observe the functioning of markets with and without government price support programs (the period without a price support program being before 2004 for rice and before 2008 for corn). This makes China to be a great case study of price dynamics and price volatility with and without price support programs.

Figure 1 shows the trajectories of Chinese rice and corn market prices (solid blue lines), minimum prices (solid red lines), and the international prices (dashed green line) from 2000 to 2014. Compared with the international market, Chinese agricultural market tend to be less volatile. Even during the crisis of 2008 (when food price volatility rose sharply in world markets), Chinese rice and corn prices stayed almost unchanged. After the price support programs were implemented (in 2004 for rice; and in 2008 for corn), market prices increased smoothly and co-moved with minimum support prices. The co-movements of market prices and minimum prices indicate that Chinese agricultural market prices have been heavily influenced by domestic support policies. The dynamic nature of these linkages are evaluated below. Interestingly, in contrast with other countries, Chinese price support programs are “seasonal”: they are implemented only for selected months every year.[8] Our analysis will evaluate the effect of policy duration on price distributions.

Over the last two decades, China is a prominent example of a developing country that has moved from taxing agriculture to supporting it (Gale, 2013; Huang, et al., 2013). During the last few decades, agricultural policy reforms related to pricing and markets have gone through three stages. In a first stage (before 1978), Chinese economic policy was to depress agricultural prices in support of industrial and urban development. This was done during a period when the state had monopoly in the purchase and marketing of grain, i.e. when government set agricultural prices and strictly controlled agricultural trading. In a second stage, following economic reform in 1978, China started moving toward a market economy. In the 1990's, government restrictions on the marketing of agricultural products were gradually eliminated. During this period, while Chinese government policy remained extensive, the government did not play a large role in agricultural pricing, and private trading increased significantly on domestic agricultural markets (Cheng, 2012). In a third stage, in the early 2000's, China began to abandon agricultural taxes and started subsidizing agriculture.[9] As part of agricultural subsidies, price support programs were introduced and had a significant impact on farm income and on the stability of domestic agricultural prices.[10]

China first established price support programs for its key agricultural commodities in 2004. These programs are similar to the "buffer stock" policies used by the US and the EU in the middle of twentieth century (see Gardner (2006) for the US, and Grant (1997) for the EU). In the programs, the government stands ready to purchasing commodities when market prices fall below the minimum prices, the purchase being used to build public stocks that can be eventually sold at auctions during periods of price spikes. Chinese rice and corn price support programs were set up in 2004 and 2008, respectively. See Table 1 for policy details.[11] In the first few years of implementation (2004-2007), the minimum prices were set relatively low and unchanged. However, after the 2008 world food crisis, the Chinese government began to increase the minimum support prices, leading to a greater involvement of government in Chinese agricultural markets. This contributed to greater subsidies of farmers and might help stabilize domestic markets. Note that, in recent years, the national grain reserve has surged dramatically.[12] As a result, the price support programs have become costly. More recently, the associated financial burden has stimulated interest in a new round of agricultural support policy reform in China. The Chinese government has begun a process of adjusting minimum price support levels and/or implement policies that reduce price distortion and liberalize commodity prices.[13] These policy reforms suggest the need for a refined assessment of the short run and long run effects of alternative economic policies on commodity prices.

IV. Econometric estimates of price dynamics

The analysis of price dynamics is based on the specification given in equation (4). It is based on monthly data of market prices (P_t) and minimum prices (p_L) for rice and corn over the period January 2000 - December 2014.[14] The data were obtained from China National Bureau of Statistics and China National Development and Reform Commission, respectively. We start with a preliminary analysis of equation (4) specified as autoregressive models of order m, AR(m). A first step involves an evaluation of the choice for the order m. Using monthly data for rice price and corn price in China, the estimates of alternative AR(m) models are reported in Table 3 for different values of m. Table 3 shows strong evidence of price dynamics, as prices lagged one month and two months are highly significant for both rice and corn. Prices lagged beyond two months are not statistically significant. This suggests that an AR(2) process provides a good representation of price dynamics for both rice and corn. This evaluation is supported using the Bayesian Information Criterion (BIC). Comparing AR(m) models with m varying from 1 to 4, Table 3 shows that the BIC criterion is minimized for m = 2 for rice as well as corn. On that basis, our analysis proceeds evaluating price dynamics allowing for effects of prices lagged one and two months.

Next, we estimate a quantile autoregression model of order 2, QAR(2). The QAR(2) model applied to price P_t includes lagged prices (P_{t-1}, P_{t-2}). It includes a time trend t accounting for structural change, and quarterly dummy variables (Q_{1t}, Q_{2t}, Q_{3t}) accounting for seasonality, where $Q_{it} = 1$ when the t^{th} observation occurs in the i^{th} quarter, $i = 1,2,3$. For policy variables G_t, we introduced two variables: $G_t = (SP_t, Dur_t)$, where SP_t measures the price support level and Dur_t measures the duration of the price support program (as applied in successive months within a year). At time t, the support price SP_t is defined as $SP_t = \max\{0, p_{L,t} - (MP_t - 4\, SD_t)\}$, where $p_{L,t}$ is the minimum price set by the government triggering government purchase and the building of public stocks, and MP_t is the mean and SD_t is the standard deviation of the commodity price at time t.[15] This definition means that the support price variable SP_t moves with the minimum price $p_{L,t}$ as long as $p_{L,t}$ is larger than $(MP_t - 4\, SD_t)$. It assumes that the minimum price p_L become ineffective when it is "very low", where "very low" is defined as p_L being less than $(MP_t - 4\, SD_t)$. The Dur variable is defined as the number of current and previous months the support program has been active in a given marketing year.[16] Table 2 reports summary statistics of market price (P_t) and support price (SP). As discussed in section 2, to allow for dynamic effects of the price support program, the SP variable is included in the model both as linear terms SP, square terms SP^2 and interaction terms with past prices $(SP * P_{t-1}, SP * P_{t-2})$.[17] For the selected quantiles $q \in (0.1,0.3,0.5,0.7,0.9)$, the estimated parameters of the QAR(2) model are reported in Table 4 for rice and in Table 5 for corn.[18] For comparison purpose, Tables 4 and 5 also report the ordinary least squares (OLS) estimates for the corresponding models. As expected, the results show evidence of price dynamics, as lagged prices often exhibit statistically significant coefficients. The exact nature of these dynamics is explored in details below. Note that the OLS estimates do not show evidence that the price support SP has a statistically significant effect on mean prices.

However, the QAR(2) estimates do show that SP does affect prices at least for some quantiles. This points out that focusing only on the effects of SP on mean prices is too narrow: it would fail to capture the effects of the price support program on the tails of the price distribution. Such effects are further evaluated below.

To evaluate the statistical relevance of the analysis, the model was subject to a series of statistical tests. They are presented in Table 6. First, in the quantile regression model, we tested whether the parameters vary across quantiles (0.1, 0.3, 0.5, 0.7, 0.9). As reported in Table 6, we strongly rejected the null hypothesis that the parameters are constant across quantiles. This indicates that the explanatory variables do affect the distribution of prices. The exact nature of these effects is further discussed below. Second, the presence of seasonality was tested. We found strong statistical evidence of seasonal effects for rice and corn from both the OLS results and the quantile regression results. This likely reflects the seasonality of agricultural production. Third, we tested for the effects of the support price SP. As noted above, while the OLS results did not find evidence of significant effects, the quantile regression results did. In particular, the SP variable was found statistically significant in quantiles (0.3, 0.6, 0.7, 0.8) for rice, and quantiles (0.1, 0.2, 0.3, 0.4, 0.5, 0.9) for corn. This shows that important aspects of the price support programs involve impacts on the price distribution away from the mean. Fourth, we tested for the effects of policy duration Dur. Table 6 shows that Dur has no statistical effects for rice. On that basis, we dropped the variable Dur in our analysis of duration and its effects on rice price dynamics. But Table 6 shows strong statistical effects of Dur on corn price dynamics, especially in the lower tail of the distribution. The implications of these effects are examined below.

V. Economic implications

The quantile estimation of price dynamics provides useful information on the nature of price volatility and price adjustments over time. First, applied to rice and corn, the quantile regression models reported in Table 4 and Table 5 were re-estimated for all quantiles, thus providing a basis to evaluate the conditional distribution function of prices. Estimates of the distribution functions of rice price and corn price are reported in Figure 2 for selected times: 2007, 2008 and 2009. Figure 2 shows that the distribution of rice price has thicker tails (both lower and upper tails) than corn price. This shows that the rice market exhibits much greater volatility than the corn market. This is consistent with rice having a more inelastic demand than corn (e.g., Chen et al., 2015).

Figure 3 reports the estimated conditional distribution over the sample period 2000-2014 for selected quantiles (0.1, 0.25, 0.5, 0.75, 0.9). It shows that the estimates track closely the evolution of market prices. Figure 4 reports the evolution of relative quantiles, defined as estimated quantiles (0.1, 0.25, 0.5, 0.75, 0.9) divided by the median. It shows a large relative volatility in the early 2000, followed by a slow decline in price volatility throughout the sample period. The determinants of this changing volatility are explored below.

Next, we used the estimated model to investigate the nature of price dynamics. The quantile estimation provides estimates of the function f_t and H_t in equations (4)-(5). As discussed in section 2, this can be used to evaluate the dominant root of the matrix $\frac{\partial H_t}{\partial w_{t-1}}$ in equation (5) across quantiles. Having a dominant root less than 1 implies that system is locally stable around the evaluation point. This dominant root is reported in Figure 5 for all quantiles under selected scenarios. Figure 5 shows that the dominant root is less than 1 almost everywhere. Thus, the analysis is broadly consistent with price exhibiting dynamic stability. However, the dominant roots can be greater than 1 in the range (0.9, 1), indicating the presence of local instability. As further discussed below, the distribution of prices has slow-evolving dynamics, stressing the need to distinguish between short run situations and longer run situations.

Figure 6 presents simulated price distributions evaluated in the short run under alternative scenarios. Here, short run means that lagged prices are taken as given. The results reported in Figure 6 are obtained based on prices observed in January 2008. Four scenarios are evaluated: 1/ without price support; 2/ under a low price support; 3/ under a medium price support; and 4/ under a high price support.[19] For rice, Figure 6 shows that, in the short run, the price support program contributes to lowering price volatility. It reveals three key results. First, as expected, the price support program shifts the lower tail of the price distribution to the right. This is an expected effect of a price floor policy that basically truncates the lower tail of the price distribution. Second, Figure 6 shows that the price support program also reduces the upper tail of the price distribution for rice. This is an important result suggesting that the buffer stock policy contributes to stabilizing the rice market by reducing the likelihood of large price decreases as well as large price increases. Third, note that the rice price support program does not have much effect around the median of the distribution. This helps explain why OLS could not find statistical evidence that the price support program affected prices (as reported in Table 6). Again, this establishes the importance of examining the effects of buffer stock policy on the whole price distribution.

Figure 6 also shows how the price support program affects the distribution of corn price. Again, as expected, increasing the price support is found to shift the lower tail of the price distribution to the right. However, for corn, as the price support increases, Figure 6 shows that the whole price distribution is shifting to the right. Thus, for corn, the analysis finds evidence that buffer stock policy contributes to increasing the median price as well as increasing the likelihood of price hikes.

Next, we evaluate the implications of our analysis for the long run. Here, the long run is evaluated treating f_t as being time invariant (with $f_t = f$ for all t), partitioning the range of price P into 40 equally-spaced intervals ($K = 40$) and using the Markov representation given in equation (6b). First, the matrix A in (6b) is found to have a unique dominant root (1), implying the existence of a long run equilibrium price distribution. Second, starting with a uniform distribution, the dynamic evolutions of the price distribution for rice and corn are simulated from equation (6b). The evolutions toward long run equilibrium are presented in Figure 7 under the conditions observed in January 2008. Figure 7 shows slow dynamics, as speeds of convergence toward stationary distribution are sluggish. Figure 7 also shows that, for both rice and corn, the long run price distributions are skewed and exhibit a longer upper-tail. Figure 8 presents similar long run results under alternative price support levels. Figure 8 shows that price support programs have very different effects on the path toward long run equilibrium for rice and corn. For rice, increasing the price support reduces both the lower tail and the upper tail of the price distribution. In this case, the price support program lessens price volatility without increasing the risk of price hikes. But for corn, increasing the price support reduces the lower tail while shifting the whole the distribution to the right. In this case, the price support program decreases the odds of facing low prices but also increases the odds of facing high prices.

Simulated price distributions are evaluated both in the short run and in the long run under selected scenarios. Summary statistics of these price distributions are presented in Table 7. For all scenarios, the distributions are found to exhibit significant positive skewness. As such, none of the simulated distributions can be represented by normal distributions. The positive skewness indicates that all distributions are asymmetric, with a higher probability of facing price increases than price decreases.

The evidence of positive price skewness is consistent with the role of storage. Indeed, when price changes can be anticipated, stocks can be build up during period of low prices and released in periods of high prices, thus contributing to decreasing price volatility (Gustafson, 1958; Williams and Wright, 1991; Deaton and Laroque.1992, 1996; Cafiero et al., 2011). But the release of stocks is possible only when stocks are positive. This implies that, while storage can reduce the prospects of facing low prices, periods of price spikes can occur when stocks are low, meaning that storage contributes to a price distribution that is skewed to the right.

For rice, the price support program is found to decrease variance and to increase skewness in the short run. But the results are different for corn, where the price support program does not affect variance but decreases skewness in the short run. In the long run, the impacts of price support are more complex. For example, in the long run, price support for both rice and corn first decreases skewness up to a point and then starts increasing skewness under a high support price.

Table 7 also reports excess kurtosis. For rice price, it shows that excess kurtosis is positive and statistically significant both in the short run and the long run, reflecting the presence of thick tails. The rice price support program tends to increase kurtosis at least in the short run. Interestingly, the distributions of corn price show less evidence of excess kurtosis. This indicates that thick tails are less common for corn price than for rice price. Table 7 also shows that, for corn price, excess kurtosis is more common in the long run than in the short run, suggesting that thick tails tend to develop as the price distribution adjusts toward its long run equilibrium.

The differences between the two markets reflect in part the nature of the goods: rice is a key food item treated as a necessity in China while corn is mostly used for animal feed. The demand for rice is very price inelastic; and it is more price inelastic than corn (Chen et al., 2015). As a result, supply shocks are expected to have a larger impact on rice prices than corn prices. This is consistent with our empirical evidence showing a higher likelihood of seeing large price swings in the food (rice) market than in the feed (corn) market.

Finally, Figures 9-10 report the simulated effects of alternative durations of the price support program, both in the short run and in the long run. In the short run, Figure 9 shows that an increase in duration shifts the lower tail of the corn price distribution to the right. This documents that, as expected, increased duration contributes to reducing the probability of facing low prices. Interestingly, such short run effects occur without much impact on the upper-tail of the distribution, i.e., with little increase in the probability of facing high corn prices. Figure 10 reports how the long run probability functions of corn price are affected by changing durations. It shows that, in the long run, higher duration contributes to shifting the whole price distribution to the right. In this case, while duration contributes to reducing the odds of facing low prices, it also increases the odds of facing high prices in the long run. This documents how the effects of policy interventions can differ in the short run versus the long run.

Our analysis provides new and useful insights on how government policy can affect pricing. It shows that the impact of a price support program can vary a lot depending on the situation considered. For rice, we find that a price support program can reduce price volatility. In particular, Figures 6 and 8 illustrate that the rice price support program reduces the prospects for both low prices and high prices. This seems to be desirable: reducing the odds of facing low rice prices is good for rice producers; and reducing the odds of facing high rice prices is good for consumers. A key finding is that, in this case, the rice price support program does not contribute to increasing either mean price or price spikes. But this result is specific to rice and does not apply to corn.

Indeed, Figures 6 and 8 present policy scenarios where the corn price support program does not reduce price volatility: it shifts the whole price distribution to the right both in the short run and in the long run. As expected, the corn price support program reduces the prospects of facing low corn prices, which benefits corn producers. But Figures 6 and 8 also show policy scenarios where the corn price support program contributes to increasing the mean price and the prospects of facing high prices. Such effects are found to be fairly large and would have adverse impacts on the welfare of all agents buying corn. Thus, our analysis finds scenarios where the corn price support program did not stabilize the domestic corn market. This is indirect evidence that the minimum price for corn was set too high during the period of analysis, thus raising questions about the economic efficiency and performance of the Chinese corn price support program.

VI. Conclusion

This paper has presented an economic analysis of commodity price dynamics and price volatility. The investigation applies under general supply-demand conditions and is implemented empirically using quantile autoregression. The analysis provides a basis to evaluate the skewness and kurtosis of the price distribution. And it can document how the price distribution evolves over time in response to shocks and policy instruments. This gives a framework to investigate how economic policy affects price volatility. And this allows a distinction between short run and long run price volatility.

The usefulness of the method was illustrated in an application to monthly price data on two markets in China: a food market (rice) and a feed market (corn). First, the econometric analysis showed how the price distributions (including skewness and kurtosis) vary across commodity markets. Second, the paper documents the dynamics of price volatility. Using a Markov chain representation, it finds slow adjustments in the price distribution as price volatility differs in the short run versus the long run. Third, the investigation provided new and useful information on the impact of economic policies on the distribution of commodity prices. It documented the effects of policy interventions and showed how such effects can vary across markets and differ between short run and long run situations. The analysis shows the Chinese price support programs have helped stabilize the domestic food market (rice) but not the feed market (corn).

The analysis presented in this paper could be expanded in several directions. First, there is a need to present applications to markets in other countries and for other commodities. Second, it would be useful to explore the effects of international trade and trade policy on commodity price volatility. Third, the linkages between dynamic price volatility and economic welfare need further investigations. These appear to be good topics for future research.

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Table 1. An Overview of agricultural price support programs for rice and corn in China

Commodity / Policy design		Rice	Corn
Policy title		Minimum Purchase Price	National Provisional Reserve
Policy initiation		2004	2008
Minimum price announcing time		Before planting	After harvesting
Purchasing volume limit		No	Yes
Implementation area (provinces)		Anhui, Jiangxi, Hubei, Hunan, Jiangsu, Jiangsu, Guangxi, Henan, Jilin, Heilongjiang and Liaoning	Neimenggu, Liaoning, Jilin and Heilongjiang
Implementation period		16 Sep -31 Mar (7 months)	14 Dec - 30 Apr (5 months)
Annual minimum price (Yuan/kg)	2004	1.50 (DNS)	-
	2005	1.50 (DNS)	-
	2006	1.50 (DNS)	-
	2007	1.50	-
	2008	1.64 (DNS)	1.50
	2009	1.90	1.50
	2010	2.10	1.5 (DNS)
	2011	2.56	1.98
	2012	2.80	2.12
	2013	3.00	2.24
	2014	3.10	2.24

SOURCE. — China National Development and Reform Commission.
NOTE. — DNS represents the program Do Not Start in that year; “-” represents programs that have not been set up yet.

Table 2: Summary statistics of the market price (P_t) and support price (SP), Yuan/kg

Variable name	Statistics	Commodity	
		Rice	Corn
Market price (P_t)	Sample period	Jan 2000- Dec 2014	Jan 2000- Dec 2014
	Observations	180	180
	Mean	1.65	2.08
	SD	0.53	0.71
	Max	2.63	3.22
	Min	0.82	1.10
Support price (SP)	Sample period	Jan 2000- Dec 2014	Jan 2000- Dec 2014
	Observations	180	180
	Mean	0.17	0.37
	SD	0.09	0.21
	Max	0.28	0.67
	Min	0.01	0.03

Table 3: Parameter estimates of selected AR processes

Variable	Parameter Estimates							
	Rice				Corn			
	AR(1)	AR(2)	AR(3)	AR(4)	AR(1)	AR(2)	AR(3)	AR(4)
Intercept	0.008 (0.007)	0.008 (0.007)	0.008 (0.007)	0.008 (0.007)	0.014 * (0.008)	0.011 (0.008)	0.011 (0.008)	0.010 (0.008)
P_{t-1}	1.001*** (0.004)	1.238*** (0.073)	1.255*** (0.076)	1.256*** (0.076)	0.997*** (0.005)	1.471*** (0.067)	1.518*** (0.076)	1.513*** (0.077)
P_{t-2}		-0.239*** (0.074)	-0.324*** (0.119)	-0.331*** (0.122)		-0.474*** (0.067)	-0.621*** (0.131)	-0.592*** (0.139)
P_{t-3}			0.069 (0.076)	0.099 (0.122)			0.100 (0.077)	0.026 (0.140)
P_{t-4}				-0.024 (0.076)				0.050 (0.079)
R-square	0.997	0.997	0.997	0.997	0.996	0.997	0.997	0.997
BIC	-750.33	-755.51	-751.19	-746.12	-674.91	-714.38	-710.94	-706.19

NOTE. — Standard errors are in parentheses below the corresponding parameter estimates. Asterisks indicate the significance level: * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Table 4: Quantile regression estimates of the Chinese rice market price for selected quantiles

Variable	OLS	Quantile regression				
		q = 0.1	q = 0.3	q = 0.5	q = 0.7	q = 0.9
Intercept	0.020	-0.022	-0.007	-0.003	0.010	0.058*
P_{t-1}	1.148***	1.034***	1.094***	1.076***	1.144***	1.303***
P_{t-2}	-0.177**	-0.078	-0.123	-0.084	-0.142	-0.301
SP	-0.003	0.087*	0.059*	0.007	-0.004	-0.056
$SP * P_{t-1}$	0.027	0.550	-0.100	-0.084	-0.130	0.819
$SP * P_{t-2}$	-0.036	-0.574	0.077	0.073	0.118	-0.808
t	0.006**	0.009**	0.006**	0.003	0.001	-0.001
Q1	0.021**	0.024*	0.025***	0.022***	0.015*	-0.010
Q2	0.003	0.031**	0.021**	0.009	0.000	-0.013
Q3	0.004	0.031***	0.022***	0.013	0.000	-0.021

NOTE. — Asterisks indicate the significance level: * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Table 5: Quantile regression estimates of the Chinese corn market price for selected quantiles

Variable	OLS	Quantile regression				
		q = 0.1	q = 0.3	q = 0.5	q = 0.7	q = 0.9
Intercept	0.036**	-0.034	0.017	0.031	0.024***	0.041
P_{t-1}	1.269***	1.258***	1.236***	1.259***	1.293***	1.200***
P_{t-2}	-0.333***	-0.311***	-0.302***	-0.325***	-0.327	-0.194
SP_t	-0.654	-0.871	-0.415	-0.374	-0.429	0.225
$SP_t * P_{t-1}$	-0.947	-3.053**	-1.497	-1.602	-0.449	1.462
$SP_t * P_{t-2}$	1.145	3.257*	1.429	1.442	0.550	-1.713
Dur_t	0.007*	0.007**	0.008***	0.007**	0.005	0.000
SP_t^2	0.019	0.057	0.028	0.022*	0.006	-0.005
t	0.030***	0.059 ***	0.040***	0.040**	0.026	0.003
Q_1	0.025***	0.050 ***	0.030***	0.029***	0.013	0.003
Q_2	0.005***	0.006 ***	0.006***	0.005***	0.003**	0.001
Q_3	0.636***	1.222 ***	2.051***	2.898***	0.704	1.196

NOTE. — Asterisks indicate the significance level: * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Table 6: Hypothesis testing for quantile effects, seasonality, support level and support duration: a comparison between OLS and Quantile Regression.

Testing items	Estimate method		Rice	Corn
			P-value	P-value
Same coefficients across quantiles	QR		0.006 ***	<2.2e-16 ***
Seasonality	OLS		0.065 **	8.2e-05 ***
	QR	q=0.1	0.070 ***	8.1e-04 ***
		q=0.3	9.7e-11 ***	8.3e-07 ***
		q=0.5	0.027 **	2.0e-05 ***
		q=0.7	0.394	0.003 ***
		q=0.9	0.848	0.96
Support level effect	OLS		0.650	0.389
	QR	q=0.1	0.489	8.1e-13 ***
		q=0.2	0.453	1.6e-04 ***
		q=0.3	0.042 **	8.3e-05 ***
		q=0.4	0.110	0.004 ***
		q=0.5	0.228	4.4e-05 ***
		q=0.6	0.070 *	0.451
		q=0.7	0.036 **	0.686
		q=0.8	0.005 **	0.069*
		q=0.9	0.573	1.3e-04 ***
Support duration effect	OLS		0.244	0.084 *
	QR	q=0.1	0.752	5.6e-05 ***
		q=0.2	0.491	5.3e-05 ***
		q=0.3	0.445	3.3e-04 ***
		q=0.4	0.110	0.004 ***
		q=0.5	0.503	2.2e-04 ***
		q=0.6	0.886	0.083 *
		q=0.7	0.765	0.203
		q=0.8	0.935	0.013**
		q=0.9	0.930	0.771

NOTE. — 1. OLS represents Ordinary Least Square, and QR represents Quantile Regression.

2. The results above are obtained using the specification $P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 P_{t-2} + \beta_3 SP_t + \beta_4 SP_t * P_{t-1} + \beta_5 SP_t * P_{t-2} + \beta_6 Dur_t + SP_t^2 + \beta_8 t + \beta_9 Q_1 + \beta_{10} Q_2 + \beta_{11} Q_3$.

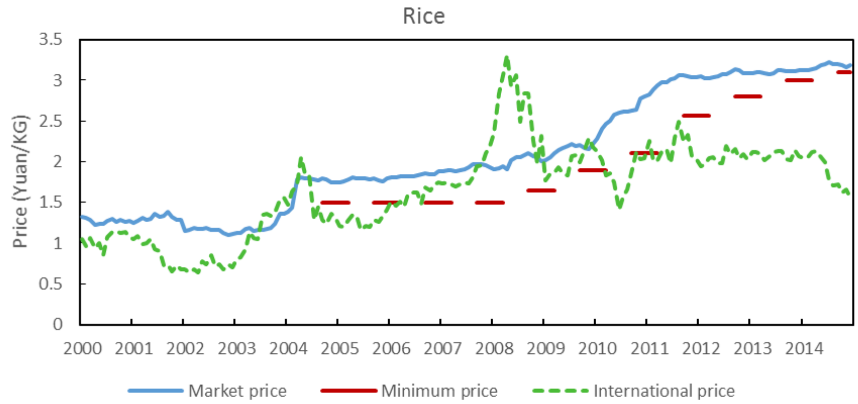
3. Asterisks indicate the significance level: * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

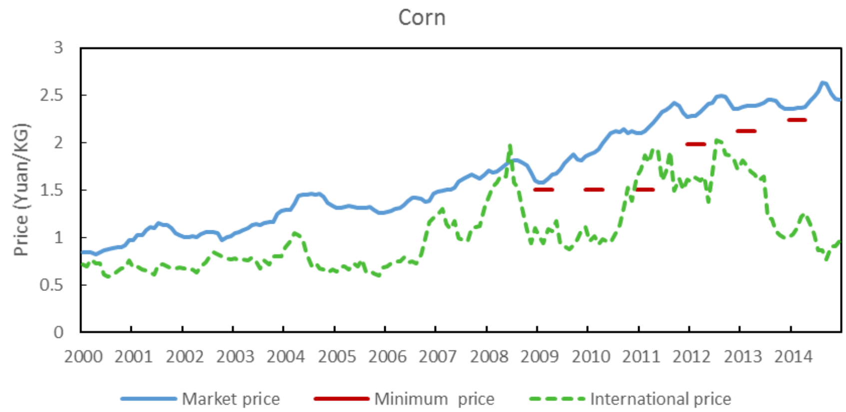
Table 7: Price distributions of short-term and long-term simulations

Variable			Rice				Corn			
			Mean	Variance	Skewness	Kurtosis	Mean	Variance	Skewness	Kurtosis
Short-term simulation	Support level effect	without SP	2.088	0.002	1.120*** (0.000)	2.151*** (0.000)	1.646	0.002	0.548*** (0.000)	-0.115 (0.686)
		with SP_low	2.087	0.001	1.487*** (0.000)	3.280*** (0.000)	1.643	0.002	0.341** (0.016)	-1.069*** (0.000)
		with SP_medium	2.086	0.001	1.978*** (0.000)	5.028*** (0.000)	1.660	0.002	0.266* (0.061)	-0.988*** (0.000)
		with SP_high	2.085	0.001	2.479*** (0.000)	7.093*** (0.000)	1.680	0.002	0.120 (0.398)	-0.970*** (0.001)
	Support duration effect	duration=4	-	-	-	-	1.638	0.002	0.309** (0.016)	-1.033*** (0.000)
		duration=5(real)	-	-	-	-	1.643	0.002	0.341** (0.030)	-1.069*** (0.000)
		duration=6	-	-	-	-	1.648	0.002	0.391*** (0.006)	-1.103*** (0.000)
Long-term simulation	Support level effect	without SP	2.368	0.042	0.775*** (0.000)	1.078*** (0.000)	1.457	0.025	0.366*** (0.010)	0.604** (0.033)
		with SP_low	2.285	0.021	0.574*** (0.000)	1.347*** (0.000)	1.486	0.026	0.271* (0.056)	0.392 (0.168)
		with SP_medium	2.300	0.027	0.564*** (0.000)	0.995*** (0.000)	1.750	0.024	0.422*** (0.003)	0.861*** (0.002)
		with SP_high	2.313	0.017	0.865*** (0.000)	2.401*** (0.000)	1.983	0.024	0.419*** (0.003)	0.611** (0.031)
	Support duration effect	duration=4	-	-	-	-	1.398	0.029	0.195* (0.056)	0.304 (0.168)
		duration=5(real)	-	-	-	-	1.486	0.026	0.271 (0.170)	0.392 (0.285)
		duration=6	-	-	-	-	1.572	0.022	0.292** (0.040)	0.402 (0.157)

NOTE. — 1. P-values are in parentheses below the corresponding skewness and kurtosis.
2. The kurtosis in this table refers to “excess kurtosis” with the value 0 for the normal distribution.
3. Asterisks indicate the significance level: * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Figure 1: Chinese market price, minimum price and international price for rice and corn





SOURCE. — The market prices are collected from China Yearbook of Agricultural Price Survey, China National Bureau of Statistics. The minimum prices are collected from China National Development and Reform Commission. International prices are collected from CBOT database, CME Group.
NOTE. — In this study, rice price refers to the price of japonica paddy.

Figure 2: Estimated distribution of the rice price and corn price in China, 2007-2009.

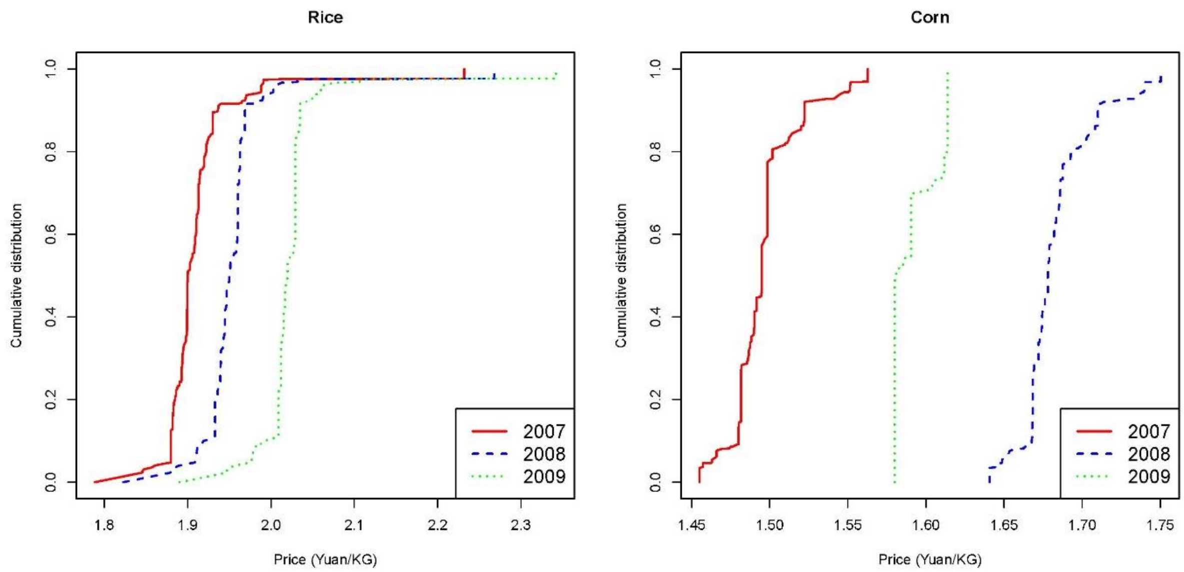


Figure 3: Quantile estimates of the distribution of rice price and corn price in China

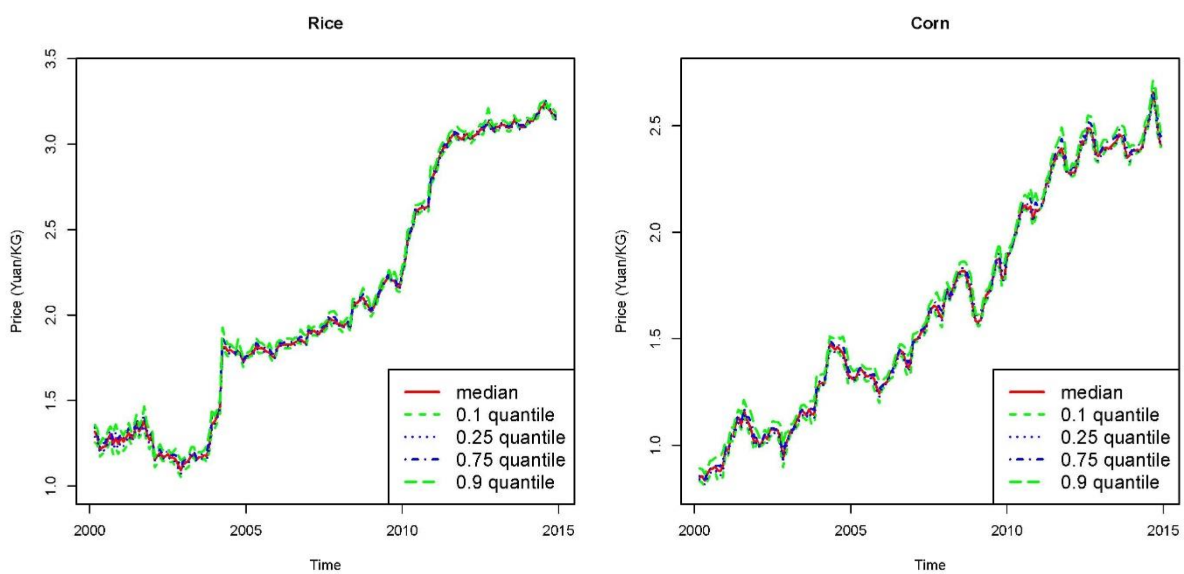


Figure 4: Estimates of relative quantiles for the distribution of rice price and corn price in China (relative to the median)

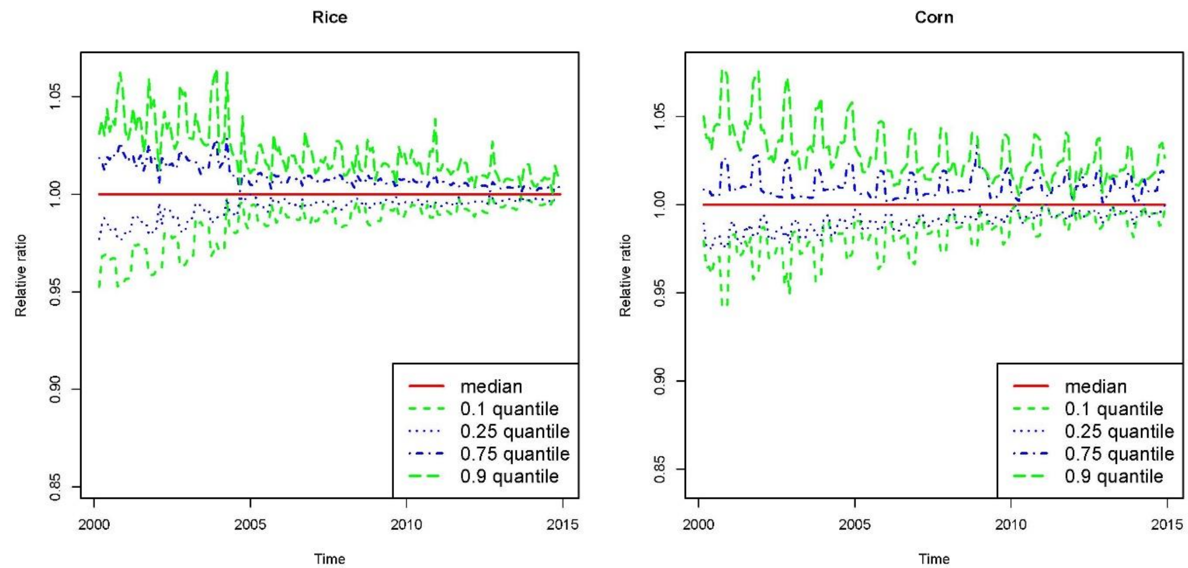


Figure 5: Modulus of the dominant root of the Markov matrix A for the dynamics of rice price and corn price (across quantiles)

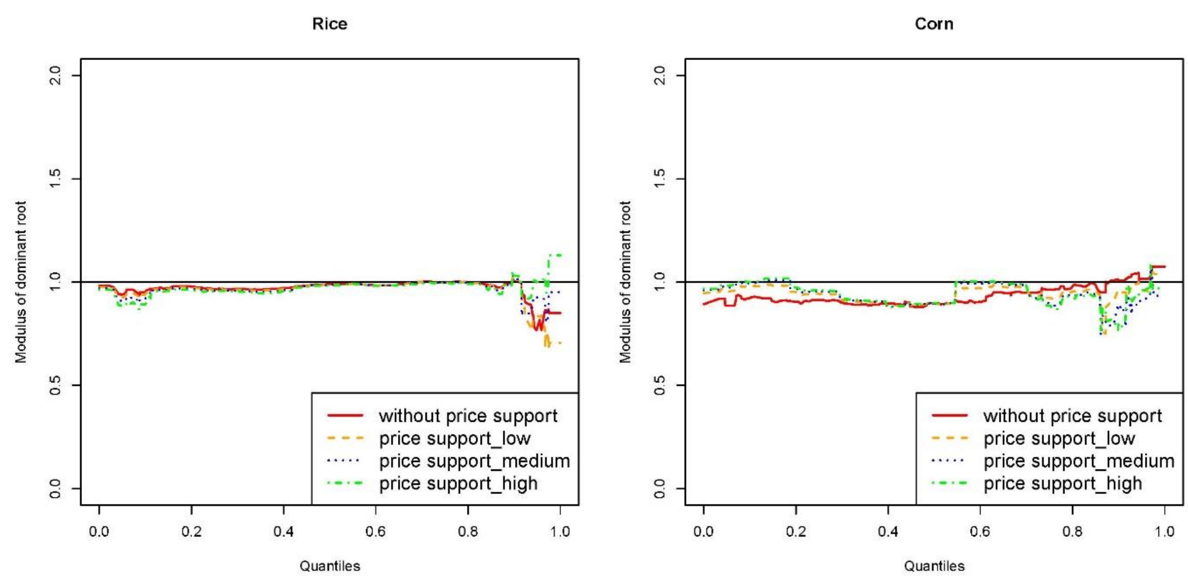


Figure 6: Simulated short-term distribution functions of rice price and corn price under different support levels

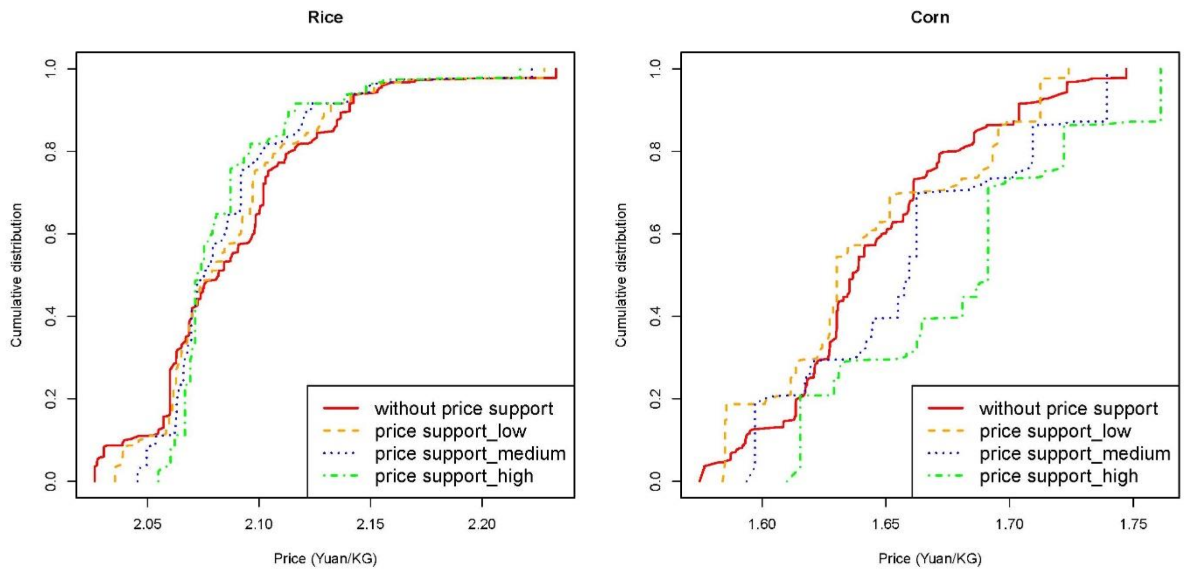
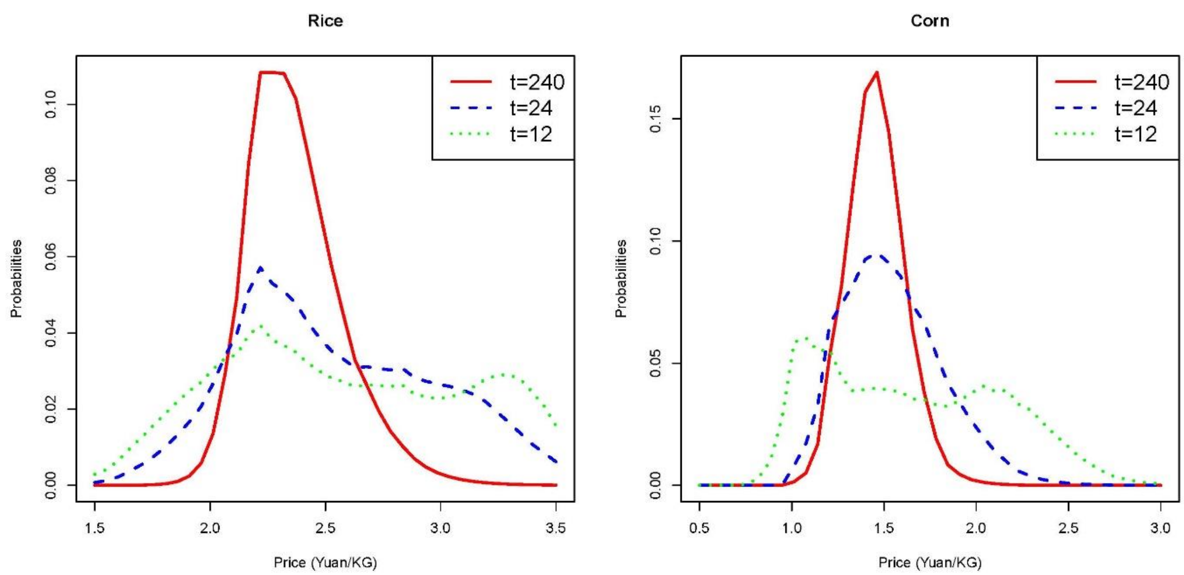


Figure 7: Simulated long-term probability functions of rice price and corn price and their path toward long run equilibrium.



NOTE. — "t=12, 24, 240" means simulated intermediate-term and long-term probability functions after 12 months, 24 months and 240 months, respectively.

Figure 8: Simulated long-term probability functions of rice price and corn price under different support levels.

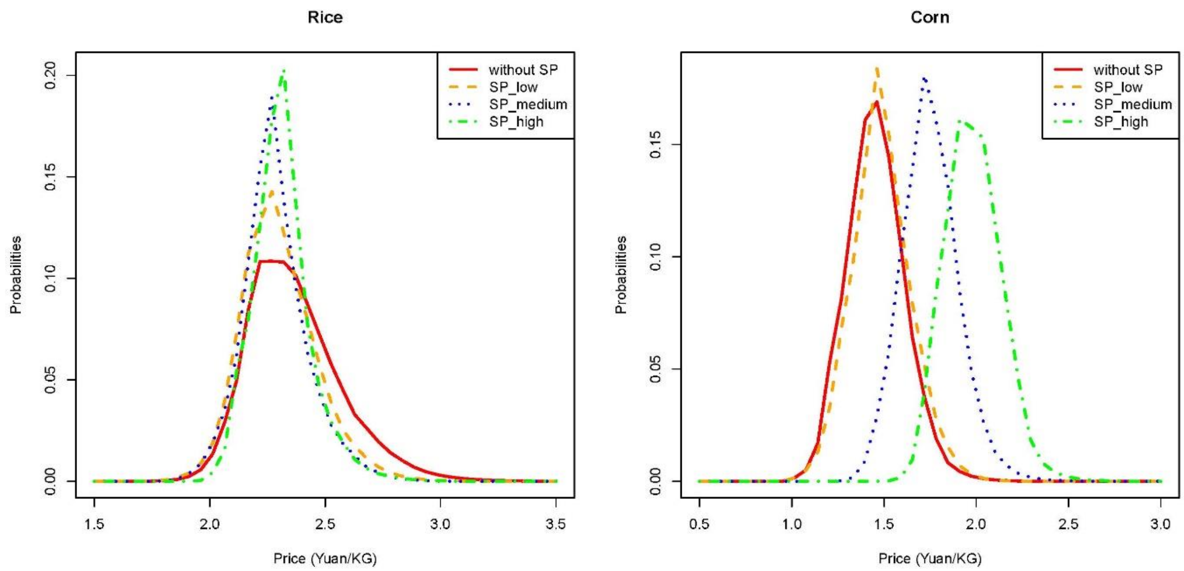
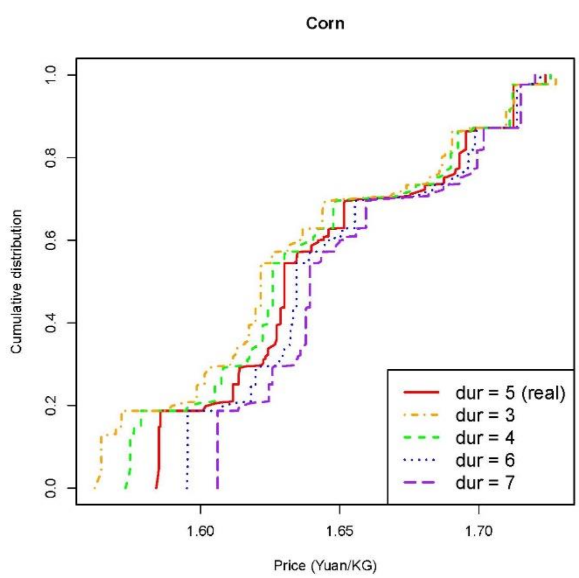
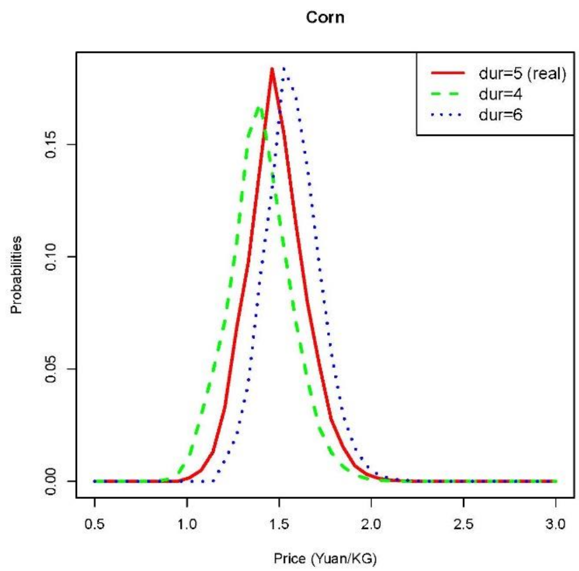


Figure 9: Simulated short-term distribution functions of corn price under different support durations.



<u>Figure 10:</u> Simulated long-term probability functions of corn price under different support durations.



Footnotes

[1] Rice is the most important food item in China. And while some corn is used for human consumption, a majority of the corn traded on the Chinese market is used for animal feed.

[2] When production decisions are made under uncertainty, then risk and risk aversion can affect supply decisions. In this case, the implicit cost of risk (as measured by a risk premium) would be included in the cost function $C_{qt}(Q_t, Z_{qt})$. In situations where government policy affects revenue risk, then policy variables (denoted by G below) would be additional shifters of the cost function.

[3] This is the assumption made in Markov representations of dynamic processes (e.g., Billingsley, 1961; Meyn and Tweedie, 1993).

[4] Note that there is no loss of generality to assume that the e_t's in (3) are independently distributed over time since any serial dependency can be captured by elements of Z_t and their associated dynamics in (2a)-(2b).

[5] The case of discrete distribution is a special case. When w_t can take s possible values $\{a_1, \dots, a_s\}$, the transition probability from $w_{t-1} = a_i$ to $w_t = a_j$ is $P(i,j) = Prob\big[w_t = a_j \,\big|w_{t-1} = a_i, w_t = h(w_{t-1}, e_t), i, j \in J\}$ where $J = \{1, \dots, s\}$. Letting $p_{j,t} = Prob[w_t = a_j]$, the dynamics is then represented by the Markov chain: $p_{j,t} = \sum_{i \in J} P(i,j)\, p_{i,t-1}, j \in J$ (e.g., Billingsley, 1961; Meyn and Tweedie, 1993).

[6] The case where $|\lambda_1(w_{t-1}, G_t, e_t, t)| = 1$ is a boundary threshold between local stability and local instability. When $|\lambda_1(\cdot)|$ is a constant, this is the case of "unit root" dynamics that has received much interest in the econometric literature (e.g., Enders, 2014).

[7] Relaxing these restrictions has led to more general model specifications allowing for dynamics in variance (e.g., the generalized autoregressive conditional heteroscedastic (GARCH) model proposed by Bollerslev (1986), Markov switching models (Hamilton, 1989)) and nonlinear dynamics (e.g., smooth transition autoregressive (STAR) model and threshold autoregression (TAR) model; see Tong (1990) and Van Dijk et al., (2002)).

[8] Chinese agricultural price support programs are implemented only during the peak months for the crop's procurement and only in designated major production areas.

[9] China began to abandon agricultural taxes in northeast provinces in 2004, and officially abandoned them nationwide in 2006.

[10] The Chinese industrial sector grew rapidly in the early 2000's, accompanied by massive migration from rural to urban areas. Along with its focus on industrial development, China saw a drop in agricultural production in the early 2000's. National food production declined from 512 million tons in 1998 to 430 million tons in 2003. This drop raised concerns about food security issues in China, contributing to a policy shift toward agriculture (Zheng et al., 2013).

[11] As shown in Table 1, there are some differences between rice and corn price support policies. In fact, there are two kinds of price support programs in China: Minimum Purchase Price (MPP, for rice and wheat) program and National Provisional Reserve (NPR, for corn, soybean, et al.) program. Although MPP and NRP programs are similarly designed and implemented, there are minor differences. For instance, minimum prices for MPP policy are announced before crops are planted, but minimum prices for NPR policy are usually set after harvest. Besides, MPP programs are implemented without purchasing volume limit, but NPR programs are usually announced with purchasing volumes in each province. These differences may generate different expectations for market participants and affect price distributions across commodities.

[12] For instance, in 2014, the purchasing volume associated with price support policies increased by 48.9% from the previous year, reaching 123.9 million tons. According to China's Central Fiscal Budget Table (2012-2014), the governmental grain and oil reserve expenditure boomed from 13.8 billion dollars in 2011 to 24.8 billion dollars in 2014, an increase of 73%.

[13] In 2015, the Chinese government lowered minimum prices for corn for the first time since these policies were implemented. And it suspended soybean and cotton price support programs and replaced them by "Target Price" programs.

[14] As discussed in section 2, under a price band policy $[p_L, p_M]$, the minimum price p_L (set by government policy) is observed. It is the price that triggers government purchase and the building of public stocks. However, the release price p_M that would trigger the sale of public stocks is not observed (either by us or by market participants). Without such information, we assume that the release price is proportional to the minimum price: $p_M = k\, p_L$, where $k > 1$ is a parameter. While our analysis treats the parameter k as a constant for each market, we allow it to vary across commodity markets.

[15] As noted in footnote 14, under a price band policy $[p_L, p_M]$, only the minimum price p_L (set by government policy) is observed. Assuming that $p_M = k\, p_L$, our analysis focuses on the dynamic effects of p_L on the price distribution. In this context, our support price variable is measured as $SP_t = \max\{0, p_{L,t} - (MP_t - 4\, SD_t)\}$, where the mean price ($MP_t$) and its standard deviation (SD_t) are obtained from regressing the commodity market price P_t on a time trend and seasonal dummy

variables. We conducted some sensitivity analysis and found our results to be fairly insensitive to our measurement of SP_t.

[16] For instance, the support program for rice starts in September and ends in the next March. Thus, the Dur variable is equal to 1 in September and 7 in March. And it has the value of 0 for the months without support programs.

[17] Note the minimum price $p_{L,t}$ is always lower than the actual price P_t in either the rice market or the corn market. Thus, in our sample data, there is no observed censoring of the market price P_t. On that basis, censoring issues are not a concern in our econometric analysis. Note that we still allow the minimum price $p_{L,t}$ to affect the distribution of prices (as reported below).

[18] The duration variable Dur and the square term SP^2 were first included in both the corn equation and the rice equation. However, they were found to be statistically insignificant in the rice equation. On that basis, they were dropped from the rice equation (as reported in Table 4). Thus, the effect of the duration variable Dur is estimated only for the corn equation as reported in Table 5.

[19] In the simulations, we set the “low price support”, “medium price support” and “high price support” at 0.25/0.50/0.75 quantile of the positive values of SP variable, respectively. This argument applies to the simulations under all scenarios in this study.