An Agent-based Simulation Model of Wheat Market Operation: The Benefit of Support Price

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Abstract. Grain security is one of the most important issues worldwide. Many developing countries, including China, have adopted the Agriculture Support Price (ASP) program to stimulate farmers’ enthusiasm for growing grain, to ensure self-sufficiency in grain and the stable development of the grain market. To propose decision support for the government in designing a more reasonable support price in the ASP program, we formulate an agent-based model to simulate the operation of the wheat market in the harvest period. To formulate the formation process of the market price influenced by farmers’ expected sale price, processors’ expected purchase price, and the ASP, the time series and regression methods are adopted. Based on the proposed market price model, to quantitatively analyze the grain transaction process and the ASP program’s impacts on market agents, we develop an agent-based simulation model to describe the adaptive evolution and interaction among market agents. Furthermore, we validate and implement the simulation model with public wheat market data. Finally, insights and suggestions about the decision of the ASP program are provided.

Keywords: Agent-based simulation (ABS), wheat market, agriculture support price, decision support, public policy

1. Introduction

Grain security is one of the most important issues worldwide. A stable grain market price is the foundation of a country’s economic system and is critical to ensure social stability. Large price fluctuations not only severely influence farmers’ revenues but also lead to higher retail food prices and costs for industries that depend on agricultural outputs (Li 2009). To maintain stable grain prices, protect farmers’ income, and to stimulate farmers’ enthusiasm in farming, the Chinese government offers the Agriculture Support Price (ASP) intervention program to farmers. The ASP program has also been adopted by many other developing countries, including Bangladesh, Brazil, India, Pakistan, the Philippines, Thailand, and Turkey (Gupta et al. 2017). When the market price of wheat falls below the announced support price during the harvest period, the government starts to procure wheat at the reported support price until the market price hits the support price.

Currently, a support price of wheat is determined based on historical wheat cost and expected profit margin. After the implementation of ASP, the wheat price fluctuation level can be maintained within 20%, which is far lower than the 50% before the implementation of the policy (data source: China agricultural product price survey Yearbook). However, the implementation of the ASP program has led to a serious inventory problem for the government. The government procures more than 100 million tons of grain each year, which is equivalent to approximately one-sixth of China’s grain reserve, and the reserved wheat can satisfy one year’s consumption for the whole
country. However, according to the FAO standard, a reasonable inventory scale for the government should be 17%-18% of a country’s annual consumption. The tremendous inventory places huge financial pressure on the government.

In the face of the above ASP implementation status, we reveal the functional relationship between government procurement volume, market operation, and the ASP. Furthermore, to help the government decide ASP more scientifically and evaluate the implementation effect of ASP in advance to alleviate the inventory issue, we formulate an agent-based simulation (ABS) model to describe the formation of wheat market price and the market participants’ sale/purchase decisions. Since the ASP policy is a market-driven intervention instrument, the ABS approach is the most typical bottom-up analysis technique. Then, we evaluate the implementation effect of ASP from the three aspects to assist the government in decision-making: 1) the fluctuations of market price under different ASP; 2) farmers’ income varies with the change of ASP and market price; and 3) government procurement volume that is impacted by ASP. The main contributions are as follows:

1. A novel ABS based wheat market operation model is proposed to evaluate the implementation effect of ASP from the perspectives of the fluctuations of market price, farmers’ income, and government procurement volume during harvesting period.
2. A forecasting model of the short-term wheat market price is formulated combining the autoregressive integrated moving average (ARIMA) and regression analysis methods. The forecasting model reveals the regulation process of ASP on the decision of participants’ pricing and the formation of market price.
3. The ABS model and market price forecasting model are verified and applied according to public wheat market data. Using simulation method, the performance of ASP and the wheat market operation can be estimated from a more systematic perspective. This study provides a novel approach to the domain of ASP studies and a new perspective for applying the ABS method in agricultural policy evaluation.

The rest of the paper is organized as follows. In Section 2, we conduct a literature review of ASP and agent-based simulation models. In Section 3, we develop the forecasting model of wheat market price and the agent-based simulation model. The simulation model is verified in Section 4. In Section 5, numerical experiments are conducted, based on which we provide decision support for the government to design reasonable support prices in the ASP program. Finally, we present the conclusions of our work in Section 6.

2. Literature Review
This paper is closely related to two bodies of knowledge: the study of ASP and multi-agent simulation applications in agricultural supply chain.

For the study of ASP, we separate the literature into the agricultural economics group and the operations management (OM) group.

1) The agricultural economics literature on ASP is extensive, and the reader can refer to Tripathi (2012) for a comprehensive discussion. Fox (1956) develops an economic model to evaluate the impact of ASP and finds that ASP can mitigate the fall in the gross national product (GNP) during a recession without accounting for price interactions between crops. Dantwala (1967) finds that despite the increasing ASP, crop market prices continue to rise because procurement-based ASP form a lower-bound on market prices (Subbarao and Governor 2011, Ramaswami et al. 2018).
outbreak of COVID-19 caused some discussion about the role that government should play in the agricultural market. Varshney et al. (2020) underline the importance of government intervention by estimating the impacts of COVID-19 on the wheat market price in India. They state that the government becomes a major buyer when implementing ASP, which is the key to keeping the supply chain intact and alleviating risk. Reardon et al. (2020) also remark that the government should be considered in the COVID-19 response for better operation of the market. However, they claim the importance of government invention instead of how to be involved efficiently. In conclusion, most agricultural economics studies start from the macro perspective and focus on empirical research and qualitative analysis.

2) In the recent agricultural OM domain, Gupta et al. (2017) examine the role of ASP in India. They model the practice of "distressed" selling of farmers under the program of ASP: farmers sell a significant portion of their wheat to other market agents at prices much lower than the support price. Other articles that examine social responsibility and public policy issues in agriculture include Alizamir et al. (2019), Akkaya et al. (2021), and Tang et al. (2015). The authors of Alizamir et al. (2019) develop a model to analyze the effect of two specific U.S. government subsidy programs: Price loss coverage (PLC) and agricultural risk coverage (ARC) on farmers’ planting decisions and social welfare. Akkaya et al. (2021) study the effectiveness of government interventions such as taxes and subsidies in the adoption of organic farming.

The traditional mathematical methods adopted in the above OM studies are highly effective tools for optimizing decisions in specific and even uncertain conditions. Nevertheless, it is difficult for them to efficiently handle complex situations where there are large numbers of events and decisions under a dynamic environment and information interactions. In addition, well-known modeling approaches in agricultural policy analysis, such as general or partial equilibrium models, carry out policy impact analysis at a higher level of aggregation, whose capabilities of accounting for individual adjustment reactions are limited (Happe et al. 2006, Macal and North 2006, Meter 2006).

The ABS can facilitate capturing heterogeneity among agents as well as dynamics (Negahban and Yilmaz 2014, Mahmood et al. 2020, Xu et al. 2016); thus, the ABS model can capture the process of market trading change endogenously and is suitable for modeling the trading processes of farmers, the government, and processors. Therefore, we review the studies on the application of ABSs related to the agricultural supply chain.

In early studies, Balmann (1997) proposed an agent-based simulation model (AgriPoliS) to analyze the regional agricultural structure change affected by the 2003 agricultural policy reform of the European Union. Agent-based simulation applications for agricultural policy analysis have been popularly adopted since 2011, whereas most of them focus on fiscal or new technology policies (Utomo et al. 2018). Wossen and Berger (2015) apply agent-based simulation to analyze how adaptation strategies and policy interventions affect the distribution of household food security. Brändle et al. (2015) adopt an agent-based model to test the policies and management options of counteracting farmland abandonment. Most of the technological policies are related to fertilizers, organic agriculture, and standards-related technology. For instance, Gagliardi et al. (2014) evaluate the impact of some innovation policies (e.g., inter alia, promotion of organic agriculture) on the system and actors. These studies suggest that ABS has seldom been applied to analyze the ASP program. Other articles that apply the ABS approach in agriculture operations and man-
agement include Chang et al. (2016), Huang and Song (2018), and Borodin et al. (2016). Chang et al. (2016) apply an agent-based simulation method to solve optimal pricing strategies in the agriculture supply chain considering customers’ preferences. They find that customer preference influences pricing strategy, and the optimal strategy changes based on different market conditions. Huang and Song (2018) develop the ABS model to capture the information interactions of bidders and their behavior preferences in the complex and growing agriculture market environment. In other complex supply chain coordination problems, Sauvageau and Frayret (2015) construct an ABS model to study the optimal procurement and production policies in the recycled paper industry. He et al. (2017) propose an ABS model in municipal solid waste (MSW) management to help policy-makers set optimal gate fees for profit maximization.

In summary, this paper combines the optimization model and idea in OM papers with the empirical analysis method in agricultural economics papers. Agricultural OM studies assume homogeneous risk-averse farmers, whereas we consider farmers with heterogeneous types. In these studies, ASP is assumed to act on the prices as a given simplified function. Instead, we describe the market price function considering ASP and other factors by analyzing the empirical data and statistical regression. To efficiently handle complex situations where there are large numbers of events and decisions under a dynamic environment and information interactions, ABS is adopted, and the model is formulated in this paper.

3. Problem Formulation

Before the introduction of the formulation, we first list the related variables and notations in Table 1 as follows.

| Table 1 The Variables and Explanation |
|---------------------------------------|
| Variables | Unit | Explanation |
| Z_{1,t} | Yuan/ton | Temporal value of farmers’ monthly sale price obtained from ARIMA model |
| Z_{2,t} | Yuan/ton | Temporal value of processors’ monthly purchase price obtained from ARIMA model |
| P_{1,t} | Yuan/ton | Farmers’ daily sales price |
| P_{2,t} | Yuan/ton | Processors’ daily purchase price |
| X_{1,t} | Yuan/ton | Daily corn market price |
| X_{2,t} | Yuan/ton | Flour corn market price |
| x | Yuan/ton | ASP |
| P_t | Yuan/ton | Wheat daily market price |
| q_{1,t} | 10^4 tons | Farmers’ sale quantity |
| q_{2,t} | 10^4 tons | Processors’ purchase quantity |
| Q_t | 10^4 tons | Wheat yield of small-scale farmers |
| Q_{f,t} | 10^4 tons | Inventory level of farmers in Day t |
| Q_{1,t} | 10^4 tons | Wheat process quantity |
| D_t | 10^4 tons | Flour daily demand |
| C_a | 10^4 tons | Processors’ maximum process capacity |
| I_{f,t} | 10^4 tons | Inventory of processors in Day t |
| Q_t | 10^4 tons | Transaction volume between farmers and processors in Day t |
| q_{3,t} | 10^4 tons | The government’s procurement quantity |
| σ_p | - | The standard deviation of wheat market price |
| R | % | Cost-benefit ratio for farmers |

3.1 General Overview

There are some challenges to designing a reasonable ASP considering the three aspects of controlling market price fluctuations, ensuring farmers’ income, and controlling the government’s procurement volume. As Figure 1 shows, the participants in the grain market include the farmer agent, the processor agent, and the government. As buyers, the relationship between processors and the government is not only competitive but also symbiotic. According to the purchase prices of the government and processors, farmers, as suppliers, sell wheat to them. Processors can choose to either sell wheat to the government or process wheat into flour and sell to the end market. Moreover, during the decision process, the farmer agent and processor agent, as private self-interested agents, hardly obtain full information about each other. For example, farmers cannot obtain exact information on the processors’ expected purchase price and purchase quantity.
Since the market price is formed in the bargaining among farmers, processors, and the intervention of the government, the market price always varies and needs to be predicted by analyzing the influencing factors.

To predict the market price, time series and regression models are developed, and the details are described in Section 3.2. Once the market price is revealed, to maximize the profit of the farmers and processors, farmers’ sale quantity, processors’ purchase quantity, and the government’s procurement volume will be determined according to their action rules. The sales rules of farmers and the purchase rules of processors are presented in Figures 2 and 3. The detailed discussions on the action rules and corresponding models presented in Figure 1 are discussed in Sections 3.3 to 3.5. Based on the market price forecasting model, the action rules and models of the agents, we further build the agent-based simulation model.

3.2 Market Price Model
To formulate the market price model, we reviewed the literature to reveal influencing factors and select forecast methods. In China, many agricultural economists analyze the influencing factors of market prices based on empirical data and historical experience (Ma et al. 2011, Zhou and Zou 2007). From their conclusions, wheat price relates to national macroeconomic situations such as the Consumer Price Index (CPI), government intervention policy, the price of end products such as flour and bran, and supply-demand. Production costs, macroeconomic factors and international market prices are major factors for the long-term fluctuation of grain prices. However, for short-term fluctuation, the reasons are different among grain price fluctuations. The main reason for the wheat price rise in recent years is the implementation of the ASP, and the main reason for corn price rise is the increase in demand driven by the deep processing of corn. Based on the conclusions above, we propose to select a suitable prediction method to formulate the market price model. The price model can reveal the interrelations of influencing factors and then help policy-makers understand the effect of ASP on market agents. Although most of the early
studies were qualitative (Yuan and Ouyang 2011, Wan and Luo 2007), many scholars have recently adopted quantitative prediction methods such as time series models, neural network models, and other machine learning methods to forecast market prices. These methods have made great progress in the long-term or short-term prediction of price signals (Kazem et al. 2013, Lee and Cheng 2020, Brusaferri et al. 2019). However, these methods cannot reveal the interrelations among independent variables. In practice, market price formation is a complex system that is influenced by many factors. The regression method can effectively reveal the relationship among independent variables, dependent variables, and the intensity of influences. In this paper, we formulate a daily market price model during the wheat harvest period combined with the regression method and time series method to comprehensively consider the influence of various independent variables and time factors on market prices.

The agents’ expected prices are often affected by historical prices with time series characteristics. To analyze the temporal factors of the wheat sale price and purchase price, two seasonal ARIMA models were built based on historical monthly data. Two multiple linear regression models reproducing farmers’ sale price and processors’ purchase price were built with the influencing factors. We adopt historical data of the China wheat market from 2013 to 2014. Finally, the market price model is established by combining farmers’ sale price model, processors’ purchase price model, and ASP.

**ARIMA Time Series Analysis:** ARIMA processes are a class of stochastic processes used to analyze time series. The time series multiplicative season model is a time series model based on the basic auto-regressive differential moving average model and the idea of multiplicative season. The modeling process includes model identification, parameter estimation, and model diagnosis. The following modeling process applies to the two time series models.

**Step 1: Model Identification.** After first-order difference, samples passed the ADF test (Augmented Dickey-Fuller test) with 95% confidence. Then, we test the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of samples after the first-order difference. Then we use the second-order difference to filter the seasonal periodicity of the data. The ACF and PACF plots of samples after the first and second-order difference are shown in Figure A1.

**Step 2: Parameter Estimation.** According to the ACF and PACF results, a seasonal ARIMA model is simplified as ARIMA \((p, d, q)(P, D, Q)_s\), where \(p, d, q\) are the order of autoregression, differential order, and moving average order; \(P, D, Q\) are the seasonal periodic order of autoregressive, differential, and moving average. According to the ACF plot of Figure A1a, the correlation between the 1-order lag and 6-order lag is significant. From the PACF plot of Figure A1b, the 3-order lag is significant. Finally, we select ARIMA \((3, 2, 0)(1, 0, 1)_6\). The seasonal ARIMA model is shown as Equation (1):

\[
Z_t = \Phi(\phi_1 Z_{t-6} + \phi_2 Z_{t-7} + \phi_3 Z_{t-8}) + e_t - \Theta e_{t-6}
\]

where \(Z_t\) is the second-order difference function of the historical price data of month \(t\). \(\Phi, \Theta\) and \(\phi_1, \phi_2, \phi_3\) are coefficients of lag terms; \(e_t\) is residual. The coefficients of the farmers’ sale price ARIMA model and processors’ purchase price ARIMA model are listed in Tables A1 and A2.

**Step 3: Model Diagnosis.** In this step, a diagnosis check is used to validate the model assumptions of Step 2. Based on the Ljung-Box statistic and quantile-quantile \((q-q)\) plots, with 95% confidence, the residuals of the two ARIMA models passed the diagnosis. The
ACF of residuals is shown in Figure A2, and the $q - q$ plots of residuals are shown in Figure A3.

**Regression Analysis:** ASP, farmers’ sale price, and processors’ purchase price are key influential aspects of short-term market price change. After regression analysis, from the farmers’ perspective, shaving off the non-significant independent variables, four factors are identified: wheat purchase price, ASP, temporal element, and the external factor corn market price. We also find that the wheat purchase price affects farmers’ pricing decisions. The difference between the wheat purchase price and ASP also significantly impacts farmers’ pricing. Similarly, from the perspective of processors, there are also four significant factors, including the wheat sale price, temporal factor, and external factors: corn purchase price and flour market price. Based on the historical data from June 8 to September 30, 2010, June 11 to September 30, 2012, June 11 to September 30, 2013, and 2014, and monthly price data predicted by the seasonal ARIMA model, the regression models are built below

$$\ln P_{1,t} = C_1 + \alpha_1 \ln Z_{1,t} + \alpha_2 \ln P_{2,t-1} + \alpha_3 (P_{2,t-1} - x) + \alpha_4 \ln X_{1,t} + \varepsilon_1$$  \hspace{1cm} (2)

where $P_{1,t}$ represents farmers’ wheat sale price on day $t$, $C_1$ is a constant term, $Z_{1,t}$ represents the temporal value of sale price obtained from the seasonal ARIMA model, $P_{2,t-1}$ is processors’ wheat purchase price on day $t - 1$, $x$ is ASP, $X_{1,t}$ represents corn market price, $\alpha_1$, $\alpha_2$, $\alpha_3$, $\alpha_4$ are regression coefficients, and $\varepsilon_1$ is a residual.

Using ordinary least squares (OLS), the regression models were fitted to the daily data from June to September in the years 2010 to 2014. The estimated parameters are shown in Table 2, the F test $p$-value $< 0.0001$, with $R^2 = 0.9883$.

$$\ln P_{2,t} = C_2 + \beta_1 \ln Z_{2,t} + \beta_2 \ln P_{1,t-1} + \beta_3 X_{1,t} + \beta_4 \ln X_{2,t} + \varepsilon_2$$  \hspace{1cm} (3)

where $P_{2,t}$ represents processors’ wheat purchase price on day $t$, $C_2$ is a constant term, $Z_{2,t}$ represents the temporal value of purchase price obtained from the seasonal ARIMA model, $P_{1,t-1}$ is farmers’ wheat sale price on day $t - 1$, $X_{1,t}$ represents corn market price, $X_{2,t}$ is flour market price, $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ are regression coefficients, and $\varepsilon_2$ is a residual.

Using ordinary least squares, the regression models were fitted to the daily data from June to September in the years 2010 to 2014. The estimated parameters are shown in Table 3. The F test $p$-value $< 0.0001$, with $R^2 = 0.9872$.

Finally, to build the model of market price, we combine the regression models of farmers’ sale price, processors’ purchase price, and the ASP factor. The multiple linear regression equation model is as follows:

$$P_t = C_3 + \varphi_1 P_{1,t} + \varphi_2 P_{2,t} + \varphi_3 x + \varepsilon_3$$  \hspace{1cm} (4)

where $C_3$ is a constant term, $\varphi_1$ and $\varphi_2$ are
regression coefficients, and $\epsilon_3$ is a residual. Using ordinary least squares, the regression models were fitted to the daily data from June to September in the years 2010 to 2014. The estimated parameters are shown in Table 4. The $F$ test $p$-value $< 0.0001$, with $R^2 = 0.9916$.

The market price is related to processors’ purchase price and ASP. Moreover, processors’ purchase prices and farmers’ sale prices are dynamic recursions. Using regression analysis, we can estimate the continuous changes in dynamic market prices within an acceptable margin of error. From the regression results, we find the following:

1) There is a significant seasonal time-series relationship among farmers’ sale price, ASP, and processors’ purchase price.

2) From the estimated results in Table 2, historical sales prices and the processors’ expected purchase prices positively affect farmers’ sale prices in the current period. The substitute price of corn negatively affects the price decision. The difference between ASP and processors’ prices that farmers observed had a slightly negative impact on the increase in the sale price.

3) According to Table 3, historical purchasing prices and farmers’ expected sale prices positively affect processors’ purchase prices. Additionally, the price of corn, which is the substitution for wheat, imports account for a high proportion, which is greatly affected by international corn prices and negatively influences the rise of the wheat purchase price. In addition, flour prices from the end product market positively impact the formation of the purchase price.

4) From Table 4, we find that the price influence weight of processors is higher than ASP and the price of farmers. Therefore, the processors have more substantial bargaining power.

### 3.3 Government Purchase Quantity Model

The action rules of government purchase quantity model are developed according to our survey of State Administration of Grain and the farmers in Baoding and Gaocheng of Hebei Provinces. During the harvest period, the government purchases wheat at ASP when ASP is higher than the market price. The govern-
Figure 2: Sale Flow of Farmers and Interactions with Processors and Government

Figure 3: Purchase Flow of Processors

3.4 Farmer Sales Quantity Model

In general, farmers determine sale quantity based on market price, annual wheat yield, and sale preference. The field survey reports from 220 samples of wheat farmers covering 4 provinces in China show that farmers can be classified as small-scale and large-scale according to the acreage of wheat planting. Farmers in the same group have similar sale preferences. The planting acreage of small-scale farmers is below 6.67 hectares, and the planting acreage of large-scale farmers is above 6.67 hectares. According to a field survey of 580 farmers in Henan Province (Zhang 2014), most farmers are used to selling grain from May to September. For small-scale farmers, the limitation of planting acreage causes a low wheat yield. They prefer to sell wheat as soon as possible due to the lack of storage conditions. Large-scale farmers are mainly engaged in grain planting and sales, aiming at minimizing production costs and maximizing profits. They often sell the grain after harvest or even in the field while harvesting. On the other hand, to maximize profit, the grain price change will impact large-scale farmers’ sales strategies (Zhu 2011, Xu et al. 2018). According to the sale preference of the farmers, we formulate the farmers’ daily sale quantity model as follows:

\[ q_{1,t} = \sigma_s \frac{Q_s}{N} + \sigma_l \frac{Q_l}{N} + \frac{P_t}{\bar{P}_t} \]  

where \( Q_s \) and \( Q_l \) represent the yield quantity of small-scale farmers and large-scale farmers, respectively. \( \bar{P}_t \) is the average market price, which changes with time, and \( N \) is the sales days of farmers. According to Zhang (2014), we assume \( N = 150 \) in this study. \( \sigma_s \) and \( \sigma_l \) are random variables representing farmers’ risk preference, and we define \( \sigma_s = 1 + N(0.1, 0) \) and \( \sigma_l = 1 + N(0.1, 0) \).
of farmers on day $t$ is defined as $I_{f,t}$, and $I_f(0) = Q_s + Q_t$. The sales process between farmers, processors, and the government is as follows:

1. When $P_t > ASP$
   (a) If $I_{f,t} > q_{2,t}$
      i. If $q_{1,t} > q_{2,t}$, the demand of processors is satisfied and the surplus grain $q_{1,t} - q_{2,t}$ is sold to the government,
      ii. Otherwise, the demand of processors is partially satisfied as $q_{1,t}$.
   (b) If $0 \leq I_{f,t} < q_{2,t}$, the demand is partially satisfied and $I_{f,t}$ is reduced to $0$.

2. When $P_t < ASP$
   (a) Farmers sell grain to the government, and $I_{f,t}$ is reduced to $I_{f,t} - q_{1,t}$.

### 3.5 Processors’ Purchase Quantity Model

Processors purchase wheat reacting to inventory level variations for an inventory target and are capable of adjusting their purchase decisions based on market prices. We originally propose the processors’ purchase quantity model according to our field survey of flour processors in Hebei Province. In general, the maximum inventory level can satisfy flour processing capacity for half a month, and the minimum inventory level can satisfy one week’s flour process. In this way, Figure 3 describes the purchase decision flow of processors, where $S$ is the maximum inventory level, and $s$ is the minimum inventory level. When processors forecast that the market price will rise, they will increase their purchase quantity to reach the maximum inventory level $S$. Otherwise, they adjust their purchase quantity to reach the minimum inventory level $s$.

**Processors’ Inventory Model:** As a reservoir in the middle of purchasing and processing, the inventory is not only affected by purchase quantity but also adjusted by flour process quantity. Flour processors widely adopt a process-on-demand strategy according to our field survey. Except for flour demand from the end market, process quantity is also limited by process capacity, which can be described as:

$$Q_{f,t} = \min\{D_t, Ca\}$$  \hspace{1cm} (6)

$$I_{p,t} = I_{p,t-1} + Q_t - Q_{f,t}$$  \hspace{1cm} (7)

where $Q_{f,t}$ represents the process quantity and $Q_t$ represents the transaction volume between farmers and processors. In addition, we assume flour daily demand follows a normal distribution, $D_t \sim N(\mu, \sigma)$, and $\mu = \frac{D_A}{360}$, which represents annual flour demand. Because the transaction volume $Q_t$ is impacted by processors’ purchase quantity $Q_{2,t}$ and farmers’ sale quantity $q_{1,t}$, the relationship between $q_{2,t}$ and $q_{1,t}$ is as follows:

1. When $P_t > ASP$
   (a) If $q_{1,t} > q_{2,t}$, $Q_t = q_{2,t}$
   (b) Otherwise, $Q_t = q_{1,t}$

2. When $P_t < ASP$
   (a) $Q_t = 0$

### 4. Model Setup and Validation

In the ABS model, the actions of the agents follow the flowchart described in Figure 1, and the decisions are made according to the models proposed in Section 3. As the decision variable, once an ASP is given, based on the above models and the value of input variables, we can gain three objective outputs: market price fluctuations ($\sigma_p$), farmers’ income ($R$), and government purchase quantity ($q_3$). Thus, the objectives can be controlled in acceptable and reasonable ranges by adjusting ASP. The agent-based simulation was implemented using the software AnyLogic. It is the first and only tool that brings System Dynamics, Discrete Event, and Agent-Based methods together within one modeling language and one model development environment. To validate the market
price model and the agent-based simulation model, we use historical data of the wheat market in China.

### 4.1 Inputs and Settings

The data sources include the China Grain Data Center, National Grain Trade Center, China Grain and Oil Network, and Statistical Data of Grain Storage Facilities 2012 (SDGSF 2012), which the State Administration of Grain publishes. Parameters are classified into two types: fixed parameters and decision variables. The values of fixed parameters remain constant throughout the simulation, while the values of the decision variables are waiting to be readjusted. To validate the model, the current values of all parameters are shown in Table 5.

#### Table 5 Fixed Input Parameters and Value of Decision Variables

| Parameters                                      | Value  |
|------------------------------------------------|--------|
| Wheat yield in 2013 (ten thousand tons)        | 11723  |
| Wheat yield in 2014 (ten thousand tons)        | 12034  |
| Wheat yield in 2015 (ten thousand tons)        | 12170  |
| Wheat consumption for flour process in 2013 (ten thousand tons) | 12678  |
| Wheat consumption for flour process in 2014 (ten thousand tons) | 12300  |
| Wheat consumption for flour process in 2015 (ten thousand tons) | 11972  |
| Farmers’ average planting cost in 2013 (RMB/ton) | 2356   |
| Farmers’ average planting cost in 2014 (RMB/ton) | 2214   |
| Farmers’ average planting cost in 2015 (RMB/ton) | 2351   |
| Flour process cost (RMB/ton)                   | 200    |
| Ratio of per unit wheat turn to wheat bran     | 20%    |
| Ratio of per unit wheat turn to flour          | 75%    |
| Flour daily process capacity (ten thousand tons) | 59.5   |
| **Decision variables**                         |        |
| **ASP in 2013 (Yuan/ton)**                    | 2240   |
| **ASP in 2014 (Yuan/ton)**                    | 2360   |
| **ASP in 2015 (Yuan/ton)**                    | 2360   |

#### 4.2 Model Validation

The market price model is the first aspect to be validated. For model training, we use the daily historical data from June 1st to September 31st between 2010 and 2014, and the model output values were compared to historical market price data from June 2015 to September 2015 to validate this model (Figure 4). A maximum training difference of 2.5 percent between both prices from 2010 to 2014 and a maximum validation difference of 1.4 percent for 2015 are acceptable. To present the difference in results between ABS model and ARIMA model, Table 6 shows the errors of the price signals in year 2015 using the indice of mean absolute percentage error (MAPE). ABS model has a better performance compared with ARIMA model. Because ABS model combines the time-series signals reflected in ARIMA model, the price interactive signals from sellers and buyers, the price signals from substitutes and end products, and the impact from ASP. Next, the validation of the entire model was carried out by comparing the output values of government purchase quantity and historical purchase quantity data during the harvest period from 2013 to 2015. The output value is an average of 100 replicates of simulation, which is presented in Table 7.

#### Table 6 The Result Differences between ABS and ARIMA Models for the Price Signals in Year 2015

| Price signals                        | Error of ARIMA | Error of ABS |
|-------------------------------------|----------------|--------------|
| Farmers’ sale price                 | 2.82%          | 2.50%        |
| Processors’ purchase price          | 3.60%          | 2.96%        |

#### Table 7 The Validation Results of the Government Purchase Quantity

| Year | Real data | Model results (95% confidence level) | Error   |
|------|-----------|--------------------------------------|---------|
| 2013 | 800       | 780(766,794)                         | −2.5%   |
| 2014 | 2500      | 2462(2360,2524)                      | −1.52%  |
| 2015 | 2000      | 2091(2068,2114)                      | 4.5%    |

### 5. Results and Analysis

#### 5.1 Numerical Analysis

We adopt historical data from the China wheat market from 2013 to 2015, and input parameters are presented in Section 3. The value range of the decision variable ASP varies from 2240...
RMB/ton to 2400 RMB/ton, following historical ASP values and market price range. The total replication of the simulation is 5000 times, and the computational time is estimated to be 2.2 hours. We then analyze the characteristics of the simulation results under the experiments below.

As mentioned earlier, a reasonable ASP should satisfy the three intervention objectives, including controlling market price fluctuations, ensuring farmers’ cost-benefit ratio, and reasonable government purchase quantity. There are two types of indices to define the fluctuation of market price: one is the increase ratio of market price, as \((P_t - P_{t-1})/P_{t-1}\), and the other index is the standard deviation of market price, which is widely used to measure price fluctuations. For example, in Sengupta (1985) and Kazaz et al. (2016), the index of standard deviation is adopted. In this paper, we use the standard deviation \(\sigma_p\) to measure market price fluctuations. According to statistical data from the State Statistical Bureau in China, from 2000 to 2018, the average cost-benefit ratio of private enterprises engaged in agricultural and sideline food processing was 6.17%, the average ratio of food manufacturing enterprises was 8.21%, and for private enterprises in the textile industry, the ratio was 5.08%. To balance the income of different industries, we assume a reasonable cost-benefit ratio for wheat planting farmers between 4%-10% (Pei and Li 2015). A reasonable government wheat reserve scale should be 17%-18% of a country’s annual consumption from the FAO report. Due to the lack of quantitative ASP decision-making, relying only on experience, there is a large gap between China’s wheat grain reserves and the FAO standard. Since the government did not specify a clear target of wheat procurement, we refer to the FAO standard and historical experience and then assume a reasonable purchase quantity of the government as 17%-20% of annual consumption. Based on the assumptions, we take 2013-2015 as an example to check the intervention effect of ASP. In 2013, a reasonable government purchase quantity should be [2155,2535] ten thousand tons, but the actual purchase quantity of 8 million tons is much lower than the reasonable level; in addition, farmers’ actual cost-benefit ratio in 2013 was 1.7%, which is smaller than 4%. In 2014, the government’s actual purchase quantity 2500 is higher than the reasonable level [2091,2460], and the actual cost-benefit ratio of 13.1% is above the reasonable level. In conclusion, the posterior objective values verified the necessity of ASP readjustment.

The feasible ASPs that satisfy the farmers’ cost-benefit ratio constraint between 4% and 10%, as well as the purchase quantity constraint between 17% of annual demand and 20% of annual demand, are listed in Table 8.

According to the optimization result of Experiment 2013, the value range of feasible ASP should be between 2330 Yuan/ton and 2370 Yuan/ton, and it is much higher than the actual ASP, 2240 Yuan/ton, in 2013. Among the feasible solutions, the ASP that leads to a minimum market price fluctuation in Experiment 2013 is 2355 Yuan/ton. The ASP values that lead to a minimum purchase quantity and a maximum cost-benefit ratio lie at the ends of the feasible range. While under the feasible solutions, the difference of \(\sigma_p\) is relatively small, at the ASP of 2370 Yuan/ton, with an increase of 1.6% compared to the minimum purchase quantity, there is an increase of 11% of farmers’ cost-benefit level. In this way, 2370 Yuan/ton should be a better choice for the government.

In Experiment 2014, the value range of feasible ASPs is between 2300 Yuan/ton and 2350 Yuan/ton, which is lower than the actual ASP value of 2360 Yuan/ton in 2014. In general, the fluctuations of market price decrease with the increase of ASP, and the optimal ASP that leads to a minimum price fluctuation is approximately 2340 Yuan/ton, while the ASP val-
Table 8 Feasible Solutions of Experiments 2013, 2014, and 2015

| Year | ASP  | q₃  | σₚ  | R   |
|------|------|-----|-----|-----|
| 2013 | 2330 | 2154| 10.6774| 4.01% |
|      | 2335 | 2221| 10.6774| 4.06% |
|      | 2340 | 2223| 10.6772| 4.13% |
|      | 2345 | 2214| 10.6772| 4.20% |
|      | 2350 | 2214| 10.6770| 4.25% |
|      | 2355 | 2214| 10.6769| 4.32% |
|      | 2360 | 2223| 10.6771| 4.36% |
|      | 2365 | 2182| 10.6773| 4.41% |
|      | 2370 | 2189| 10.6777| 4.46% |
|      | 2300 | 2051| 20.4621| 9.35% |
|      | 2305 | 2060| 20.4494| 9.40% |
|      | 2310 | 2065| 20.4542| 9.45% |
|      | 2315 | 2078| 20.4283| 9.52% |
|      | 2320 | 2056| 20.4528| 9.57% |
|      | 2325 | 2117| 20.4546| 9.65% |
|      | 2330 | 2123| 20.4365| 9.70% |
|      | 2335 | 2075| 20.4304| 9.77% |
|      | 2340 | 2133| 20.4137| 9.84% |
|      | 2345 | 2117| 20.4238| 9.87% |
|      | 2350 | 2165| 20.4289| 9.94% |
| 2014 | 2380 | 2343| 11.3114| 3.95% |
|      | 2385 | 2345| 11.3176| 4.05% |
|      | 2390 | 2400| 11.3209| 4.09% |
|      | 2395 | 2398| 11.3255| 4.16% |
|      | 2400 | 2382| 11.3293| 4.21% |

Values that lead to a minimum purchase quantity and a maximum cost-benefit ratio lie at the ends of the feasible range. In conclusion, the government should choose a suitable ASP according to the priority of the three regulation objectives.

In Experiment 2015, the feasible region of ASP is between 2380 Yuan/ton and 2400 Yuan/ton, which is higher than the actual ASP value of 2360 Yuan/ton in 2015. Market price fluctuations in Experiment 2015 increase with ASP. In this way, if the government aims to minimize purchase quantity and price fluctuations, the government should choose 2380 Yuan/ton; otherwise, 2400 will be a better choice to maximize farmers’ cost-benefit ratio.

As a conclusion of the numerical experiments, the feasible region of ASP varies based on the changes in the agriculture supply chain environment. The proposed framework provides flexibility to policy-makers since it considers a more reasonable ASP under multiple regulation objectives. Thus, policy-makers can choose any solution from the feasible region according to their regulation priority and management strategy, which provides great improvement potential for the government in regulating the agriculture industry. Comparing the output results of the cases, we find the following. 1) When the government takes the stabilizing price as a primary regulation goal, the procurement level is higher. Nevertheless, compared with other regulation goals, the regulation effect is not significant. 2) ASP has a positive effect on improving farmers’ income, but from the economic point of view, the government should decide ASP to ensure a suitable purchase quantity.

5.2 Sensitivity Analysis

To verify the important exogenous variables of wheat yield and corn price on the grain inventory of processors and the government at the end of the harvesting period. The sensitivity analysis is shown in Figure 5 and Figure 6 based on the numerical example of 2015. According to the analysis, we find some results.

From Figure 5, the increase in wheat yield will correspondingly raise the procurement quantity of the government with a decrease in processors’ purchase quantity. A possible reason is that the demand for the end product, flour, does not increase with wheat yield, and the wheat supply is sufficient. It is economical for processors to keep low inventory processors. Therefore, the surplus wheat has to be sold to the government.

From Figure 6, processors’ purchase quantity increases with the corn price. Because corn is the major substitute for wheat, the rising
price of corn will inevitably lead processors to buy more wheat at lower prices to reduce production costs. When the corn price decreases, wheat procurement of the government increases.

6. Conclusion
This paper proposes an agent-based model to simulate the operation of the wheat market under the intervention of the ASP policy. Before the formulation of the ABS model, a short-term wheat market price forecasting model is developed combining ARIMA and regression methods. Based on the forecasting model, according to the sales and purchased action rules of farmers, processors and the government, the bottom-up wheat market operation model is built. To verify the model, public wheat market data are analyzed. Based on the simulation results, a reasonable ASP is proposed that comprehensively considers the intervention objectives of controlling market price fluctuations, ensuring farmers’ income, and controlling the government’s grain procurement volume. Finally, combined with the sensitivity analysis, some insights and suggestions of ASP are provided as follows:

1. The difference between ASP and processors’ prices that farmers observed had a slightly negative impact on the increase in the farmers’ sale price. In addition, flour prices positively impact the formation of the purchase price. To reasonably regulate the market price, the decision of ASP needs to comprehensively consider the above price signal transmission effect.
2. When the government takes the stabilizing price as a primary regulation goal, the procurement level is higher. Never-
theless, compared with other regulation goals, the regulation effect is not significant. The implementation of ASP cannot achieve the optimal effect of the three intervention objectives at the same time. Comprehensively considering economy and effectiveness, ASP has the most significant effect on ensuring grain reserves.

This paper focuses on the operation of the wheat market during the harvest period. However, to fully understand the effectiveness of ASP, the production period should be combined to analyze the change in production costs and production decisions. In addition, for further study, a multiple-crop case should be considered. Under the problem setting with a longer time cycle and more complex decision-making factors, ABS may become unsuitable because of having overly specific and factitious models.
Appendix A

(a) ACF and PACF: The Farmers’ Sale Price Samples after First Order Difference

(b) ACF and PACF: The Farmers’ Sale Price Samples after Second Order Difference

Figure A1 ACF and PACF: The Farmers’ Sale Price Samples after First Order Difference and Second Order Difference

Table A1 The Coefficients of Farmers’ Sale Prices ARIMA model

| Coefficients | $\phi_1$ | $\phi_2$ | $\phi_3$ | $\Phi$ | $\Theta$ |
|--------------|---------|---------|---------|-------|--------|
| Estimator    | -0.4350 | -0.3449 | -0.4104 | 0.9525 | -0.7472 |
| Standard Deviation | 0.1345  | 0.1434  | 0.1422  | 0.2724 | 0.7218  |

$\hat{\sigma}^2_e = 1149$, Log likelihood=$-231.6$, ACI=475.2

Table A2 The Coefficients of Processors’ Purchase Prices ARIMA Model

| Coefficients | $\phi_1$ | $\phi_2$ | $\phi_3$ | $\Phi$ | $\Theta$ |
|--------------|---------|---------|---------|-------|--------|
| Estimator    | -0.4098 | -0.3125 | -0.4796 | 0.5260 | -0.2522 |
| Standard Deviation | 0.1302  | 0.1329  | 0.1272  | 0.4361 | 0.4855  |

$\hat{\sigma}^2_e = 2178$, Log likelihood=$-243.14$, ACI=498.27
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