How Have China’s Agricultural Price Support Policies Affected Market Prices?: A Quantile Regression Evaluation

J. Li[1]; J.-P. Chavas[2]

1: Huazhong Agricultural University, College of Economics and Management, China, 2: University of Wisconsin, Department of Agricultural and Applied Economics, United States of America

Corresponding author email: hzaulj@126.com

Abstract:

This paper evaluates the effects of pricing policy on the distribution of agricultural prices, with an application to China. It investigates the effects of China’s price support programs on price enhancement and price stabilization in two key Chinese markets: rice and corn. The analysis relies on Quantile autoregression (QAR) which provides a refined and flexible way to capture the effects of pricing policy on price distributions (including mean, variance, skewness and kurtosis). Based on monthly data over the period 2000-2014, the econometric analysis documents the price effects of policy interventions and shows how such effects can vary across markets. The paper finds slow adjustments in the price distribution and important differences between short run and long run effects. The empirical evidence shows that the Chinese price support program increased the price of corn and shifted its price distribution to the right. The analysis also finds that China’s price support for rice contributed to stabilizing the domestic rice market without much price enhancement for rice.

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JEL Codes: E31, C18

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

JEL: C1, E3, Q1

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1. Introduction

Evaluating the effects of agricultural policy has been an important subject for economists and policy makers. One such policy is a price support policy that establishes a floor or minimum price on market prices. Historically, agricultural price support policies have been widely used in developed countries before 1990 (e.g., in the US and EU). Since 1990, agricultural policy in US and Europe has shifted away from relying on price support programs (Anderson et al., 2013). But agricultural price support policies continue to be used in developing countries (e.g., in China and India). Previous studies have evaluated various aspects of the effects of price support policies: on agricultural production, farmer's behavior, farm income and land prices (see reviews in Sumner et al., 2010 and Myers et al., 2010). The attention of economists and policy makers has focused on two effects of price support programs: their price stabilization effects and their price enhancement effects (e.g., Gouel, 2013). Their price stabilization effects have the potential to reduce market price volatility (e.g., Newbery and Stiglitz, 1981; Chavas et al., 2014). But their price enhancement effects can have adverse impacts on economic efficiency and agricultural trade (e.g., Williams and Wright, 1991; Anderson et al., 2013). These adverse effects motivated the WTO case brought in September 2016 by the US against China price support policy. But these arguments raise several important questions. How effective are price support programs in reducing price volatility? How much do they contribute to enhancing prices? In general, the impacts of such programs can depend on how they are implemented. If so, could it be that their stabilization effects and price enhancement effects vary across markets? The objective of this paper is to address these issues and to provide answers to these questions in the context of China agricultural price support policies.

While most developed countries moved away from price support policies, China increased its reliance on such programs during last decade. The economic impacts of those policies are significant. Previous work has studied the effects of China's policies on the supply response (Yi, et al, 2015), the trade and domestic distortion (Huang et al., 2009; Huang et al., 2011) and the price stabilization effect during world food crisis (Yang et al., 2008). However, as far as we are aware of, there is not much research on evaluating the policy effects on market price distribution. The underlying challenge is the absence of grain storage data in China. The absence of stock data makes it difficult to rely on structural models to evaluate the effects of agricultural support price policy in China. But reduced-form models remain available to evaluate such policies. This is the approach used in this paper. As showed below, a reduced-form approach provides very useful information of the effects of price supports on agricultural price dynamics and price volatility in China.

This paper investigates empirically the effects of China's price support programs on price stabilization and price enhancement in two key Chinese markets: rice and corn. Evaluating price stabilization effects requires assessing the distribution of market prices. This done by relying on Quantile autoregression (QAR) which provides a refined and flexible way to capture the effects of pricing policy on price distributions (including mean, variance, skewness and kurtosis). The QAR analysis is applied to a reduced-form representation of price dynamics, conditional on the policy instruments (including price floors) used in Chinese agricultural policy. This provides a useful framework to examine policy effects on price enhancement as well as price stabilization. Of special interest are the effects of China's price support programs on price dynamics and price volatility. First, the QAR approach captures the dynamic effects of pricing policy. The presence of dynamics will stress the importance of distinguishing between short run and long run effects. Second, this paper appears to present the first empirical investigation about the effects of China's price support policy on market price distribution. Importantly, we document how the effects of price support programs (e.g., price stabilization effects versus price enhancement effects) can vary across markets. The analysis provides useful insights on the effects of economic policy on the functioning of Chinese agricultural commodity markets.

Our empirical analysis is based on monthly price data over the period 2000-2014 for two key Chinese agricultural markets: rice and corn. Relying on QAR, the research investigates the effects of price support policy on price distribution in these two markets. It finds that price volatility and policy effects vary across commodity markets. We document that the rice market exhibits greater price volatility than the corn market. We find slow dynamic adjustments in the price distribution as price volatility differs in the short run versus the long run. Perhaps more importantly, we uncover evidence of differences in price policy effects across markets. We find that the Chinese price support programs helped stabilize the domestic rice market without much increase of its mean price. But we also find that the price support program contributed to domestic price increases and did not stabilize the Chinese corn market. Thus, our analysis indicates heterogeneous effects of price support policies: the price stabilization effects dominated in the rice market; but the price enhancing effect dominated in the corn market. In other words, our results show that China's rice price support program has been effective in reducing price volatility without much price enhancement. But our empirical analysis appears to reflect significant inefficiencies from China's corn price support program: obtaining price enhancement without price stabilization is a sign of significant market distortions. Along these lines, we note that China started a process of agricultural policy reform and discontinued its price support program for corn in 2015.

The paper is organized as follows. Section 2 describes the agricultural price support policies in China. Section 3 presents the econometric method of quantile autoregression with short-run and long-run price effects. The econometric results are reported in section 4. Economic implications are discussed in section 5. Finally, Section 6 concludes.

2. Agricultural price support policies in China

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; Anderson et al., 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 interventions 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. As part of agricultural subsidies, price support programs were introduced and had a significant impact on agricultural production and on the stability of domestic agricultural prices.

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 such programs, the government stands ready to purchase 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. 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, China's national grain reserve has surged dramatically. As a result, the price support programs have become costly. Besides, Chinese agricultural price support programs have caused a new WTO case brought by the US challenging that the "market price support" exceeded its WTO commitments. This is stimulating a new round of agricultural support policy reform in China. The Chinese government has begun a process of reducing minimum price support levels and/or implement new policies that reduce price distortion and liberalize commodity prices. Those policy reforms suggest the need for a refined assessment of the short run and long run effects of alternative economic policies on commodity prices.

Using monthly price data over the period 2000-2014, this paper investigates the effects of price support policies for rice and corn markets in China. 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. As noted above, government price support programs were put in place in 2004 for rice and in 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 provides a basis to study commodity price dynamics and price volatility with and without price support programs. Note that, in contrast with other countries, Chinese price support programs are "seasonal": they are implemented only for selected months every year.[1] Hence, our analysis will evaluate the effects of both policy level and policy duration on price distributions.

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 tends 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.

3. Econometric Methodology

As an important research area in agricultural economics, empirical modeling agricultural prices consists of two main frameworks: 1/ structural approach based on econometric estimation of supply, demand and market equilibrium models, and 2/ nonstructural approach which provides a "reduced-form" representation for variables from time-series data. (see Myers (2010) for a review). When evaluating the price effects of China's price support policy, it appears difficult to use the common structural storage models due to lack of data on grain stocks. For structural models, omitting key variables would be a misspecification creating "omitted variable bias". In contrast, reduced-form approach has the advantage of not requiring direct measurements on the supply-demand variables. Thus, the reduced-form approach can capture the net dynamics of prices, including indirect effects involving adjustments in omitted variables.

As noted in the introduction, this study presents an economic analysis based on a reduced-form approach. Our analysis applies Quantile autoregression (QAR) technique proposed by Koenker and Xiao (2006) to assess the policy effects on the price volatility and the evolving price distribution in China. Compared with conventional mean regression (i.e., Least Squares), QAR is a flexible method that can catch the dynamic policy effects, especially on the tails of the price distribution.

Our analysis relies on a reduced-form equation that gives a valid representation of the net effects of past prices and of support price program G on current price P_t at time t.

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

where $P_t \in \mathbb{R}_+$ is the commodity price at time t, P_{t-j} are past prices, m is the largest number of lags reflecting the "memory" of the dynamic system,[2] the variables G_t reflect the nature of government price support policy, e_t is a scalar representing unobservable effects (e.g., unpredictable weather shocks). We assume that e_t is identically and independently distributed with a given distribution function. As an m-th order stochastic difference equation, equation (1) provides a general representation of the dynamics of market prices. Note that, it can be alternatively written as the first-order difference equation.

$$w_t \equiv \begin{bmatrix} p_t \\ p_{t-1} \\ \vdots \\ p_{t-m+1} \end{bmatrix} = \begin{bmatrix} f_t(p_{t-1}, \dots, p_{t-m}, G_t, e_t) \\ p_{t-1} \\ \vdots \\ p_{t-m+1} \end{bmatrix} \equiv H_t(w_{t-1}, G_t, e_t) \tag{2}$$

where $w_t \in \mathbb{R}_+^m$. Assuming differentiability of $H_t(w_{t-1}, G_t, e_t)$, let the derivative of $H_t(w_{t-1}, G_t, e_t)$ with respect to w_{t-1} be the $(m \times m)$ matrix DH. Then we can obtain the dominant root $\lambda_1(w_{t-1}, G_t, e_t, t)$ that gives meaningful insights on price dynamics. At evaluation point (w_{t-1}, G_t, e_t, t), the price dynamics is locally stable if and only if the dominant root is in the unit circle ($|\lambda_1(w_{t-1}, G_t, e_t, t)| < 1$); and is locally unstable if the dominant root is outside the unit circle ($|\lambda_1(w_{t-1}, G_t, e_t, t)| > 1$). In this context, $|\lambda_1(w_{t-1}, G_t, e_t, t)|$ provides information about the speed of dynamic adjustments in the neighborhood of point (w_{t-1}, G_t, e_t, t), and $\ln(|\lambda_1(w_{t-1}, G_t, e_t, t)|)$ further reflects the rate of divergence of prices along a forward path in the neighborhood of (w_{t-1}, G_t, e_t, t).

To evaluate the long run effects of policy on price distribution, price dynamics can be alternatively written in terms of a Markov chain using equation (1). 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

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

$$P_{t-1} \in v_{j1}, P_{t-2} \in v_{j2}]\, Prob[P_{t-1} \in v_{j1}, P_{t-2} \in v_{j2}]\} \tag{3a}$$

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 (3a) can be written as

$$p_t = A(G)\, p_{t-1} \tag{3b}$$

where $p_t = \left(p_{t,1}, \dots, p_{t,K^2}\right)' = \left(Prob(P_t \in v_1, P_{t-1} \in v_1), \dots, Prob(P_t \in v_1, P_{t-1} \in v_K); \dots; Prob(P_t \in v_K, P_{t-1} \in v_1), \dots, Prob(P_t \in v_K, P_{t-1} \in v_K)\right)'$, 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 (3b) 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.

Based on the reduced-form equation in (1) or (2), we can define the conditional distribution function $F(c\,|P_{t-1}, \dots, P_{t-m};\ G_t, t) = Prob[P_t \leq c \mid P_{t-1}, \dots, P_{t-n};\ G_t, t] = Prob[f_t(P_{t-1}, \dots, P_{t-m};\ G_t\ , e_t) \leq c\,|P_{t-1}, \dots, P_{t-m};\ G_t,\ t]$. Its inverse function corresponds to the associated conditional quantile function ,which can be denoted as $Q(q\,|P_{t-1}, \dots, P_{t-m}\ ;\ G_t,$ $t) \equiv inf_c\ \{c\colon F(c\,|P_{t-1}, \dots, P_{t-m};\ G_t,\ t) \geq q\}$ where q is the q^{th} quantile, $q \in (0, 1)$. Given the general specification of price dynamics in equation (1), both the distribution function $F(c\,|P_{t-1}, \dots, P_{t-m};\ G_t, t)$ and the quantile function $Q(r\,|P_{t-1}, \dots, P_{t-m};\ G_t, t)$ provide a complete characterization of the dynamics of P_t. In the following parts of this paper, we will make extensive use of the quantile function $Q(q\,|P_{t-1}, \dots, P_{t-m};\ G_t, t)$ in the analysis of policy effects on the price dynamics and price volatility.

In this study, we consider the case where $Q(q\,|P_{t-1}, \dots, P_{t-m};\ G_t, t) = X(P_{t-1}, \dots, P_{t-m};\ G_t, t)\ \beta_q = \beta_{0,q}(G_t, t) + \sum_{i-1}^{m} \beta_{i,q}(G_t)\ P_{t-i}\ , q\ \in (0, 1)$, where $X(\cdot)$ is a $(1 \times K)$ vector and $\beta_q \in \mathbb{R}^K$ is a $(K \times 1)$ vector of parameters. This specification reduces to a standard autoregressive (AR) model when the autoregression parameters are treated as constants $(\beta_{i,q}(G_t) = \beta_i, i = 1, \dots, m)$. Although the AR(m) specification allows policy variables G_t to shift the intercept, it would restrict the autoregression parameters $(\beta_1, \dots, \beta_m)$ to be constant (i.e., not to change with policy variables or across quantiles). Thus, the standard AR(m) model imposes two strong restrictions on the nature of price dynamics. First, all the autoregression parameters

$(\beta_1, \dots, \beta_m)$ are treated as constant across quantiles. Second, the conditional quantiles are restricted to be linear in $(P_{t-1}, \dots, P_{t-m})$. In contrast, our quantile specification relaxes both restrictions. It allows the functions $X(P_{t-1}, \dots, P_{t-m}; G_t, t)$ to be nonlinear, which can capture nonlinear policy effects on price dynamics.

Compared with the AR specification, our quantile specification appears more refined in at least three aspects. First, in the QAR specification, allowing the intercept $\beta_{0,q}(G_t, t)$ to vary across quantiles $q \in (0, 1)$ provides a flexible representation of all moments of the price distribution, including mean, variance, skewness and kurtosis. Second, allowing the autoregression parameters $\beta_{i,q}(G_t)$ to vary across quantiles can capture flexible dynamics for any moment of the price distribution. Third and more importantly, allowing the policy variables G to affect the intercept $\beta_{0,q}(G_t, t)$ and the autoregression parameters $\beta_{i,q}(G_t)$ can provide very useful information about the policy effects on market price.

In an empirical application, consider a sample of n observations on (P, X), where the i^{th} observation is denoted as (P_i, X_i), $i \in N \equiv \{1, \dots, n\}$. Following Koenker (2005), for a given quantile $q \in (0, 1)$, the quantile regression estimate of β_q is

$$\beta_q^e \in argmin_\beta \{\textstyle\sum_{i \in N} \rho_q(P_i - X_i\, \beta)\}, \tag{4}$$

where $\rho_q(w) = w\,[q - I(w < 0)]$ and $I(\cdot)$ is the indicator function. By solving linear programing problems, the quantile estimator β_q^e in (4) can be obtained with desirable statistical properties (Koencker, 2005).[3] Below, we apply this quantile approach to evaluate how China's price support policy affected market price dynamics and price volatility.

4. Econometric Estimates of Policy Effects on Price Distribution

The analysis of policy effects on market price distribution is based on the specification given in equation (1). It is based on monthly data of market prices (P_t) and government minimum prices (p_L) for rice and corn over the period January 2000 - December 2014. 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 (1) 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 the key policy variables G_t, Chinese price support programs are somewhat different from other countries: they are implemented only for selected months every year. Both support levels and support duration might have affected market price distributions. Thus, we further 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.[4] 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 becomes 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. 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 $(SP * P_{t-1}, SP * P_{t-2})$.[5] 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. 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.

Next, we tested for the effects of the key policy variables: support price SP and policy duration Dur. 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. 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.

5. Economic Implication

The quantile estimation provides useful information on the effects of China's price support policy on market 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 greater volatility than the corn market. This is consistent with rice having a more inelastic demand than corn in China (e.g., Chen et al., 2015).

Figure 3 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's, 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 policy effects on price dynamics. The quantile estimation provides estimates of the function f_t in equation (1) (or H_t in equation (2)). 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 (2) 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 4 for all quantiles under selected scenarios. Figure 4 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 long run situations.

Figure 5 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 5 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. For rice, Figure 5 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 5 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 5 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 5 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 (3b). First, the matrix A in (3b) is found to have a unique dominant root (equal to one), 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 (3b). The evolutions toward long run equilibrium are presented in Figure 6 under the conditions observed in January 2008. Figure 6 shows slow dynamics, as speeds of convergence toward stationary distribution are sluggish. Figure 6 also shows that, for both rice and corn, the long run price distributions are skewed and exhibit a longer upper-tail. Figure 7 presents similar long run results under alternative price support levels. Figure 7 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 built 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 significantly 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 8-9 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 8 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 9 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.

6. Conclusion

This paper has evaluated how China's price support policy affected market price distribution. The analysis examines both price stabilization effects and price enhancing effects of Chinese agricultural pricing policies. The evaluation is implemented empirically using Quantile autoregression (QAR). It documented 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 dynamics and price volatility. The analysis distinguishes between in the short run and long run.

Based on monthly rice and corn data over the period 2000-2014, our evaluation generated new and interesting results on price volatility and the effects of Chinese price support policies. First, compared with conventional mean regression (i.e., Least Squares), QAR provides a more refined way to capture the effects of pricing policy on price distributions (including mean, variance, skewness and kurtosis). Second, using a Markov chain representation, the analysis finds slow adjustments in the price distribution as price volatility differs in the short run versus the long run. Third, our research 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 rice market. But it also indicates significant inefficiencies from China's corn price support program: obtaining price enhancement without price stabilization is a sign of significant distortions in the Chinese corn market.

The analysis presented in this paper could be expanded in several directions. First, the QAR approach could be applied to evaluate the price effects of alternative policy instruments. And it could also be applied to other markets. Second, it would be useful to explore the effects of international trade and trade policy on agricultural price volatility. Third, there is a need to investigate further the links between dynamic price volatility and economic welfare. 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

Policy design \ Commodity		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	0.008	0.008	0.008	0.014 *	0.011	0.011	0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
P_{t-1}	1.001***	1.238***	1.255***	1.256***	0.997***	1.471***	1.518***	1.513***
	(0.004)	(0.073)	(0.076)	(0.076)	(0.005)	(0.067)	(0.076)	(0.077)
P_{t-2}		-0.239***	-0.324***	-0.331***		-0.474***	-0.621***	-0.592***
		(0.074)	(0.119)	(0.122)		(0.067)	(0.131)	(0.139)
P_{t-3}			0.069	0.099			0.100	0.026
			(0.076)	(0.122)			(0.077)	(0.140)
P_{t-4}				-0.024				0.050
				(0.076)				(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. Asterisks indicate the significance level: * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Table 4. QAR and OLS estimates of the Chinese rice price

Variable	OLS	Quantile regression				
		q = 0.1	q = 0.3	q = 0.5	q = 0.7	q = 0.9
Intercept	0.020 (0.017)	-0.022 (0.027)	-0.007 (0.014)	-0.003 (0.015)	0.010 (0.016)	0.058* (0.036)
P_{t-1}	1.148*** (0.082)	1.034*** (0.181)	1.094*** (0.093)	1.076*** (0.085)	1.144*** (0.111)	1.303*** (0.245)
P_{t-2}	-0.177** (0.081)	-0.078 (0.189)	-0.123 (0.093)	-0.084 (0.081)	-0.142 (0.108)	-0.301 (0.245)
SP	-0.003 (0.053)	0.087* (0.053)	0.059* (0.032)	0.007 (0.044)	-0.004 (0.048)	-0.056 (0.077)
$SP * P_{t-1}$	0.027 (0.574)	0.550 (0.619)	-0.100 (0.463)	-0.084 (0.485)	-0.130 (0.511)	0.819 (1.122)
$SP * P_{t-2}$	-0.036 (0.573)	-0.574 (0.616)	0.077 (0.461)	0.073 (0.482)	0.118 (0.512)	-0.808 (1.127)
t	0.006** (0.003)	0.009** (0.005)	0.006** (0.003)	0.003 (0.003)	0.001 (0.003)	-0.001 (0.005)
Q1	0.021** (0.008)	0.024* (0.011)	0.025*** (0.006)	0.022*** (0.008)	0.015* (0.009)	-0.010 (0.033)
Q2	0.003 (0.010)	0.031** (0.013)	0.021** (0.009)	0.009 (0.010)	0.000 (0.010)	-0.013 (0.021)
Q3	0.004 (0.009)	0.031*** (0.010)	0.022*** (0.007)	0.013 (0.008)	0.000 (0.010)	-0.021 (0.016)

Note: Standard errors are in parentheses.

Table 5. QAR and OLS estimates of the Chinese corn price

Variable	OLS	Quantile regression				
		q = 0.1	q = 0.3	q = 0.5	q = 0.7	q = 0.9
Intercept	0.036** (0.016)	-0.034 (0.028)	0.017 (0.016)	0.031 (0.021)	0.024 (0.022)	0.041 (0.036)
P_{t-1}	1.269*** (0.079)	1.258*** (0.117)	1.236*** (0.085)	1.259*** (0.104)	1.293*** (0.114)	1.200*** (0.204)
P_{t-2}	-0.333*** (0.079)	-0.311*** (0.121)	-0.302*** (0.082)	-0.325*** (0.106)	-0.327*** (0.114)	-0.194 (0.195)
SP_t	-0.654 (0.403)	-0.871 (0.563)	-0.415 (0.611)	-0.374 (0.627)	-0.429 (0.804)	0.225 (0.938)
$SP_t * P_{t-1}$	-0.947 (0.962)	-3.053** (1.538)	-1.497 (1.190)	-1.602 (0.987)	-0.449 (1.145)	1.462 (1.609)
$SP_t * P_{t-2}$	1.145 (1.006)	3.257* (1.677)	1.429 (0.123)	1.442 (1.022)	0.550 (1.267)	-1.713 (1.747)
Dur_t	0.005* (0.003)	0.006 ** (0.003)	0.006*** (0.002)	0.005** (0.002)	0.003 (0.003)	0.001 (0.003)
SP_t^2	0.636 (1.009)	1.222 (1.404)	2.051 (1.530)	2.898* (1.486)	0.704 (2.409)	1.196 (2.011)
t	0.007*** (0.002)	0.007*** (0.002)	0.008*** (0.002)	0.007*** (0.003)	0.005 (0.004)	0.000 (0.006)
Q_1	0.019*** (0.007)	0.057*** (0.014)	0.028*** (0.007)	0.022*** (0.008)	0.006 (0.012)	-0.005 (0.020)
Q_2	0.030*** (0.007)	0.059 *** (0.015)	0.040*** (0.009)	0.040*** (0.011)	0.026** (0.011)	0.003 (0.017)
Q_3	0.025*** (0.006)	0.050 *** (0.014)	0.030*** (0.007)	0.029*** (0.010)	0.013 (0.012)	0.003 (0.018)

Note: Standard errors are in parentheses.

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

Testing items	Estimation method		Rice	Corn
			P-value	P-value
Same coefficients across quantiles	QAR		0.006 ***	<2.2e-16 ***
Seasonality	OLS		0.065 **	8.2e-05 ***
	QAR	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
	QAR	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 *
	QAR	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

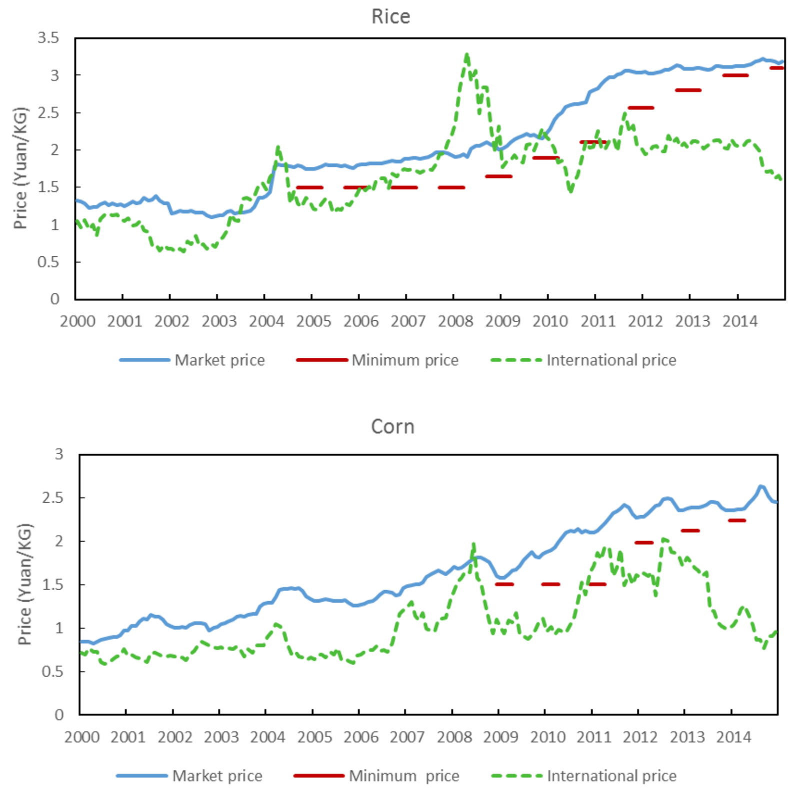
Note: The results above are obtained using the specification $P_t = \beta_0 + \beta_1 P_{t-1} + \beta_2 P_{t-2} + \beta_3 SP_t + \beta_4 SP_t * P_{t-1} + \beta_5 SP_t * P_{t-2} + \beta_6 Dur_t + SP_t^2 + \beta_8 t + \beta_9 Q_1 + \beta_{10} Q_2 + \beta_{11} Q_3$.

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		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)
	Support level effect	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	-	-	-	-	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		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)
	Support level effect	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	-	-	-	-	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. The kurtosis in this table refers to “excess kurtosis” with the value 0 for the normal distribution.
2. P-values are in parentheses.

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.

Figure 2. Estimated price distribution functions for rice and corn in China, 2007-2009.

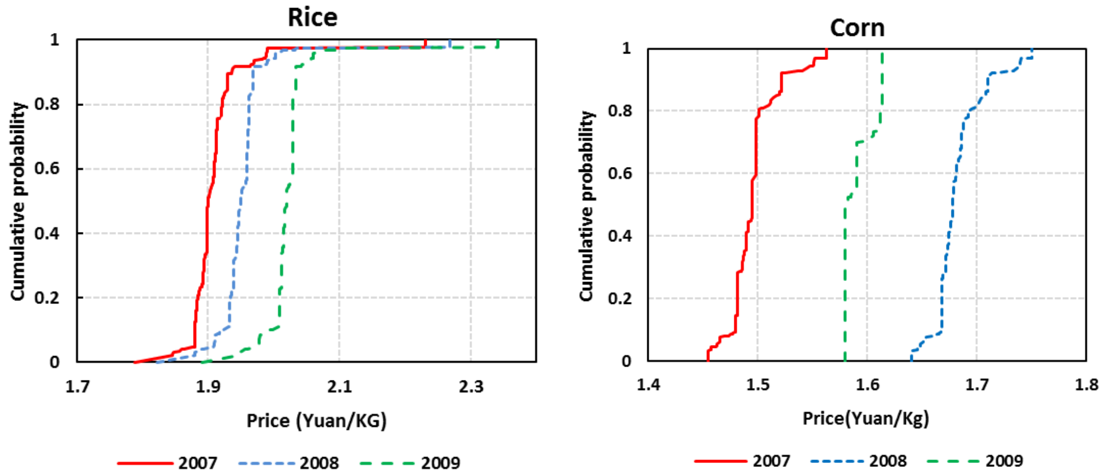


Figure 3. Evolution of relative quantiles for price distributions (relative to the median), rice and corn

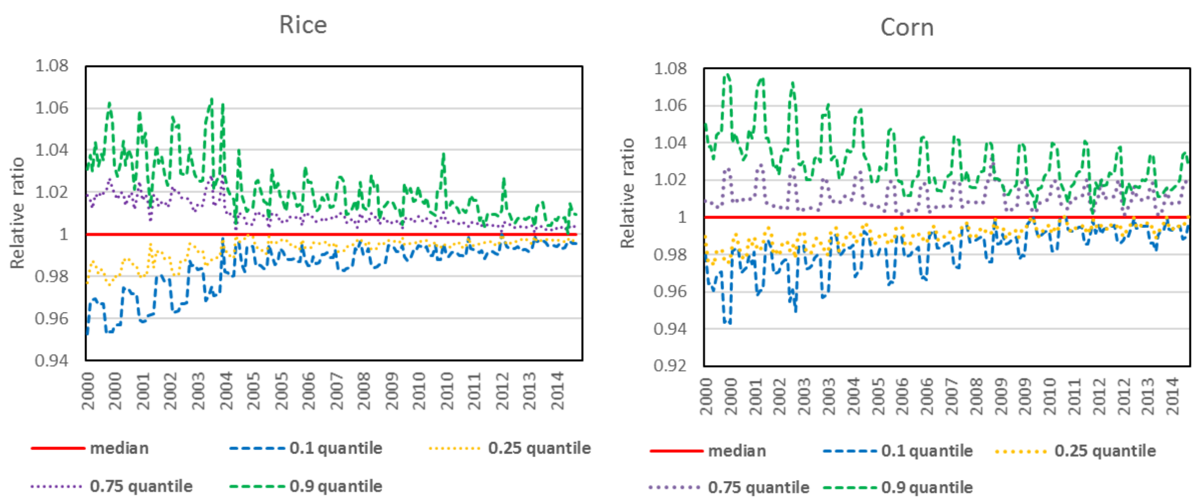


Figure 4. Modulus of the dominant root of the Markov matrix A for the dynamics of rice price and corn price (across quantiles)

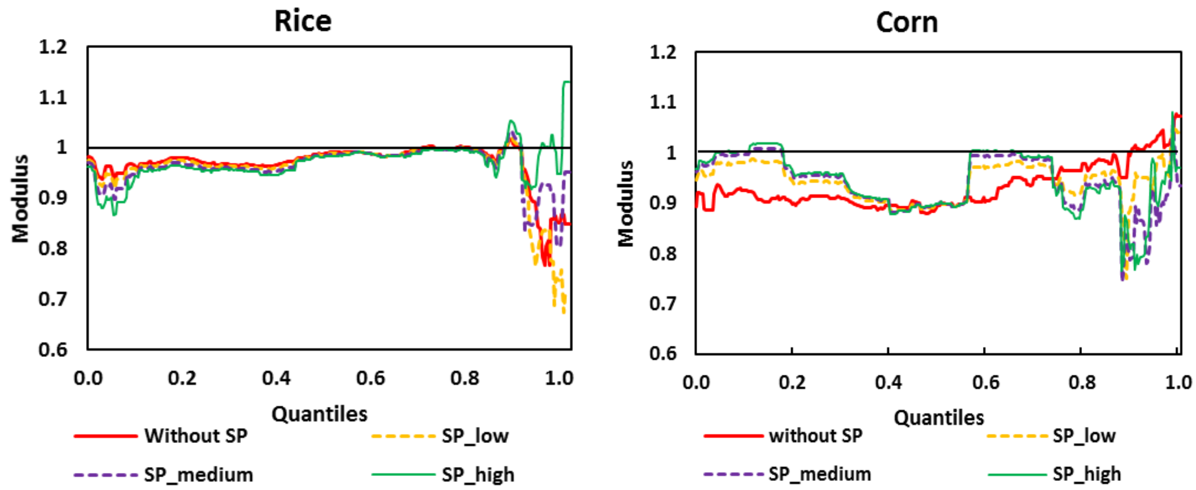


Figure 5. Simulated short-term price distribution functions for rice and corn under different support levels

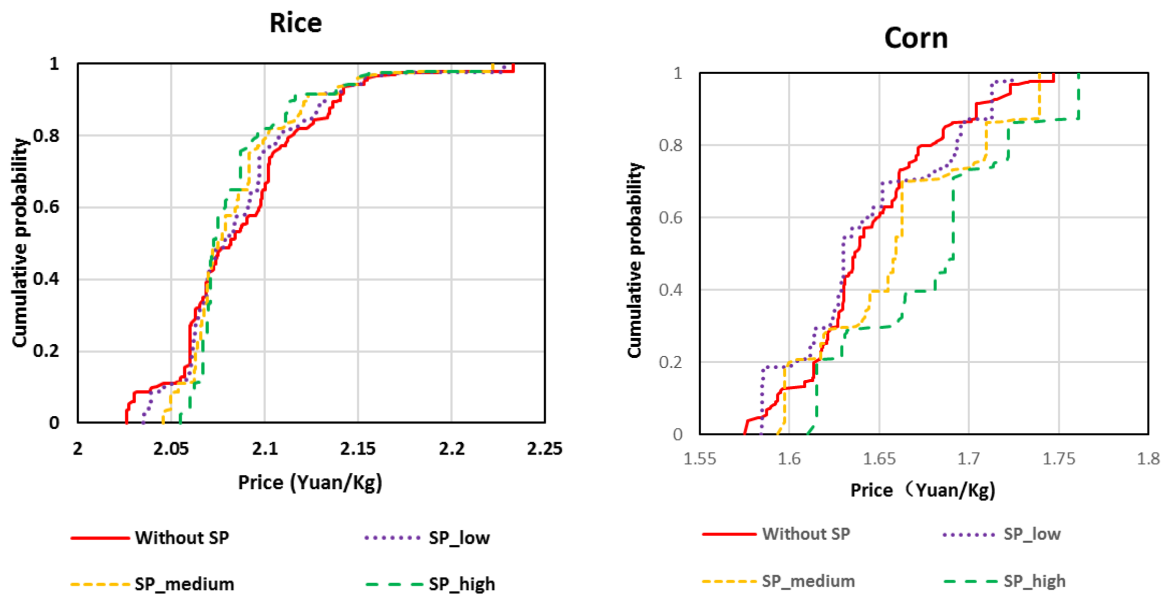
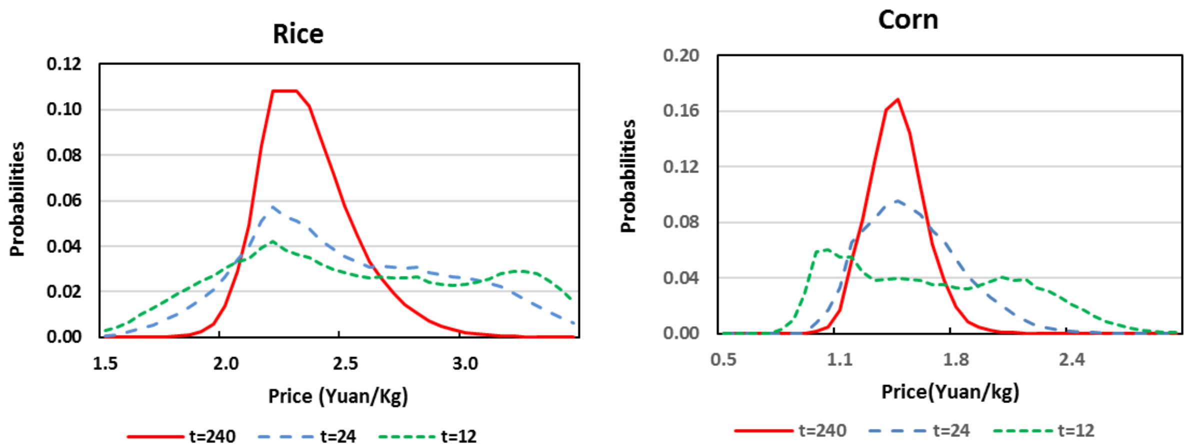


Figure 6. Simulated long-term probability functions of rice price and corn price and their path toward long run equilibrium.



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

Figure 7. Simulated long-term probability functions of rice price and corn price under different support levels.

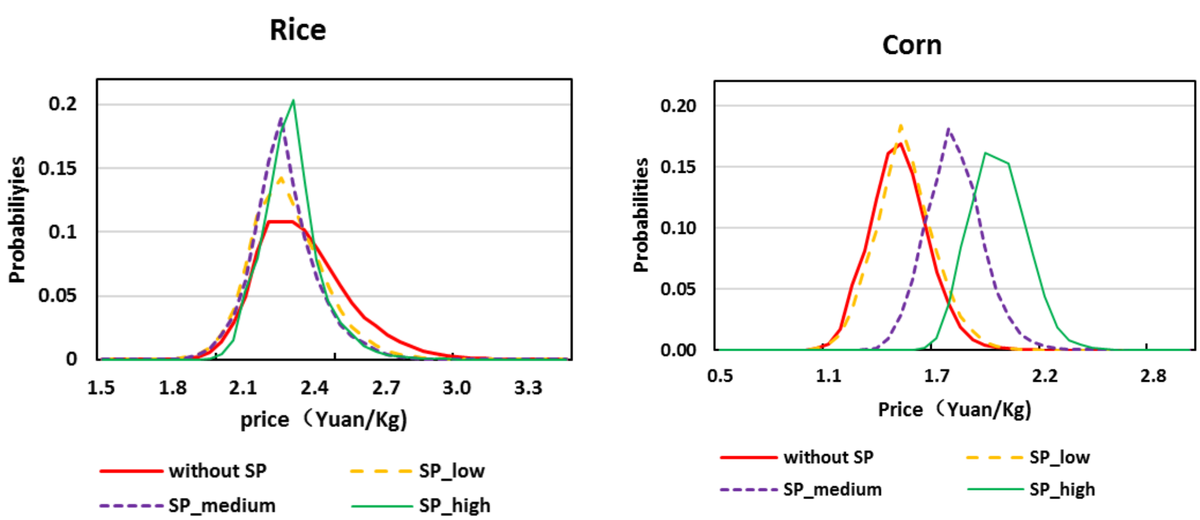


Figure 8. Simulated short-term distribution functions of corn price under different support durations.

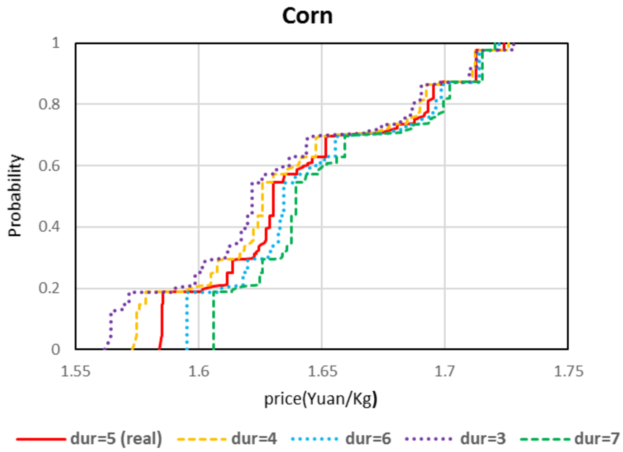
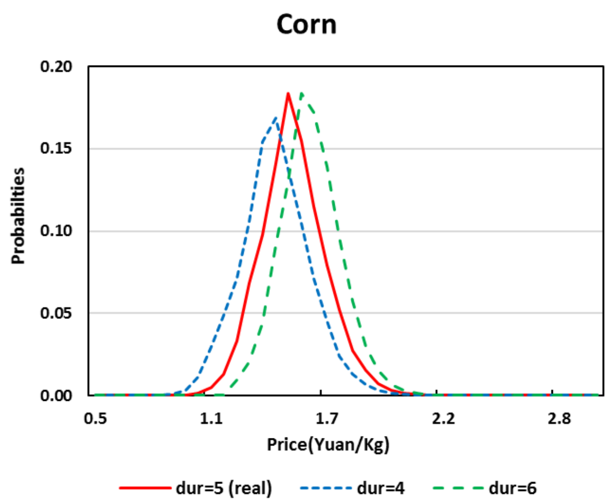


Figure 9. Simulated long-term probability functions of corn price under different support durations.



Footnotes

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

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

[3] Koencker and Xiao (2006) show that the QAR estimators β_q^e are consistent and satisfy a central limit theorem under some regularity conditions.

[4] 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 sensitivity analysis and found our results to be fairly insensitive to our measurement of SP_t.

[5] 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).