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Research Article

Asymmetric Price Volatility Transmission in Agricultural Supply Chains: Evidence from the Chinese Pork Market

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The asymmetric price volatility transmission issue in agricultural supply chains has been ignored in the previous literature. This paper applies an asymmetrical MGARCH-BEKK model to investigate the asymmetric price volatility transmission in agricultural supply chains with an application to the Chinese pork market. Additionally, we use the Zivot–Andrews unit root test with a structural break to examine whether the piglet, hog, and pork prices have structural breaks. The results show that pork's market prices have a structural breakpoint in 2007M03 and support the existence of the asymmetric volatility transmission in Chinese pork supply chains. Furthermore, the volatility spillover effects are different before and after 2007M03.

1. Introduction

Price volatility transmission can be defined as the degree to which price uncertainty in one market affects price uncertainty in other markets [1]. Beginning in 2007, the agricultural price volatility has received considerable research attention due to the global food price crisis, in which the nominal prices of almost all food commodities increased by more than 50% from 2007–2008, and global food price spikes and surges were witnessed again from 2010–2011 [2]. High price volatilityhas significantimpacts on the participants in agricultural supply chains. Specifically, it can lead to income instability issues for farmers [3], force food and agricultural companies to change their decisions [4], and enhance food security concerns to consumers, especially to the poor [5]. These chain profound economic implications of price volatility stress the importance of investigating the price volatility transmission along the chain [6].

Although some scholars argue that agricultural price volatility is more dangerous than high food prices [7], most scholars have paid much more attention to the agricultural price transmission rather than the agricultural price volatility transmission [6]. As a result, we know very little about how price instabilities are transmitted along the food chain. Especially, for the asymmetrical price volatility transmission, we found no study addressing asymmetric price volatility spillovers along vertical agricultural supply chains. However, there is little evidence that rising agricultural prices have the same impact as falling prices [8]. With asymmetric volatility spillovers, the burden and benefits of sudden price changes distribute unevenly across markets and can have welfare implications for producers as well as consumers [3]. In addition, the asymmetric price volatility transmission can also reflect the functioning and efficiency of the price system.

Thus, we applied the asymmetrical BEKK-MGARCH model to study the asymmetrical volatility transmission in an agricultural supply chain. Little literature [3, 9] has used this method to study the asymmetrical volatility transmission between food and energy markets, while no scholars have focused on this issue in an agricultural supply chain. We analyze the asymmetrical price volatility spillover between agricultural input, agricultural output, and retail prices in an agricultural supply chain, which can fill a gap in the existing literature. This is the first contribution of our paper.

The second contribution is that we pay attention to the impacts of structural breaks on the asymmetrical volatility transmission in an agricultural supply chain and try to find different characteristics of asymmetrical volatility transmission before and after the structural breakpoints. To the best of our knowledge, no literature has addressed this issue.

The third contribution is that we study the asymmetric price volatility transmission in a vertical sector with the Chinese pork market as a case. Studying the asymmetrical volatility transmission of the Chinese pork market chain is interesting, not only from the perspective of the Chinese market but also at the global levels. First, China has the largest pork market in the world in terms of both production and consumption [10]. Second, China has liberalized its pork market since 1985 and has seen much more volatile pork prices, especially after it joined the World Trade Organization in 2001. Since 2006, the pork cycle has become a big concern for the Chinese government, farmers, and consumers. Third, China is the world's largest pork importer, and the main sources of Chinese pork imports are the Europe Union, the United States, Brazil, and Canada [11], so the pork's market price volatility can influence the pork production and farmers' income in many other main pork exported countries.

Our paper has obtained several interesting conclusions. First, piglet, hog, and pork prices have a structural break in 2007M03, and the correlation relationships between piglet, hog, and pork prices and the estimation results of the asymmetric MGARCH-BEKK model before and after 2007M03 are different. Second, the estimation results of the asymmetric MGARCH-BEKK model by using full sample are similar to those of subsamples II based on the signs and significance levels of coefficients, which means the characteristics of relationships between pork's market prices are mainly determined in subsample II. Third, the impact analysis of price volatility between piglet, hog, and pork can show the asymmetrical price volatility transmission. Hog breeding is an important stage to control the risk in pork supply chains of China. Fourth, the piglet, hog, and pork price volatility responds differently to positive and negative piglet, hog, and pork price changes, indicating asymmetric volatility-spillover effects. Finally, by using the Newey–West robust standard error and standard error, respectively, and different distributions of residuals, we find that our estimation results are robust.

The rest of the paper is organized as follows: In the second section, we review the literature on price volatility transmission. The data description and the Zivot–Andrews unit root test with a structural break are discussed in the third section. Sections four and five report the MGARCH-BEKK specification and estimation results. Section six presents the robust test of empirical results. Finally, the paper ends with the concluding remark section.

2. Literature Review

Due to the important role in making decisions for economic agents and policy makers ,the relationship between prices in agricultural supply chains is a very interesting research topic. As noted, the majority of studies have focused on the interdependence of price levels. In contrast, the price volatility transmission has received little attention [2]. The price volatility transmission has a close relationship with risk management, which is a very important factor influencing the income, consumption, and decision of different economic agents in food supply chains. Thus, more and more scholars have begun to study the price volatility transmission in food supply chains. Assefa et al. reviewed the price volatility transmission in food supply chains [6].

Most of the earliest studies used univariate generalized autoregressive conditional heteroskedasticity (GARCH) models. For example, Natcher and Weaver applied the univariate GARCH models to investigate volatility spillover effects in the beef supply chain of the United States (U.S.) [12]. Similarly, Buguk et al. established univariate exponential GARCH (EGARCH) models to analyze the price volatility spillover between feed, farm, and wholesale in the U.S. wholesale catfish supply chain [13]. Uchezuba et al. also applied the univariate EGARCH models to investigate volatility spillover effects in the South African farm-retail broiler chain [14].

Due to the limitation of unidirectional relationships between prices at different levels in agricultural supply chains, multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models have been applied widely. Apergis and Rezitis used the MGARCH model to evaluate price volatility spillovers along agricultural input, agricultural output, and retail prices in Greece [1]. Rezitis and Stavropoulos estimated the price volatility transmission between consumer and producer prices in the Greek broiler sector by using two MGARCH models, namely, DVEC (1,1) and BEKK (1,1), respectively [15]. Sidhoum and Serra applied the MGARCH model to assess price volatility spillovers along the Spanish tomato marketing chain [2]. Hassouneh et al. applied the MGARCH model to study the price volatility spillover in the Slovenian wheat market [16].

The abovementioned literature has ignored the asymmetric price volatility transmission in agricultural supply chains. However, the asymmetric price volatility transmissions between energy and agricultural (or financial) markets can be worthwhile references for our paper. For example, the earlier literature addressed the asymmetric price volatility transmission between food and energy markets [3, 9, 17], and the recent literature has paid much attention to the asymmetric price volatility transmission between oil and financial markets [18–20].

Finally, little literature studied the structural breaks of price volatility transmission in agricultural supply chains. Serra analyzed the effect of the bovine spongiform encephalopathy crisis on volatility transmission along the Spanish beef marketing chain, using a smooth transition conditional correlation GARCH model [21]. Nazlioglu et al. identified the different characteristics of the volatility spillover between oil and agricultural commodity markets before and after the food price crisis. The abovementioned literature paid no attention to the asymmetrical price volatility spillover along agricultural supply chains [22].

As for Chinese scholars, they paid much attention to the price volatility spillover between domestic and international markets. For example, Xiao et al. applied BEKK-MGARCH to study the volatility transmission effects between domestic and international grain prices [23]. Similarly, Li et al. also used the same method to study the above issues under the different backgrounds of grain market opening up and rapid import growth, respectively [24, 25]. However, Chinese scholars have paid little attention to the price volatility transmission in agricultural supply chains; only Zheng et al. investigated the price volatility spillover along an egg vertical supply chain by using the BEKK-MGARCH model [26]. To the best of our knowledge, there is no literature about the asymmetrical price volatility transmission in an agricultural supply chain. Thus, studying the asymmetrical price volatility spillover and identifying the different characteristics before and after the breakpoints in the Chinese pork supply chain are novel.

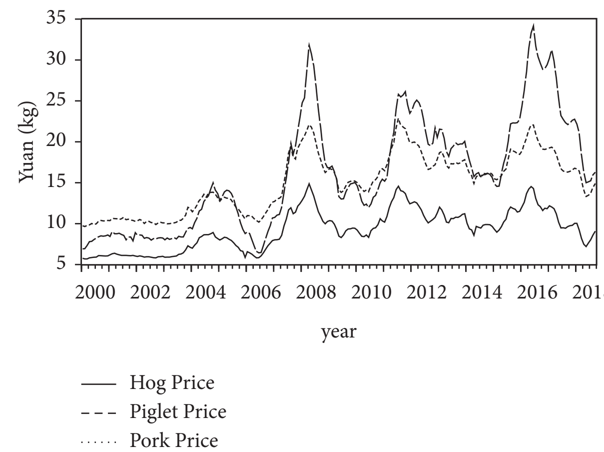

Figure 1: Prices of hog, piglet, and pork from 2000.01 to 2018.09.

3. Data Description and the Unit Root Test

We use the monthly piglet, hog, and pork prices (unit: RMB per kilogram) from January 2001 to September 2018. The data are obtained from the National Bureau of Statistics of China (http://www.stats.gov.cn/). All of these variables are deflated by the Consumer Price Index (CPI) to get the real piglet, hog, and pork prices. In addition, the Chinese pork market exhibits seasonality [27]. To account for seasonality effects, all prices are seasonally adjusted using the $X13$ method to get the seasonalized real piglet price (l_t), the seasonalized real hog price (h_t),and the seasonalized real pork price (p_t). Finally, to reduce influence of heteroskedasticity, we transform the price series into the logarithm format ($\ln l_t$, $\ln h_t$, and $\ln p_t$); then, we can use the first differences series ($\triangle \ln l_t$, $\triangle \ln h_t$, and $\triangle \ln p_t$) to represent the returns of piglet, hog, and pork. Figures 1 and 2 show that the piglet, hog, and pork prices and their returns have the similar trends, showing a comovement during the period between 2000M01 and 2018M09.

The first step to construct volatility modeling is to perform the unit root test. Due to the external shocks to the pork market in China, piglet, hog, and pork prices may receive structural changes, so we use the Zivot–Andrews unit root test with a structural break to examine if there are breakpoints in the price time series [28].

The test results (see Table 1) allow for the acceptance that piglet, hog, and pork prices, in terms of level and logarithm formats, contain unit roots at the significance level of 5%, while the first difference of logged prices is stationary at the significance level of 1%. For the breakpoints, they are in the interval between 2006M03 and 2008M04, which coincides with the food price crisis from 2007–2008, and almost half of the variables have breakpoints in 2007M03, and all coefficients of breakpoints in the equation of the Zivot–Andrews unit root test have a higher significance level (1%), so we choose 2007M03 as a breakpoint to divide the full sample into two subsamples: subsample I (2000M01-2007M02) and subsample II (2007M03-2018M09). From Figures 1 and 2, we can see that the piglet, hog, and pork prices in terms of level and returns are much volatile after 2007M03. The summary statistics of the data are presented in Table 2.

From Table 2, we can see that the piglet return has the highest standard error, showing the largest volatility, followed by hog price and pork returns in full sample and subsamples I and II, and the volatility in subsample II is higher than that in subsample I. Similarly, the piglet return has the highest mean, followed by hog and pork returns, but the mean of prices in subsample II is lower than that in subsample I. This indicates that the higher volatility in subsample II leads to higher risks, which decrease actors' returns at different levels of China's pork supply chain, compared with those in subsample I.

Table 3 reports the correlation coefficients for the three variable returns. The correlation matrices in different sample ranges show that the correlation between the pork return and the hog return is higher than the correlation between the pork return and the piglet return. In addition, the piglet return and the hog return have the lowest correlation among different sample ranges. By comparing the correlation matrices between subsample I and II, we find that the relationships between piglet, hog, and pork returns have become much closer in subsample II. This means that vertical integration of pork market returns has become higher, indicating that the system risk of the pork market has become greater. This may be the reason why the pork prices are much more volatile in subsample II than those in subsample I.

4. The Determination of Asymmetrical MGARCH-BEKK Specification

The GARCH model should include the conditional mean equation and conditional variance equation (29). To determine the specification of asymmetrical MAGRCH-BEKK, we first need to choose the optimal specification of the conditional mean equation, and we use the autoregressive (AR), moving average (MA) and autoregression moving average (ARMA), and vector autoregression (VAR) model to capture the dynamic characteristics of piglet, hog, and pork returns, respectively. The estimation results are shown in Table 4.

From the results in Table 4, we find that according to the Schwarz Information Criterion (BIC) and the Akaike Information Criterion (AIC), all series follow the AR (1) process compared with ARMA (1, 1) and AR (2). Then, we

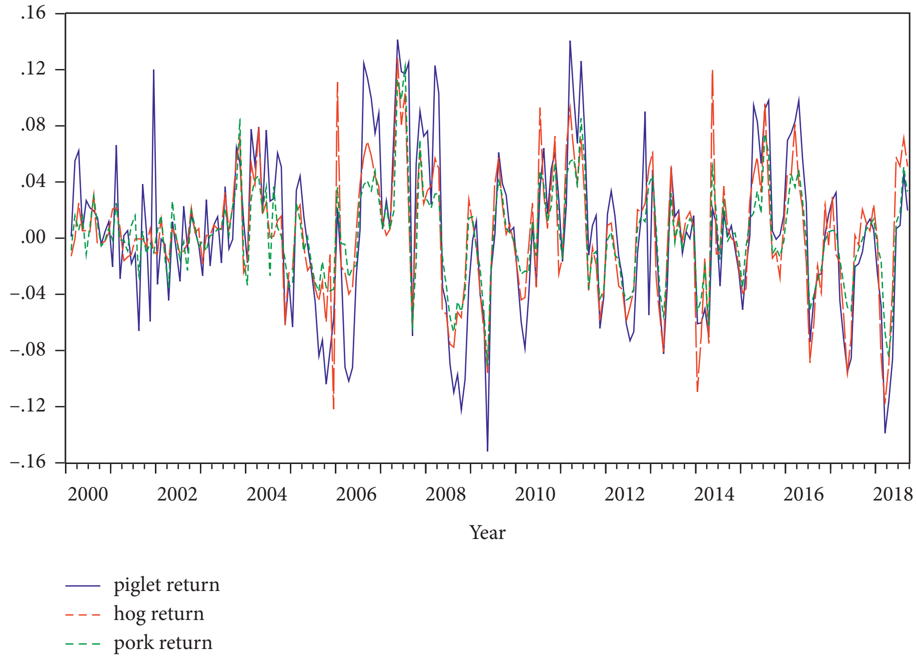

Figure 2: Returns of piglet, hog, and pork from 2000.01 to 2018.09.

Table 1: Zivot–Andrews unit root test results.

Variables	ZA-statistics	Breakpoints	Coefficients	t-statistics	p-values
l_t	−4.066	2007M03	0.447**	2.076	0.039
h_t	−4.372	2007M03	0.325***	2.894	0.004
p_t	−4.502	2007M03	0.434***	3.164	0.002
$\ln l_t$	−3.908	2007M03	0.032***	2.492	0.013
$\ln h_t$	−4.061	2006M06	0.034***	3.191	0.002
$\ln p_t$	−4.211	2007M03	0.028***	3.105	0.002
$\Delta \ln l_t$	−7.767***	2006M05	0.023**	2.026	0.044
$\Delta \ln h_t$	−8.955***	2008M04	−0.018*	−1.780	0.077
$\Delta \ln p_t$	−10.422***	2006M06	0.015*	1.734	0.084

Note. The critical values of the ZA test at 1% and 5% significance levels are −5.340 and −4.800, respectively. The coefficients, t-statistics, and p values are breakpoint's related statistics in the equation of the ZA test. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2: Statistics description of piglet, hog, and pork price returns.

	Variable	Mean	Median	Max	Min	Std	Skewness	Kurtosis	Jarque–Bera	p values
Full sample	$\Delta \ln l_t$	0.004	0.005	0.142	−0.152	0.057	0.036	2.860	0.230	0.891
	$\Delta \ln h_t$	0.002	0.002	0.128	−0.122	0.044	−0.049	3.398	1.570	0.456
	$\Delta \ln p_t$	0.002	0.002	0.122	−0.091	0.033	0.316	3.947	12.083	0.002
Subsample I	$\Delta \ln l_t$	0.005	0.005	0.125	−0.104	0.050	0.038	2.972	0.023	0.989
	$\Delta \ln h_t$	0.004	0.002	0.111	−0.122	0.033	0.002	5.884	29.463	0.001
	$\Delta \ln p_t$	0.003	0.002	0.084	−0.038	0.024	0.385	3.289	2.394	0.302
Subsample II	$\Delta \ln l_t$	0.003	0.005	0.142	−0.152	0.061	0.051	2.711	0.544	0.762
	$\Delta \ln h_t$	0.001	0.002	0.128	−0.118	0.049	0.014	2.699	0.528	0.768
	$\Delta \ln p_t$	0.001	0.003	0.122	−0.091	0.038	0.331	3.484	3.895	0.143

Table 3: The correlation coefficients of piglet, hog, and pork returns.

	Full sample				Subsample I				Subsample II		
	$\triangle\ln l_t$	$\triangle\ln h_t$	$\triangle\ln p_t$		$\triangle\ln l_t$	$\triangle\ln h_t$	$\triangle\ln p_t$		$\triangle\ln l_t$	$\triangle\ln h_t$	$\triangle\ln p_t$
$\triangle\ln l_t$	1			$\triangle\ln l_t$	1			$\triangle\ln l_t$	1		
$\triangle\ln h_t$	0.810***	1		$\triangle\ln h_t$	0.707***	1		$\triangle\ln h_t$	0.849***	1	
$\triangle\ln p_t$	0.845***	0.896***	1	$\triangle\ln p_t$	0.713***	0.798***	1	$\triangle\ln p_t$	0.894***	0.920***	1

Note. The symbols *** indicate statistical significance at the 1% level.

Table 4: The determination of the conditional mean equation specification.

Model	Piglet return		Hog return		Pork return	
	AIC	SIC	AIC	SIC	AIC	SIC
AR (1)	**−3.311**	**−3.280**	**−3.668**	**−3.637**	−4.335	**−4.304**
ARMA (1,1)	−3.305	−3.259	−3.658	−3.613	**−4.343**	−4.297
AR (2)	−3.039	−3.261	−3.654	−3.608	−4.341	−4.295
VAR (1)	−3.449	**−3.387**	−3.661	**−3.600**	−4.506	**−4.445**
VAR (2)	**−3.486**	−3.379	**−3.681**	−3.574	**−4.546**	−4.439
VAR (3)	−3.474	−3.320	−3.660	−3.506	−4.524	−4.370

The bold values given in Table 4 are the minimum value in the column, the minimum value of statistics are the optimal choose, which have no links with significance levels, so the significance levels are not given according to the common practice.

estimate VAR models including piglet, hog, and pork returns; the results of BIC values show that the VAR (1) model is better than VAR (2), but VAR (2) is an optimal model based on AIC. Because BIC is likely to choose a simplified model compared with AIC [30], combining with numbers of samples and estimated parameters, we choose a VAR (1) specification with the returns of the piglet, hog, and pork prices as the dependent variables.

The conditional mean equation takes the following form:

$$\mathrm{Y_t} = \alpha + \varnothing \mathrm{Y_{t-1}} + \varepsilon_t, \tag{1}$$

where $\mathrm{Y_t} = \begin{bmatrix} \triangle lnl_t \\ \triangle lnh_t \\ \triangle lnp_t \end{bmatrix}$ and $\triangle \ln l_t$, $\triangle \ln h_t$, and $\triangle \ln p_t$ represent the returns of the piglet, hog, and pork prices, respectively; $\varepsilon_t = \begin{bmatrix} \varepsilon_{l,t} \\ \varepsilon_{h,t} \\ \varepsilon_{p,t} \end{bmatrix}$ and $\varepsilon_t \mid \Omega_{t-1} \sim (0, \mathrm{E_t})$; $E_t = \begin{bmatrix} e_{ll,t}\, e_{lh,t}\, e_{lp,t} \\ e_{hl,t}\, e_{hh,t}\, e_{hp,t} \\ e_{pl,t}\, e_{ph,t}\, e_{pp,t} \end{bmatrix}$; $\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix}$, $\varnothing = \begin{bmatrix} \varnothing_{11}\, \varnothing_{12}\, \varnothing_{13} \\ \varnothing_{21}\, \varnothing_{22}\, \varnothing_{23} \\ \varnothing_{31}\, \varnothing_{32}\, \varnothing_{33} \end{bmatrix}$ are vectors of constant and regression coefficients.

To test whether the MGRACH model is suitable for our data, we first estimate the VAR (1) model and then perform heteroskedasticity and autocorrelation tests for VAR residuals (see Table 4). The heteroskedasticity test shows that $x^2(36) = 83.054$, rejecting the null hypothesis that VAR residuals have no heteroskedasticity at the 1% significance level, and we also use the LM test to examine if VAR residuals have a serial correlation; the test result shows that LM-stat = 36.916, rejecting the null hypothesis that VAR residuals have no serial correlation at the 1% significance level. In addition, residuals do not follow the normal distribution at the 1% significance level. Thus, using the MGRACH model to study the relationships between the piglet, hog, and pork returns could be a suitable method.

For the conditional variance equation, we use the asymmetric form of the BEKK (1, 1, 1) specification following Kroner and Ng [29]. The model takes the following form:

$$E_t = CC' + A'\varepsilon_{t-1}\varepsilon_{t-1}{}'A + B'E_{t-1}B + D'v_{t-1}v_{t-1}{}'D, \tag{2}$$

where E_t is the conditional variance-covariance matrix defined in (1). $A, B, C,$ and D are 3×3 matrices of parameters to be estimated. C is a 3×3 lower triangular matrix to ensure the positive definite property of E_t. Matrices A and B represent the ARCH and GARCH terms, respectively, which are indicators of short-term and long-term persistent volatility. Specifically, the elements of matrix A are the coefficients of the autoregressive conditional heteroskedasticity (ARCH) term, in which diagonal elements (i.e., a_{11}, a_{22}, and a_{33}) identify the effect of a price change on their own market and off-diagonal elements (i.e., a_{ij}, where $i \neq j$) reflect the spillover effects of the markets' conditional volatility on each other. Similarly, the diagonal elements (i.e., b_{11}, b_{22}, and b_{33}) and off-diagonal elements (i.e., b_{ij}, where $i \neq$) of matrix B are used to show the effects of the past volatility on their own market and the effects of past volatility spillovers from the other markets on the conditional volatility of each market.

It is noteworthy to mention that asymmetries are captured by adding the term $D'v_{t-1}v_{t-1}{}'D$ in asymmetrical BEKK (1, 1, 1). In this term, $v_{t-1} = \varepsilon_{t-1} o I_{\varepsilon<0}(\varepsilon_{t-1})$, where o is the Hadamard product (element-by-element multiplication) of the vectors, and the elements of matrix D characterize the potential asymmetric volatility transmission between piglet, hog, and pork returns. In fact, the diagonal elements (i.e., d_{11}, d_{22}, and d_{33}) are indicators of the significance of the asymmetric effect for own market, and off-diagonal elements (i.e., d_{ij} where $i \neq j$) are indicators of the significance of asymmetric effects between the vertical markets. The specific model introduction and the estimation method can be referred to Abdelradi and Serra and Saghaian et al. [3, 9].

To find the much more suitable models, we estimate three asymmetrical MGARCH-BEKK models, which presume that the residual follows normal, student-t, and GED distribution, respectively. The optimal models are selected according to the log likelihood values, and the results are shown in Table 5.

Table 5: The selection of residual distribution.

	Normal	Student-t	GED
Full sample	1627.420	1648.856	**1649.923**
Subsample I	**655.227**	No converge	654.496
Subsample II	1046.817	**1059.794**	1055.498

The bold values given in Table 5 are the minimum value in the column, the minimum value of statistics are the optimal choose, which have no links with significance levels, so the significance levels are not given according to the common practice.

The results in Table 5 indicate that the asymmetrical MGARCH-BEKK model with residuals following GED distribution in the full sample has the largest log likelihood value, which can be considered as an optimal model. Similarly, we choose the optimal models with residuals following normal distribution and student-t distribution in subsamples I and II, respectively.

5. Empirical Results

Based on the above analyses, we apply the quasi-maximum likelihood method to estimate three asymmetrical MGARCH-BEKK models with residuals following GED, normal, and student-*t* distributions for full sample, subsample I, and subsample II, respectively. The estimation results are shown in Table 6.

Table 6: Estimation results for the asymmetrical BEKK-MGARCH model.

Parameter	Full sample		Subsample I		Subsample II	
	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error
Conditional mean equation						
α_1	0.001	0.002	−0.001	0.002	0.002	0.002
ϕ_{11}	0.324***	0.080	−0.317***	0.109	0.374***	0.061
ϕ_{12}	0.937***	0.108	0.425***	0.146	0.952***	0.105
ϕ_{13}	−0.540***	0.159	0.917***	0.204	−0.652***	0.170
α_2	0.001	0.002	0.001	0.001	0.001	0.002
ϕ_{21}	0.091	0.062	−0.018	0.057	0.153***	0.055
ϕ_{22}	0.781***	0.147	0.185*	0.101	0.941***	0.104
ϕ_{23}	−0.482***	0.168	0.334**	0.139	−0.814***	0.168
α_3	−0.001	0.001	0.001	0.001	−0.001	0.001
ϕ_{31}	0.046	0.039	−0.073	0.044	0.069**	0.033
ϕ_{32}	0.687***	0.073	0.574***	0.082	0.731***	0.071
ϕ_{33}	−0.290***	0.099	−0.013	0.100	−0.385***	0.117
Conditional variance equation						
c_{11}	0.013***	0.003	0.009***	0.003	0.014***	0.005
c_{21}	0.010***	0.003	−0.004**	0.002	0.004	0.005
c_{22}	0.008***	0.002	0.002	0.003	0	0.004
c_{31}	0.004**	0.002	0.001	0.001	−0.001	0.003
c_{32}	0.005***	0.001	−0.001	0.001	0	0.004
c_{33}	0	0.004	0	0.003	0	0.002
a_{11}	0.422***	0.112	0.148	0.134	0.473***	0.187
a_{12}	0.041	0.083	−0.314***	0.081	−0.091	0.134
a_{13}	−0.018	0.046	−0.179***	0.047	−0.103	0.081
a_{21}	−0.286**	0.139	0.013	0.235	−0.646***	0.2
a_{22}	0.043	0.135	0.670***	0.15	−0.387**	0.183
a_{23}	−0.179***	0.073	0.632***	0.114	−0.544***	0.113
a_{31}	−0.086	0.191	0.706***	0.232	0.226	0.313
a_{32}	0.042	0.153	0.219	0.144	0.737***	0.229
a_{33}	0.421***	0.104	−0.023	0.145	1.015***	0.207
b_{11}	0.403***	0.123	0.289	0.186	0.142	0.205
b_{12}	−0.153*	0.092	0.312***	0.089	−0.405***	0.11
b_{13}	−0.169***	0.071	−0.065	0.057	−0.182**	0.079
b_{21}	−0.498**	0.175	0.722**	0.315	0.068	0.168
b_{22}	0.559***	0.062	0.105	0.229	1.161***	0.116
b_{23}	−0.141***	0.041	0.027	0.147	0.280***	0.072
b_{31}	1.363***	0.231	−0.190	0.225	0.989***	0.298
b_{32}	0.526***	0.135	0.110	0.145	−0.020	0.233
b_{33}	1.130***	0.097	0.665***	0.097	0.670***	0.164
d_{11}	0.452**	0.186	1.713***	0.261	1.306***	0.363
d_{12}	0.359***	0.131	0.283*	0.154	1.606***	0.337
d_{13}	0.176***	0.072	0.335***	0.1	0.635***	0.183
d_{21}	−0.561***	0.193	0.184	0.367	−1.148***	0.387
d_{22}	−0.684***	0.185	0.583**	0.278	−1.000***	0.317
d_{23}	−0.358***	0.113	0.638***	0.187	−0.357	0.223
d_{31}	−0.094	0.374	−2.512***	0.576	−0.241	0.562
d_{32}	0.048	0.27	−1.130***	0.31	−1.239***	0.448
d_{33}	−0.099	0.184	−1.530***	0.253	−0.639**	0.334
Shape (GED) or t-degree	2.038***	0.187	−−	−−	4.049***	0.922

Note. Subscripts 1, 2, and 3 refer to piglet, hog, and pork, respectively. Parameters in the conditional mean and variance equations are as defined in the model. The shapes in full sample and subsample II are the shape of GED distribution and t-degree of student-t distribution. The symbols *, **, and ***indicate statistical significance at the 10%, 5%, and 1% level, respectively.

According to the abovementioned asymmetrical MGARCH-BEKK model, we know that diagonal and off-diagonal elements of matrix A can be used to reflect the volatility spillover effects of piglet, hog, and pork returns from their own or other price volatility and matrix D can capture the volatility spillover effects of piglet, hog, and pork returns from the positive or negative price changes in piglet, hog, and pork returns. Here, we focus on the analysis of matrices A and D.

Table 6 shows the estimation results in different sample ranges. In the conditional mean equation, we can see that the means of piglet, hog, and pork returns are influenced by their own lagged returns and cross-market lagged returns. Comparing the results in three sample ranges, we find that the results in subsamples I and II are quite different, showing the different relationships between piglet, hog, and pork returns before and after the structural breakpoint, so it is needed to divide the sample into different periods to investigate the different dynamic characteristics of relationships between pork market prices in China. In addition, the results in the full sample are similar to those in subsample II in terms of signs and significance levels of coefficients, which also exist in the conditional variance equation. This means that the characteristics of relationships between pork market prices are mainly determined by those in subsample II.

In the conditional variance equation, we first analyze the characteristics of matrix A. The estimation results for the volatility spillovers are indicative of ARCH effects. Specifically, the current piglet and pork price volatility are affected positively by their own lagged volatility ($\widehat{a}_{11} = 0.422$, $\widehat{a}_{33} = 0.421$), while the hog return has no persistent ARCH effect. According to the cross-market volatility spillover results, we can observe two unidirectional volatility spillovers from hog to piglet and pork, since $\widehat{a}_{21} = -0.28$ and $\widehat{a}_{23} = -0.179$ are significant at the 5% significance level, but $\widehat{a}_{12}$ and $\widehat{a}_{32}$ are insignificant, indicating that lagged hog return volatility has a negative impact on piglet and pork price volatility, while the piglet price volatility and pork price volatility have no influences on the hog price volatility. This shows that hog breeding is an important stage to control the risk in pork supply chains in China.

Further, comparing the results in subsamples I and II, we find that the results are quite different from each other in terms of signs and significance of coefficients. Specifically, the volatility spillovers are indicative of strong ARCH effects in subsample II, with the current volatility of piglet, hog, and pork returns affected significantly by their own lagged volatility ($\widehat{a}_{11} = 0.473$, $\widehat{a}_{22} = -0.387$, $\widehat{a}_{33} = 1.015$), in which the pork return has the most persistent ARCH effect. However, only the volatility of hog returns has been affected by its own lagged volatility ($\widehat{a}_{22} = 0.670$) in subsample I. As for the cross-market volatility spillovers, in subsample II, we can observe bidirectional volatility spillover effects between hog and pork prices ($\widehat{a}_{23} = -0.544$, $\widehat{a}_{32} = 0.737$) and unidirectional volatility spillover effects from hog to piglet ($\widehat{a}_{21} = -0.646$), so the pork price volatility has a positive impact on the hog price volatility, but the hog price volatility can influence both piglet and pork price volatility negatively. This means that the growth of the pork price volatility can increase the growth of the hog price volatility and vice versa; the hog price volatility can decrease the pork price volatility and so forth, showing the process of the self-repairing system to keep price stability of the pork market. In addition, in subsample I, the piglet and pork prices have significant bidirectional volatility spillover effects ($\widehat{a}_{13} = -0.179$, $\widehat{a}_{31} = 0.706$), and there are two unidirectional volatility spillover effects from piglet to hog and from hog to pork ($\widehat{a}_{12} = -0.081$, $\widehat{a}_{23} = 0.632$). This indicates that the piglet price volatility has two ways to influence the pork price volatility; that is, one direct way is that the piglet price volatility can influence the pork price volatility negatively, and another indirect way is that the piglet price volatility influences the pork price volatility positively through the hog price volatility. In turn, the pork price volatility has a positive impact on the piglet price volatility, making an influent circle from the piglet return to the hog return, then to the pork return, and finally to the piglet return. The abovementioned analyses show that piglet, hog, and pork prices volatility spillover effects have changed significantly after 2007M03. In subsample I, piglet, hog, and pork price volatility can impact each other without a key stage; however, in subsample II, the hog price volatility is the most important stage influencing the other two prices in the pork supply chain.

Moreover, the results in subsample II are similar to those in the full sample according to the signs and significance levels of coefficients, while the absolute values of coefficients in subsample II are much higher than those in the full sample, showing the higher influences of piglet, hog, and pork return volatility in their own markets and cross markets. For example, the coefficients $\widehat{a}_{11} = 0.473$ and $\widehat{a}_{33} = 1.015$ in subsample II, which is larger than $\widehat{a}_{11} = 0.422$ and $\widehat{a}_{33} = 0.42$ in the full sample. However, there are still two significant differences between results of subsample and full sample. First, the hog return volatility is not influenced by the lagged hog return volatility in the full sample but is influenced negatively by the lagged hog return volatility in subsample II. Second, $\widehat{a}_{32}$ is insignificant in the full sample but is significant at the 1% significance level in subsample II, indicating that the pork price volatility has a positive influence on the hog price volatility.

The results from matrix D reflecting the effects of positive and negative price changes can also be indicative of the asymmetrical volatility spillover transmission. From the estimation results of matrix D, we can see that $\widehat{d}_{11} = 0.452$, 1.713, and 1.306 in full sample, subsample I, and subsample II, respectively, which are significant at 5% significance levels. This shows that the positive piglet price change is related with its own higher volatility spillover, while the negative piglet price change is not, and the magnitude of the asymmetrical price volatility response has decreased after 2007M03. On the contrary, the hog price volatility spillover is sensitive to negative rather than positive hog price changes ($\widehat{d}_{22} = -0.684$ in full sample and $\widehat{d}_{22} = -1.000$ in subsample II), while the reverse is true before 2007M3 ($\widehat{d}_{22} = 0.583$). Similarly, although $\widehat{d}_{33}$ is insignificant in the full sample, the higher pork price volatility spillovers are associated with the negative rather than the positive pork price change ($\widehat{d}_{33} = -1.530$ and $\widehat{d}_{33} = -0.639$ in subsamples I and II), showing the decreasing volatility spillover effects in response to the pork price increase.

In addition, positive rather than negative piglet price changes are associated with the higher volatility spillover of hog and pork prices, regardless of sample ranges. In contrast, negative rather than positive hog price changes are associated with the higher volatility spillover of piglet and pork prices in full sample and subsample II, while the reverse is true before 2007M3. Moreover, negative rather than positive pork price changes are associated with the higher volatility spillover of piglet in subsample I and hog

Table 7: Estimation results of the asymmetrical BEKK-MGARCH model based on the robust standard error.

Parameter	Full sample		Subsample I		Subsample II	
	Coefficients	Std error	Coefficients	Std error	Coefficients	Std error
a_{11}	0.422***	0.154	0.148	0.154	0.473	0.297
a_{12}	0.041	0.084	−0.314***	0.098	-0.091	0.142
a_{13}	−0.018	0.044	−0.179***	0.038	-0.103	0.081
a_{21}	−0.286*	0.152	0.013	0.254	-0.646***	0.174
a_{22}	0.043	0.169	0.670***	0.136	-0.387	0.246
a_{23}	−0.179**	0.073	0.632***	0.124	-0.544***	0.134
a_{31}	−0.086	0.184	0.706***	0.194	0.226	0.399
a_{32}	0.042	0.160	0.219**	0.102	0.737***	0.235
a_{33}	0.421***	0.099	−0.023	0.165	1.015***	0.266
d_{11}	0.452**	0.178	1.713***	0.249	1.306***	0.353
d_{12}	0.359******	0.140	0.283**	0.144	1.606***	0.306
d_{13}	0.176***	0.068	0.335***	0.095	0.635***	0.184
d_{21}	−0.561***	0.173	0.184	0.327	-1.148***	0.411
d_{22}	−0.684***	0.208	0.583***	0.264	-1.000***	0.301
d_{23}	−0.358***	0.114	0.638***	0.153	-0.357	0.271
d_{31}	−0.094	0.452	−2.512***	0.547	-0.241	0.486
d_{32}	0.048	0.259	−1.130***	0.275	-1.239***	0.413
d_{33}	−0.099	0.179	−1.530***	0.241	-0.639*	0.339
Shape (GED) or t-degree	2.038***	0.183			4.049***	0.996

Note. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: Estimation results for the asymmetrical BEKK-MGARCH model based on different distributions of residuals.

Parameters	GED		Student-t		Normal	
	Coeff	Std error	Coeff	Std error	Coeff	Std error
a_{11}	0.422	0.112*** (0.154***)	0.526	0.160*** (0.281*)	0.362	0.126*** (0.217*)
a_{12}	0.041	0.083 (0.084)	0.055	0.112 (0.150)	−0.212	0.103** (0.138)
a_{13}	−0.018	0.046 (0.044)	0.004	0.064 (0.057)	−0.135	0.057** (0.053**)
a_{21}	−0.286	0.139** (0.152*)	−0.453	0.228**(0.362)	0.361	0.191* (0.250)
a_{22}	0.043	0.135 (0.169)	−0.015	0.211 (0.317)	0.915	0.203*** (0.381**)
a_{23}	−0.179	0.073** (0.073**)	−0.394	0.121*** (0.161**)	0.318	0.146**(0.320)
a_{31}	−0.086	0.191 (0.184)	0.007	0.248 (0.226)	−0.311	0.296 (0.388)
a_{32}	0.042	0.153(0.160)	0.123	0.210 (0.207)	−0.279	0.242 (0.285)
a_{33}	0.421	0.104*** (0.099***)	0.758	0.123*** (0.110***)	0.384	0.179** (0.234*)
d_{11}	0.452	0.186** (0.178**)	−0.090	0.364(0.621)	0.404	0.203** (0.229*)
d_{12}	0.359	0.131*** (0.140***)	−0.411	0.235* (0.327)	0.031	0.178 (0.181)
d_{13}	0.176	0.072** (0.068***)	−0.252	0.120** (0.143*)	−0.005	0.110 (0.095)
d_{21}	−0.561	0.193*** (0.173***)	0.446	0.264*(0.280)	−0.065	0.325 (0.285
d_{22}	−0.684	0.185*** (0.208***)	0.942	0.270*** (0.378**)	0.252	0.372 (0.409)
d_{23}	−0.358	0.113*** (0.114***)	0.504	0.177*** (0.208**)	0.263	0.217 (0.268)
d_{31}	−0.094	0.374 (0.452)	0.611	0.639 (1.059)	−0.433	0.480 (0.417)
d_{32}	0.048	0.270 (0.259)	−0.007	0.455 (0.675)	−0.060	0.461 (0.510)
d_{33}	−0.099	0.184 (0.179)	0.308	0.270 (0.336)	−0.355	0.286 (0.334)
Shape (GED) or t-degree	2.038	0.187*** (0.183***)	5.339	1.057*** (1.020***)		

Note. The values in parenthesis are Newey–West robust standard errors. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

prices in both subsamples I and II. This indicates that the government, consumers, and market participants in the pork supply chain should pay much attention to the growth of the piglet price and the decrease of hog and pork prices to reduce the price volatility risk. Overall, the piglet, hog, and pork price volatility responds differently to positive and negative piglet, hog, and pork price changes, indicating asymmetric volatility-spillover effects. Hence, price volatility transmits unevenly along the vertical pork supply chain, leading to uneven distribution of the effects during sudden price changes, with welfare implications for market agents.

6. Robust Test

6.1. Robust Test of the Standard Error. To test whether the above results are robust, we estimate the asymmetrical BEKK-MGARCH model by using the Newey–West robust standard error and compare the significance levels of the coefficients based on the Newey–West robust standard error (see Table 7) and the normal standard error (see Table 6). We only list the estimation results of matrix A and D, which can reflect the asymmetrical price volatility transmission to save the space. The estimation results in Tables 6 and 7 have the same significant coefficients in matrix D, regardless of sample ranges. For matrix A, there are almost the same significant coefficients in the full sample, while only estimated coefficients $\widehat{a}_{32}$ in subsample I and $\widehat{a}_{11}$, $\widehat{a}_{22}$ in subsample II show the different significance levels. Thus, the results in Table 6 are robust to a larger extent, indicating that there may be no autoregression and heterogeneity in residuals of asymmetrical BEKK-MGARCH models.

6.2. Robust Test of Residual Distribution. In addition, we also estimate the asymmetrical BEKK-MGARCH model by using the standard error and the Newey–West robust standard error, respectively, based on different distributions of residuals in the full sample (see Table 8). From the results, we can see that the significant coefficients and levels based on the Newey–West robust standard error are fewer and lower than those based on the standard error in the asymmetrical BEKK-MGARCH models with residuals following student-t and normal distributions, while there are no differences in the models with residuals following GED distribution, no matter if the standard error or the robust standard error is used. These results show that the asymmetrical BEKK-MGARCH model with residuals following GED distribution is a better choice. Similarly, we also estimate the asymmetrical BEKK-MGARCH model based on different distributions of residuals in subsamples I and II. The estimation results show that the models with residuals following normal distribution in subsample I and following student-t distribution in subsample II are optimal models. The above estimation results are available from the authors upon request.

7. Conclusions

In this paper, based on the monthly data of piglet, hog, and pork prices over the period 2000M01-2018M09, we use the Zivot–Andrews unit root test with a structural break to study the time series property of piglet, hog, and pork prices and then investigate the asymmetric price volatility transmission in the agricultural supply chain by using the asymmetric MGARCH-BEKK model. Our application to the Chinese pork market illustrates the following useful conclusions:

First, our estimation results of the Zivot–Andrews unit root test reveal that piglet, hog, and pork prices have a structural break in 2007M03, so we divide the full sample into subsample I (2000M01-2007M02) and subsample II (2007M03-2018M09). It shows that the piglet, hog, and pork prices in terms of level and returns are much volatile after 2007M03.

Second, the correlation matrices in different sample ranges show that the correlation between pork and hog returns is highest, followed by the correlation between pork and piglet returns, and piglet and hog returns have the lowest correlation. Moreover, we find that the relationships between piglet, hog, and pork returns become much closer in subsample II, which means the higher the vertical integration of pork market returns, the greater the system risk of the pork market. This may be the reason why the pork prices are much more volatile in subsample II than those in subsample I.

Third, the estimation results of the asymmetric MGARCH-BEKK model in subsample II are similar to those in the full sample according to the signs and significance levels of coefficients, while the absolute values of coefficients in subsample II are much higher than those in the full sample, showing the higher influences of piglet, hog, and pork return volatility in their own markets and cross markets. This means that the characteristics of relationships between pork market prices are mainly determined by those in subsample II.

Fourth, the impact analysis of price volatility between piglet, hog, and pork can show the asymmetrical price volatility transmission. We can see that the current piglet price volatility and pork price volatility are affected positively by their own lagged volatility, and the hog return has no persistent ARCH effect. The lagged hog return volatility has a unidirectional negative impact on piglet and pork price volatility, showing that hog breeding is an important stage to control the risk in pork supply chains of China. In addition, piglet, hog, and pork prices volatility spillover effects have changed significantly after 2007M03. In subsample I, piglet, hog, and pork price volatility can impact each other in a circular way from the piglet return to the hog return, then to the pork return, and finally to the piglet without a key stage, while the hog price volatility is the most important stage influencing the other two prices in the pork supply chain in subsample II. Overall, controlling the hog price volatility can be an effective way to stabilize the pork market prices in China.

Fifth, the piglet, hog, and pork price volatility responds differently to positive and negative piglet, hog, and pork price changes, indicating asymmetric volatility-spillover effects. Specifically, positive rather than negative piglet price change can be associated with its own higher volatility spillover, while the hog (pork) price volatility spillover is sensitive to negative rather than positive hog (pork) price changes. Moreover, positive rather than negative piglet price changes are associated with the higher volatility spillover of hog and pork prices, regardless of sample ranges. In contrast, negative rather than positive hog (pork) price changes are associated with the higher volatility spillover of piglet and pork prices based on different sample ranges. Thus, the government, consumers, and market participants in the pork supply chain should pay much attention to the increase of the piglet price and the decrease of hog and pork prices, which is helpful to reduce the price volatility risk.

Finally, to test whether the above results are robust, we estimate the asymmetrical BEKK-MGARCH model by using the Newey–West robust standard error and the standard error, respectively, and also estimate the asymmetrical BEKK-MGARCH model based on different distributions of residuals in the full sample. We find that our estimation results are robust, and the assumption of residual distributions in our models is optimal and reasonable.

Although our empirical analysis has focused on the Chinese pork market, it could be extended in several directions. First, our analysis did not consider the nonlinearity in conditional mean equations of the MGARCH model, exploring such issues (e.g., the presence of threshold effects and smooth transition effects) may be worthy of additional attention. Second, there is a need to investigate how the frequency of data can influence the robustness of estimation results. Except the monthly data, the study using daily data or quarterly data can be used to test the robustness of our estimation results. Third, it would be useful to explore price dynamics in other markets. This could include pork markets in other regions as well as other commodity markets, which seems important as the increased price volatility is now prevalent in many markets. Finally, our study relies on national time series data. Conducting the research based on panel data across provinces may provide additional insights into the price volatility transmission of regional markets. Exploring these issues are good topics for future research.

Data Availability

The data supporting the findings of this study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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