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Price Linkage and Volatility Spillover of Beer Inputs

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Price Linkage and Volatility Spillover of Beer Inputs

Abstract

Driven in part by increasing demand of beer, the rising price of critical inputs, such as hops and barley, reduce the profit margin of the craft breweries in United States. However, brewers are left with limited tools to manage risk. Considering cross-hedging in futures market, we investigate price linkages and volatility spillover among hops, barley, and other selected agricultural products. Based on previous studies, hard red wheat, soft red wheat and corn are selected as the grain inputs most relevant to the brewery industry. We use monthly price data and nearby future price data, estimate VAR and VEC models to capture short and long-run price relationships, then estimate a BEKK-ARCH model to analyse the volatility spillover effects. The empirical results provide evidence supporting bidirectional long-run price relationship between hops and barley, but only short-run relationships between hops and other grain inputs. For barley, the long-run price relationships are found in all barley related pairs, e.g. barley-soft red wheat, barley-hard red wheat and barley-corn. Moreover, we identify volatility spillover transmission from soft red wheat and barley to hops. And soft red wheat, hard red wheat and corn exhibit volatility spillover effects on barley. In addition, the in-sample prediction shows the great fitting performance. This provides the empirical evidence to cross hedge the price risk of hops and barley using soft red wheat, hard red wheat and corn in brewery industry for the future studies.

Keywords: Beer inputs, Agricultural products, Price linkage, Volatility spillover, VAR, VECM, ARCH

1. Introduction

With increasing beer consumption in recent years, the number of breweries in the U.S. have grown rapidly. Based on the report of Brewer Association, the total number of U.S. breweries reached 5301 in 2016, which is a 114% rise from 2012. And the total beer market itself contributed 107.6 billion dollars to the economy in 2016. However, significant growth in beer consumption also requires additional critical inputs, which are hops and barley. High beer demand directly has led to an increased price of inputs. According to U.S. Census Bureau, the historically highest export price of hops cone was about 16 dollars per bushel in 2017, compared to about 9 dollars per bushel in 2012 with an increase over 77%. Input price risk will mainly affect the profit margin of the craft breweries, which accounts for 98.7% of total U.S. brewery counts. Therefore, it will be of great interest for craft breweries to manage the price risk of hops and barley.

Quantifying price linkages and volatility for hops and barley is essential to manage price risk. While hedging could be considered as a common management tool in agriculture marketing, there is no hops future contracts and the barley future contracts are mainly traded in Canada. That said, cross-hedging of hops and barley should be considered, which requires an understanding of price linkages and volatility spillovers among hops, barley and other related agriculture products. Common factors (e.g. geographical, seasonality, climate) in agricultural products and the general substitute or complement relationships make agriculture products interrelated to some extent (Malliaris and Urrutia, 1996; Gardebroek et al., 2013). Also, there exists some relationships among hops, barley and other cereal grains which could also be used in beer brewery. These provide the opportunities to explore the price relationships. And understanding the price relationships are very helpful for craft beer breweries, growers and policy makers.

Based on previous research (Prera, Fortenbery and Marsh, 2017) and the related cereal grains used in brewery industry, we choose corn, soft red wheat and hard red wheat as the cross-related future products for hops and barley. As price leaders, corn and wheat have relationships with most of the other agriculture products. Besides, using these two future products may provide price management because of their presence in agriculture future markets. Thus, given the above agriculture products, this article tries to address the following questions: First, are there any long-run relationships existing for hops or barley with the chosen agricultural products? Second, how barley or hops react to the price change of other products (hard red wheat, soft red wheat and corn) in the short run? Third, if there are volatility spillover effects transferred from soft red wheat, hard red wheat and corn to hops and barley?

There are various studies related to the beer market. However, most of them focus on the beer consumption, pricing or industry organization. For example, Toro-González et al. (2014) explore the elasticities of different beers and find that beer is a normal good with inelastic demand. Clemons et al. (2006) evaluate the effectiveness of product differentiation in craft beer market, and the results show that the craft beer industry is hyper differentiation. Few studies pay attention to the risk management in the brewing sector. Among them, Ugwuanyi and Ibe (2012) find that risk management has positive effect on brewery industry in Nigeria. Geppert et al. (2013) compared four leading multinational brewery corporations and concluded that market type and ownership will lead to different risk-taking strategies for acquisitions.

For risk management, only a handful of studies aim to reducing the risk from the input side of the brewery sector. One existing paper is Gabrielyan and Marsh (2012). They examine the formation of hops price and their AR (2) model shows that lagged hops price has positive impact on current price. The most recent and related study by Prera, Fortenbery and Marsh (2017) use minimum variance method with quarterly data to estimate a hedge ratio through the vector error correction model (VECM) among hops, barley, soft red wheat, hard red wheat and corn.

In the literature cited above, no one has explored the price linkage and volatility spillover effects for hops and barley. Compared to the previous literature, we update the data frequency from quarterly to monthly, which increases the degree of freedom and gives more information to complete the analysis. To our best knowledge, this paper is the first attempt to give a quantitative result for price linkage and volatility analysis for hops, barley and other related agricultural products in bivariate economic framework. We choose a bivariate framework, because of our lower frequency data (i.e., monthly relative to daily or hourly) and, hence, smaller sample size.

To investigate the price linkage and volatility spillover effects, the basic time series analysis including stationary and cointegration are applied first. For those commodity pairs who do not have the long-run cointegration relationship, we use the Vector Autoregression (VAR) model to obtain the short-run effects. However, if there exists the cointegration relationship, we can capture both short-run and long-run effects by Vector Error Correction (VEC) model. After the estimation of above mean conditional models, a volatility analysis with Autoregressive Conditional Heteroskedasticity (ARCH) model is used to examine volatility spillover. Using the monthly data from 2002 January to 2017 April, we implement the logarithmic transformation for each commodity price. Thus, for either VAR or VEC model, the logarithmic price returns are treated as dependent and independent variables.

Based on the tests of cointegration, hops predominately have short-run relationships with the other commodities. The only exception is the hops-barley system that exhibits a long run cointegration relationship. That means, VAR model will be chosen for hops-corn, hops-soft red wheat and hops-hard red wheat systems and for the hops-barley system we apply a VEC model.

Based on empirical results, the hops price return will be negatively affected by its own lagged price return and positively affected by lagged price return of soft red wheat and hard red wheat in the short run. There exists a long run relationship between hops and barley, and hops has a very quick reaction to the deviation of this long-run path, which will take only five months to converge. By using the results of VAR and VEC model, the ARCH model shows that there are volatility spillover effects transferred from soft red wheat and barley to hops in hops-soft red wheat and hops-barley systems.

For the barley related commodity pairs, the long-run relationships are confirmed in all systems. However, only the long-run relationship in barley-corn system is bidirectional. For other pairs, such as barley-soft red wheat and barley-hard red wheat, the long run relationship is only unidirectional, that means only barley will react to the change of the soft red wheat or hard red wheat in the long run. The volatility analysis for barley shows that soft red wheat, hard red wheat and corn have spillover effects on the volatility of barley. The spillover effects are all bidirectional.

The remainder of this paper is structured as follows: we first discuss the data and related statistical tests in the next section. Then the empirical models will be introduced in methodology section. The following section presents empirical results. Finally, a conclusion is provided.

2. Data

2.1 Data Description

The data used in this article are monthly prices for barley, hops, soft red wheat future, hard red wheat future and corn future in United States. The data ranges from 2002 January to 2017 April for a total of 184 observations. The soft red wheat future and corn future prices are collected from Chicago Board of Trade (CBOT), hard red wheat future price comes from Kansas City

Board of Trade (KCBT). The price of barley is collected from the website of USDA NASS agricultural price report. To be consistent with the purpose of this paper, the barley is specified as malting barley. For hops, we use the export hops cone pellet price from the website of U.S. Census Bureau. The hops pellet is the most common used form of hops in brewery industry due in part because of its storage advantage. All the above products are measured as dollar per bushel ($/bu), and averaged by month. We make logarithmic transformation for each commodity price, which will be denoted as $\log(p_t)$ where the change of logarithmic price or logarithmic price return is defined as r_t. The logarithmic price series are plotted in figure 1 and the summary statistics including both logarithmic prices and logarithmic price returns are showed in table 1 and table 2.

Figure 1: The Logarithmic Price Series Plot

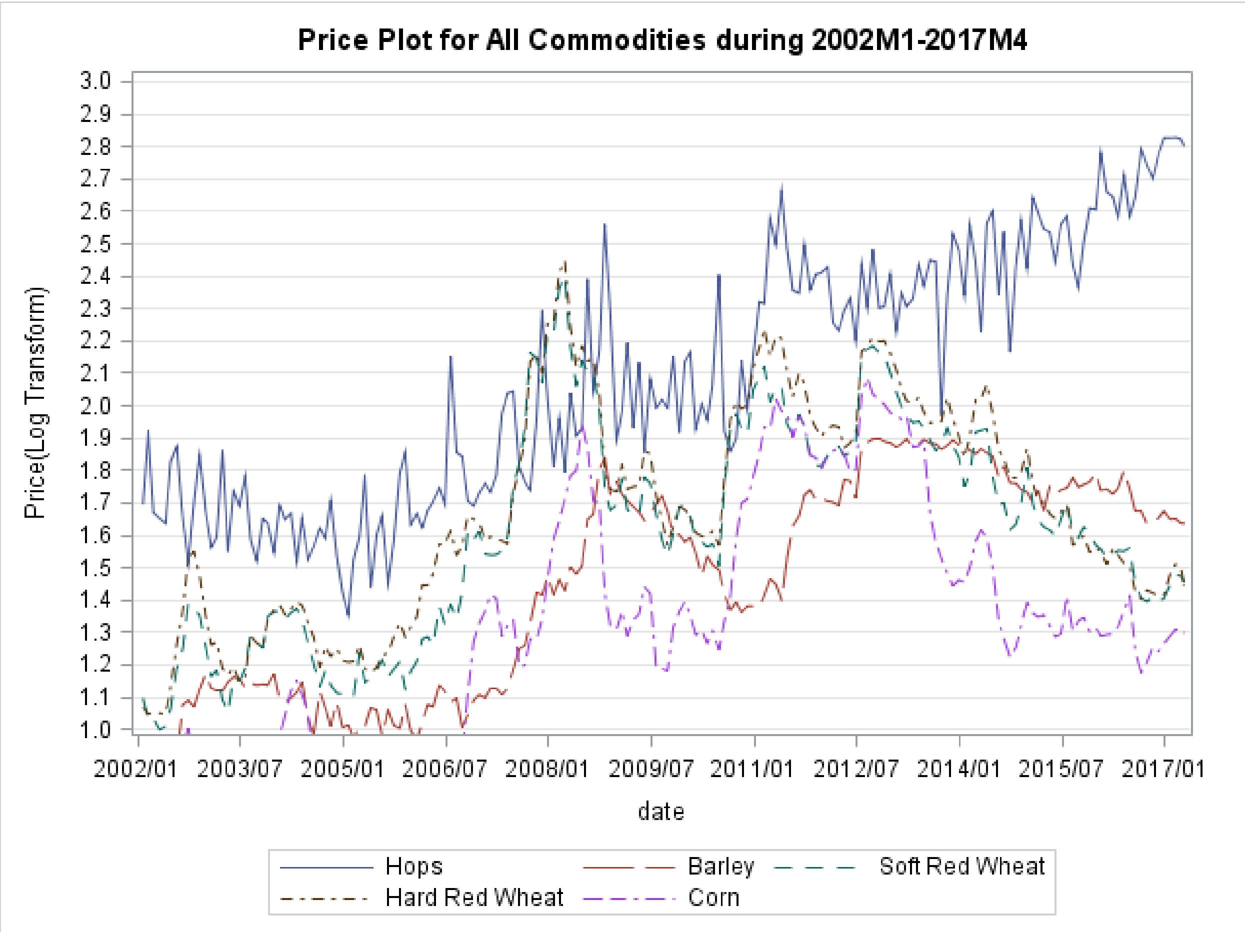

Table 1: Summary Statistics and Diagnostic Test for Logarithmic Price

Variable	N	Mean	Min	Max	S. D	Range	Skewness	Kurtosis	Normality	Autocorrelation
Hops	184	2.09118	1.35109	2.8251	0.39093	1.474	0.10922	-1.22273	<0.0001	<0.0001
Barley	184	1.45407	0.892	1.89612	0.32361	1.00412	-0.21885	-1.5172	<0.0001	<0.0001
Soft Red Wheat	184	1.61184	0.99599	2.39964	0.33499	1.40366	0.07373	-0.92324	<0.0001	<0.0001
Hard Red Wheat	184	1.67179	1.0445	2.44519	0.33694	1.40069	0.08202	-0.97872	<0.0001	<0.0001
Corn	184	1.30605	0.65746	2.08386	0.39343	1.4264	0.1597	-0.93193	<0.0001	<0.0001

1.Normality test is using Jarque-Bera test with null hypothesis: Normality. The values in table are P-Values.
2.Autocorrelation test is using Ljung-Box test (6) with null hypothesis: No correlation. The values in tables are P-Values.

Table 2: Summary Statistics and Diagnostic Test for Logarithmic Price Return

Variable	N	Mean	Min	Max	S. D	Range	Skewness	Kurtosis	Normality	Autocorrelation
Hops	183	0.006	-0.483	0.460	0.172	0.943	-0.132	0.156	0.953	0.0002
Barley	183	0.0039	-0.115	0.171	0.048	0.285	0.629	1.449	<0.0001	0.0311
Soft Red Wheat	183	0.0020	-0.245	0.280	0.075	0.524	0.509	1.935	<0.0001	0.0877
Hard Red Wheat	183	0.0021	-0.237	0.254	0.071	0.491	0.430	1.882	<0.0001	0.0078
Corn	183	0.0030	-0.281	0.230	0.074	0.511	-0.516	2.020	<0.0001	00014

1.Normality test is using Jarque-Bera test with null hypothesis: Normality. The values in table are P-Values.
2.Autocorrelation test is using Ljung-Box test (18) with null hypothesis: No correlation. The values in tables are P-Values.

From the price series plots of figure 1, we can see that most of the commodities have some similarity in pattern, especially for soft red wheat and hard red wheat. However, the hops and corn appear to fluctuate more when compared with other commodities. Also notice that hops shows a different trend in many periods and starts to increase from 2012. Thus, we may not expect long-run relationships between hops and the other commodities. But when observing the price trend of barley, the pattern is more similar with the other commodities. Thus, there could exist long-run relationships between barley and other commodities.

Based on above summary statistics, hops and corn have the largest standard deviation in logarithmic price, which are both about 0.39. This is consistent with the prices plotted in the figures and this indicates higher volatility. Also, both statistic tables show that soft red wheat and hard red wheat prices are very similar. Except hops in logarithmic price return, the Jarque-Bera normality test for all commodities are significant, which indicates the rejection of normality. The Ljung-Box autocorrelation tests are also rejected for all commodities for both tables. These outcomes support the existence of ARCH type effects. We also examined the logarithmic price return for each commodity (figures in appendix). Observing from these plots, all logarithmic price returns fluctuate along the zero line, which possibly exhibiting the stationary property. And the fluctuation shape of each graph also indicates the existence of ARCH effects.

2.2 Test on Stationary and Cointegration

2.2.1 Stationary Test

Follow the standard procedure of time series analysis, we first need to test for stationarity to satisfy model assumptions. Results are shown in table 3 for the Augmented Dickey-Fuller (ADF) test. Three model types, which are no constant and no trend, only constant and constant plus trend, are included. The tests show that all the logarithmic prices are non-stationary except for hops in the constant plus trend model. After taking the first difference, all the commodities for every model is stationary at 1% significant level. Thus, each commodity satisfies $I(1)$. Based on the results, we will use the change of logarithmic price or logarithmic price return in the following analysis.

Table 3: The Augmented Dickey Fuller Test for Stationary

	Logarithmic Price (P-Value)			Logarithmic Price Return (P-Value)		
Variables	**No Constant and No Trend**	**only Constant**	**Constant and Trend**	**No Constant and No Trend**	**Only Constant**	**Constant and Trend**
Hops	0.9504	0.7938	0.0136**	<0.0001***	<0.001***	<0.001***
Barley	0.8942	0.5803	0.9079	<0.0001***	<0.001***	<0.001***
Corn	0.6174	0.5001	0.7042	<0.0001***	<0.001***	<0.001***
Soft Red Wheat	0.6619	0.4784	0.7291	<0.0001***	<0.001***	<0.001***
Hard Red Wheat	0.6452	0.4325	0.6856	<0.0001***	<0.001***	<0.001***

1. The values in table is P-Values. 2. *, **, *** represent 10%, 5% and 1% significance level. 3. The null hypothesis of the ADF test: non-stationary or unit-root

2.2.2 Cointegration Test

To decide which conditional mean model (VAR or VEC) should be used, we need to confirm if there exists the long run relationship between commodities. And the cointegration relationship implies testing for a long run equilibrium relationship. Thus, we use Johansen trace test to identify the existing of cointegration relationship between each commodity pairs. Based on the stationary results, all the logarithmic price shows I (1) property, we then use the logarithmic price turn in the cointegration test. The optimal lag term is chosen based on information criterion (AIC and BIC). The test results are summarized in following table 4.

Table 4: Johansen Trace Test for Commodity Pairs

	Eigenvalue	P-Value	Results
Hops and Barley (p=2)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0679	0.0283	Rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	00054	0.3725	Not rejected
Hops and Soft red wheat (p=2)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0425	0.2320	Not rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0009	0.7415	Not rejected
Hops and Hard red wheat (p=2)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0378	0.3145	Not rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0005	0.7988	Not rejected
Hops and Corn (p=2)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0417	0.2410	Not rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0011	0.7088	Not rejected
Barley and Soft red wheat (p=1)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.1167	0.0003	Rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0003	0.8393	Not rejected
Barley and Hard red wheat (p=1)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.1120	0.0005	Rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0006	0.7795	Not rejected
Barley and Corn (p=1)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0984	0.0035	Rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0000	0.9832	Not rejected
Soft red wheat and Hard red wheat (p=1)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0596	0.0755	Rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0000	0.9894	Not rejected
Soft red wheat and Corn (p=1)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0590	0.0759	Rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0006	0.7932	Not rejected
Hard red wheat and Corn (p=1)			
$H_0: Rank = 0$ VS $H_0: Rank > 0$	0.0509	0.1351	Not rejected
$H_0: Rank = 1$ VS $H_0: Rank > 1$	0.0005	0.8101	Not rejected

Since the cointegration test is applied in a bivariate system, there is at most one cointegration relationship. Therefore, if there exists the cointegration relationship, we expect to see the rejection of the first hypothesis test and do not reject of the second hypothesis test. Based on the above table, all the hops related commodity pairs exhibit no cointegration relationship except hops-barley system. That means there only exists a long run relationship between hops and barley. For barley related commodity pairs, all pairs exhibit cointegration. These results are consistent with the price plots above. Thus, for the conditional mean model, we will use Vector Autoregression (VAR) models for those that do not have long run cointegration relationship. The Vector Error Correction (VEC) model will be used for those with the long-run cointegration relationship. The model specification of this two and the ARCH model will be discussed in the following section.

3. Methodology

3.1 Vector Autoregression (VAR) Model

Since we are going to use the logarithmic price return as the variables in the model, we first define logarithmic price return as below:

$$r_t = \log(p_t) - \log(p_{t-1}) = \log(\frac{P_t}{P_{t-1}})$$

Here p_t indicates the price vector of commodities at time t and p_{t-1} is the price vector of commodities at time t-1.

From the results of the cointegration tests, we will use the VAR model to capture the short-run relationships for hops related commodity pairs except hops-barley. The VAR model generalizes the AR model by allowing other endogenous variables. Each variable is explained by the lagged term of itself and the lagged term of other variables. The model is given in following:

$$r_t = \sum_{s=1}^{p} a_s r_{t-s} + \epsilon_t, \quad \epsilon_t | I_{t-1} \sim (0, H_t)$$

where r_t is vector of the logarithmic price returns. Since we model the pairwise commodities, r_t is a 2 by 1 vector. The index s ranges from 1 to p, and p represents the optimal maximum lag terms chosen by the information criterion (AIC and BIC). Thus, a_s is a 2 by 2 parameter matrix capturing the short run effects from the own s lagged terms and the s lagged terms of other variables. The residual ϵ_t conditional on past information is 2 by 1 vector with mean zero and conditional variance-covariance matrix H_t, which is 2 by 2.

3.2 Vector Error Correction (VEC) model

For those commodity pairs, which have the cointegration relationship, we can use Vector Error Correction (VEC) model. This model will give us not only the short-run effects and long-run relationship, it will also allow us to identify how long the price return will react to the long-run path if there exists a shock. The VEC model can be written as:

$$r_{1,t} = \Pi_1 ECT_{t-1} + \sum_{j=1}^{p-1} a_{11,j} r_{1,t-j} + \sum_{j=1}^{p-1} a_{12,j} r_{2,t-j} + \epsilon_{1,t}$$
$$r_{2,t} = \Pi_2 ECT_{t-1} + \sum_{j=1}^{p-1} a_{21,j} r_{1,t-j} + \sum_{j=1}^{p-1} a_{22,j} r_{2,t-j} + \epsilon_{2,t}$$
$$ECT_{t-1} = \log(p_{1,t-1}) - \beta_0 - \beta_1 \log(p_{2,t-1})$$
$$\begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix} = \boldsymbol{\epsilon_t} | \boldsymbol{I_{t-1}} \sim (\mathbf{0}, \boldsymbol{H_t})$$

The term ECT_{t-1} is the error correction term, and the equation of ECT_{t-1} reflects the long-run equilibrium relationship for $\log(p_{1,t-1})$ and $\log(p_{2,t-1})$, which β_0 and β_1 are the parameters. Thus, the term ECT_{t-1} measures the deviation of the long-run equilibrium. The parameters Π_1 and Π_2 named as the long-run adjustment parameters, it represents the speed of logarithmic price reacting to the deviation. The sign of Π_1 should be negative and Π_2 should be positive. But both of their absolute value ranges from 0 to 1. The reason of different signs for Π_1 and Π_2 is that we normalize the parameter before $\log(p_{1,t-1})$ as 1. For example, if $\log(p_{1,t-1})$ has an increase deviation, which resulting in $ECT_{t-1} > 0$. We must have Π_1 be negative and therefore $r_{1,t}$ be negative (hold other effects fix). Based on the definition of logarithmic price returns, this will guarantee $\log(p_{1,t})$ decreases and converge back to the equilibrium. And this adjustment will also be similar for an increase deviation of $\log(p_{2,t-1})$, the difference only requires Π_2 be positive. Besides, $a_{11,j}, a_{12,j}, a_{21,j}$ and $a_{22,j}$ are parameters of own and cross short run effects. Again, the residual vector ϵ_t conditional on past information satisfy normal with zero mean and conditional variance-covariance matrix H_t.

3.3 Autoregressive Conditional Heteroscedastic (ARCH) Model

Next we define a model to better assess volatility. Given the results of conditional mean models mentioned above, the residual vector of each system is obtained and assumed as bivariate normal distribution with zero mean and conditional variance-covariance matrix H_t. We can then use ARCH model to define H_t:

$$H_t = C'C + A'\epsilon_{t-1}\epsilon'_{t-1}A$$

In the above ARCH model, C is a 2 by 2 constant matrix which elements can be represented as C_{ij}. Assumptions of the model require the constant C matrix is symmetric and positive definite. The parameter matrix A reflects the ARCH effects, which is also 2 by 2. The elements in A can be written as A_{ij}, if $i = j$, the parameter refers to the own lagged innovation effects on the volatility. If $i \neq j$, the parameter A_{ij} stands for the lagged cross innovation effects on volatility. Thus, the ARCH model requires the absolute value of A_{ij} less than 1, but no restriction on the sign and symmetric. This specification of above ARCH model is known as the BEKK form, which guarantees the positive definite of A matrix.

4. Empirical Results and Analysis

4.1 Results for VAR Model

The VAR model mainly measures the short-run effects between commodities. Given the results of cointegration test, we apply the VAR model for hops related commodity pairs except hops-barley. The hard red wheat-corn pair is also included here as no cointegration relationship. For each VAR model, we use the logarithmic price return as the dependent or explanatory variable. Thus, the parameters of short-run effects can be simply interpreted as elasticities. The results are shown in table 5. The optimal lag term is chosen by information criterion (AIC and BIC).

From table 5, the hops price return will be negatively affected by its first and second lagged price return in all hops related systems, where the elasticities is averaged about -0.466 and -0.3 (average over three systems). That means, if the lag one hops return increases by 1%, the current hops return will decrease by 0.466%. And the lag two hops return increase 1%, the current hops return will decrease by 0.3%. Thus, in another word, hops price will self-adjust to some extent in the short run. However, the lag two price return of soft red wheat and hard red wheat both have positive short-run effects on hops return. This make economic sense as the important status of wheat in agriculture market. Notice that corn has no short-run effects on hops. There are many studies confirm the relationship among corn, ethanol, crude oil and other biofuel related products (Wu et al., 2010; Jiang et al., 2015; Zhang et al., 2009;). And as the development of EPA 2005 and ELSA 2007, the connection of corn and other biofuel products becomes closer rather than agriculture products.

For the other commodities of this table, like soft red wheat, hard red wheat and corn, the short-run effects mainly come from their own lagged effects. All these effects are positive. The reason may be not only due to the change in demand and supply but also due to the effects from financial market (e.g. the behavior of speculate).

Table 5: Pairwise VAR Model

Parameter	Estimates	t-Value	Parameter	Estimates	t-Value
Empirical model:					
$r_{i,t} = \sum_{s=1}^{p} a_s^{i,i} r_{i,t-s} + \sum_{s=1}^{p} a_s^{i,j} r_{j,t-s} + \epsilon_{i,t}$, $r_{j,t} = \sum_{s=1}^{p} a_s^{j,i} r_{i,t-s} + \sum_{s=1}^{p} a_s^{j,j} r_{j,t-s} + \epsilon_{j,t}$ i, j =hops, soft red wheat,…					
Hops and Soft red wheat (p=2)					
$a_1^{hops,hops}$	-0.44591***	-7.01	$a_1^{srw,srw}$	0.12878*	1.74
$a_2^{hops,hops}$	-0.25152***	-4.04	$a_2^{srw,srw}$	-0.05838	-0.88
$a_1^{hops,srw}$	0.16026	1.02	$a_1^{srw,hops}$	-0.06644*	-1.86
$a_2^{hops,srw}$	0.25332*	1.87	$a_2^{srw,hops}$	-0.03152	-1.05
Hops and Hard red wheat (p=2)					
$a_1^{hops,hops}$	-0.46782***	-6.92	$a_1^{hrw,hrw}$	0.2268***	3.01
$a_2^{hops,hops}$	-0.32804***	-3.71	$a_2^{hrw,hrw}$	-0.05371	-0.75
$a_1^{hops,hrw}$	0.12957	0.88	$a_1^{hrw,hops}$	-0.05796	-1.59
$a_2^{hops,hrw}$	0.35253**	2.24	$a_2^{hrw,hops}$	-0.00607	-0.20
Hops and Corn (p=2)					
$a_1^{hops,hops}$	-0.48369***	-4.77	$a_1^{corn,corn}$	0.25976***	3.33
$a_2^{hops,hops}$	-0.32934***	-3.21	$a_2^{corn,corn}$	0.04160	0.50
$a_1^{hops,corn}$	0.12454	0.49	$a_1^{corn,hops}$	-0.04126	-0.89
$a_2^{hops,corn}$	0.24400	1.54	$a_2^{corn,hops}$	0.00119	0.02
Hard red wheat and Corn (p=1)					
$a_1^{hrw,hrw}$	0.27877***	2.87	$a_1^{corn,corn}$	0.25316***	2.78
$a_1^{hrw,corn}$	-0.03456	-0.38	$a_1^{corn,hrw}$	0.04367	0.43

*, ** and *** represents 10%, 5% and 1% significance level.

4.2 Results for VEC Model

An advantage of VEC model comparing with VAR model is that the long-run equilibrium relationship can be identified besides the short run effects. Based on previous test outcomes, the barley related commodity pairs and barley-hops can be assessed in the VEC model. The results are shown in table 6 where optimal lag terms are chosen by information criterion (AIC and BIC).

Observe from table 6 that long-run relationships are confirmed for all barley related commodity pairs and the long-run relationships are all positive. This suggest an increase of one price will increase another price. However, only barley-hops and barley-corn systems exhibit bidirectional relationships. That said, for these two systems both commodities will react to long-run deviations. For other systems, only barley will react to the long-run deviation.

For barley-hops system, the long-run relationship parameter is about 0.88. And if there is deviation, hops will make an adjustment at a speed of 20.8% per month, which will take about 4.8 month to converge to the long-run path. But barley converges much slower in this system, which the adjustment speed is only 3% per month. The reason may due to the existing of other long-run equilibrium relationship outside hops-barley system. Besides, the model shows that the lagged hops price return has negative short run effects on its current price return, this is consistent with the results in above VAR model.

The results of barley-soft red wheat and barley-hard red wheat are very similar, there is only small difference in magnitude. The long-run relationships are unidirectional, only barley will react to the deviation of long-run equilibrium in each system, which the speed are 5.2% and 5.8% per month.

Another bidirectional long-run relationship in the VEC results is the barley-corn system. It exhibits faster convergence speed when compared with other systems, which is about 7.1% per month. However, the convergence speed of corn is as low as 0.125%. The explanation is similar as previous that corn is more connected with biofuel products and the relationship with agriculture products become weaker.

Finally, we also confirm the long-run relationship between soft red wheat and corn. Comparing with other systems, soft red wheat and corn both have relatively high speed to react to this long-run path. The convergence speed of corn is 10.9% per month. This reflects the important role of both soft red wheat and corn in agriculture market.

Table6: Pairwise VEC model

Empirical model:

$r_{1,t} = \Pi_1 ECT_{t-1} + \sum_{j=1}^{p-1} a_{11,j} r_{1,t-j} + \sum_{j=1}^{p-1} a_{12,j} r_{2,t-j} + \epsilon_{1,t}$
$r_{2,t} = \Pi_2 ECT_{t-1} + \sum_{j=1}^{p-1} a_{21,j} r_{1,t-j} + \sum_{j=1}^{p-1} a_{22,j} r_{2,t-j} + \epsilon_{2,t}$
$ECT_{t-1} = logp_{1,t-1} - \beta_0 - \beta_1 \log(p_{2,t-1})$ [3]

Parameter	Estimates	t-Value	Parameter	Estimates	t-Value
Barley and Hops(p=2)					
$a_{11,1}$	-0.11090	-1.51	$a_{21,1}$	-0.04995	-0.21
$a_{12,1}$	0.00047	0.02	$a_{22,1}$	-0.27077***	-3.71
Π_1	-0.03014***2		Π_2	0.20803***2	
β_0	-0.38070***1				
β_1	0.88128***1				
Barley and Soft red wheat (p=2)					
$a_{11,1}$	-0.17924***	-2.59	$a_{21,1}$	-0.17268	-1.50
$a_{12,1}$	0.05801	1.27	$a_{22,1}$	0.18281**	2.41
Π_1	-0.05762***2		Π_2	0.00314[2]	
β_0	-0.20137***1				
β_1	1.07308***1				
Barley and Hard red wheat (p=2)					
$a_{11,1}$	-0.17396**	-2.50	$a_{21,1}$	-0.11077	-1.03
$a_{12,1}$	0.06390	1.32	$a_{22,1}$	0.26023***	3.48
Π_1	-0.05211***2		Π_2	0.00564[2]	
β_0	-0.30352***1				
β_1	1.09903***1				
Barley and Corn (p=2)					
$a_{11,1}$	-0.17695**	-2.55	$a_{21,1}$	-0.16360	-1.48
$a_{12,1}$	0.01099	0.23	$a_{22,1}$	0.28313**	3.80
Π_1	-0.07089***2		Π_2	0.00125*2	
β_0	0.38977***1				
β_1	0.86218***1				
Soft red wheat and Corn (p=2)					
$a_{11,1}$	0.19352**	2.07	$a_{21,1}$	-0.00404	-0.05
$a_{12,1}$	-0.01066	-0.12	$a_{22,1}$	0.25284***	2.93
Π_1	-0.01877***2		Π_2	0.10922***2	
β_0	0.50722***1				
β_1	0.83952***1				

[1] The significance test depends on the restricted long-run coefficient test with null hypothesis: $\beta = 0$
[2] The significance test depends on the weak exogeneity test with null hypothesis: variable do not react to long-run deviation
[3] For ECT_{t-1} equation, we normalize the parameter of commodity 1 as 1, which is the first commodity for each pair.
[4] *, ** and *** represents 10%, 5% and 1% significance level.

4.3 Results for Volatility

The results of ARCH effects are reported in table 7. From the table, the parameter A_{ij} measures the own ($i = j$) or cross ($i \neq j$) spillover effects. And the significance of the parameter A_{ij} will indicates whether the spillover effects exist or not. However, the estimates do not directly reflect the magnitude of the volatility dues to the specification of this BEKK ARCH form.

For hops related commodities pairs, the current volatility of hops will not affect by its own past shock. And, there is spillover effects transferred from barley ($A_{21} = 0.74388$) and soft red wheat ($A_{21} = -0.91778$). That means if there is a shock on soft red wheat and barley in the previous time, the spillover effects of this shock will pass from soft red wheat and barley to the current hops volatility. However, the spillover effects in barley-hops is only unidirectional. For hops-soft red wheat, hops also has spillover effects on the volatility of soft red wheat. Besides, the spillover effects of hops can also be transferred to hard red wheat.

For barley, the spillover effects are found in the system with soft red wheat, hard red wheat and corn. And the spillover effects in these systems are all bidirectional. In other words, the past shock of soft red wheat, hard red wheat and corn will transfer to the current volatility of barley return. Also, the past shock of barley will transfer to the current volatility of these three commodities.

4.4 The Prediction and Model Performance

After above analysis of conditional mean and conditional variance, we plot price linkage and volatility spillover effects for hops and barley with other future commodities including soft red wheat, hard red wheat and corn. To test the performance of these models, we also plot the prediction versus the real for hops and barley in figure 2 and figure 3. For the VAR model, we plot the predicted logarithmic price returns with the real. And for VECM model, we plot the predicted logarithmic prices with the real. Besides, the 95% confidence interval considering ARCH effects are also added.

For hops prediction in figure 2, there are many deviations between the predicted and real value for all VAR type models especially in some large volatility time periods. But considering the ARCH effects, it still makes the prediction and the real be covered in the confidence interval. The last plot is the prediction for hops-barley system using VEC model, and it shows the prediction versus the real for logarithmic prices. The prediction is much improved comparing with other system, this may due to the existing of long-run relationship.

Observe from the prediction plot for barley in figure 3, all the deviation is relatively small. And for some high volatility periods, the confidence interval can still exhibit the same fluctuation and cover the real and predicted. These reflects the great performance of the model fits the data in this analysis.

Table 7: Pairwise ARCH Model Results

Empirical Model

$$\boldsymbol{e_t}\left|\boldsymbol{I_{t-1}} = \begin{pmatrix} e_{i,t} \\ e_{j,t} \end{pmatrix}\right|\boldsymbol{I_{t-1}} \sim N(0, \boldsymbol{H_t}) \quad \text{i, j } = \text{hops, barley, soft red wheat, hard red wheat, corn}, \ i \neq j$$

$$\boldsymbol{H_t} = \begin{pmatrix} C_{11} & C_{12} \\ C_{12} & C_{22} \end{pmatrix} + \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}' \begin{pmatrix} e_{i,t-1} \\ e_{j,t-1} \end{pmatrix} \begin{pmatrix} e_{i,t-1} \\ e_{j,t-1} \end{pmatrix}' \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}, \ \text{i, j } = \text{hops, barley, soft red wheat, hard red wheat, corn}, \ i \neq j$$

Parameter	Estimates	t-Value	Parameter	Estimates	t-Value
Hops and Soft Red Wheat					
C_{11}	0.01833***	7.75	A_{11}	0.13650	1.25
C_{12}	0.00009	0.12	A_{12}	-0.26938***	-4.28
C_{22}	0.00323***	5.59	A_{21}	-0.91778***	-3.32
			A_{22}	0.34012***	3.02
Hops and Hard Red Wheat					
C_{11}	0.02013***	7.64	A_{11}	0.30996	1.51
C_{12}	-0.00005	-0.05	A_{12}	-0.28585***	-4.97
C_{22}	0.00282***	5.72	A_{21}	-0.10098	-0.18
			A_{22}	0.12436	0.88
Hops and Corn					
C_{11}	0.02166***	3.55	A_{11}	0.13582	0.21
C_{12}	-0.00110	-0.51	A_{12}	-0.08806	-0.5
C_{22}	0.00483***	5.74	A_{21}	0.24469	0.17
			A_{22}	-0.04454	-0.10
Hard red wheat and Corn					
C_{11}	0.00433***	7.20	A_{11}	0.30475	1.37
C_{12}	0.00294***	6.91	A_{12}	-0.22556	-0.96
C_{22}	0.00482***	8.12	A_{21}	-0.31719*	-1.67
			A_{22}	020993	1.01
Barley and Hops					
C_{11}	0.00204***	6.53	A_{11}	-0.20348	-1.03
C_{12}	0.00105*	1.70	A_{12}	0.74388*	1.79
C_{22}	0.02223***	8.23	A_{21}	0.07208	1.35
			A_{22}	0.11006	0.80
Barley and Soft red wheat					
C_{11}	0.00161***	6.64	A_{11}	-0.04806	-0.41
C_{12}	0.00008	0.31	A_{12}	-0.50330***	-2.76
C_{22}	0.00466***	8.04	A_{21}	-0.25538***	-2.80
			A_{22}	0.11378	0.90
Barley and Hard red wheat					
C_{11}	0.00159***	7.05	A_{11}	-0.02674	-0.18
C_{12}	-0.00004	-0.16	A_{12}	-0.49480***	-2.92
C_{22}	0.00410***	8.05	A_{21}	-0.27896***	-3.28
			A_{22}	0.05111	0.48
Barley and Corn					
C_{11}	0.00152***	7.05	A_{11}	0.05573	0.35
C_{12}	-0.00011	-0.32	A_{12}	0.70754***	4.44
C_{22}	0.00393***	7.72	A_{21}	-0.31485***	-4.02
			A_{22}	-0.06854	-0.47
Soft red wheat and Corn					
C_{11}	0.00537***	9.45	A_{11}	0.01539	0.07
C_{12}	0.00310***	5.99	A_{12}	-0.38482**	-2.18
C_{22}	0.00429***	7.20	A_{21}	-0.09887	-0.56
			A_{22}	0.19997	1.22

5. Conclusions

The increasing demand for beer in recent years has required more input of barley and hops. Thus, the risk in price volatility of barley and hops may lead to the risk in profit for craft beer sector in United Stated. It is very important to use the possible financial instrument such as cross-hedging to deal with the price risk. However, the lack of evidence of price linkage and volatility effects with related agricultural products may affect the performance of price management for craft breweries.

The purpose of this paper is to investigate the price linkage and volatility effects for barley and hops with soft red wheat, hard red wheat and corn. The results of these relationships provide useful information for the craft beer sector and growers to manage the price risk from barley and hops. It also offers economic suggestions for policy makers.

Using the data from 2002 January to 2017 April, we perform diagnostic tests and apply VAR models for hops related systems, finding that hops price is mainly affect by its own previous price and the previous prices of soft red wheat and hard red wheat in the short-run. The only long-run equilibrium for hops exists in a hops-barley system. Hops has a very quick reaction to the deviation of this long-run path at speed of 20.8% per month. For barley, the long-run relationships are confirmed in all systems including barley-soft red wheat, barley-hard red wheat and barley-corn, in which barley will make the fastest reaction in barley-corn system at a speed of 7.1% per month. There are also short-run effects for barley among these systems, but all of them are from its own lagged effects.

Regarding the volatility effects analysis, we employ the BEKK-ARCH model after the analysis of conditional mean model. We show that the volatility of hops is caused by the spillover effects of its own past shock and the spillover effects from soft red wheat and barley. Spillover effects are bidirectional for hops-soft red wheat, that means hops will also transfer the spillover effects on the volatility of soft red wheat. However, for the volatility of barley, the bidirectional spillover effects are confirmed in barley-soft red wheat, barley-hard red wheat and barley-corn.

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Appendix

Figure 2: The Plots for Logarithmic Price Return

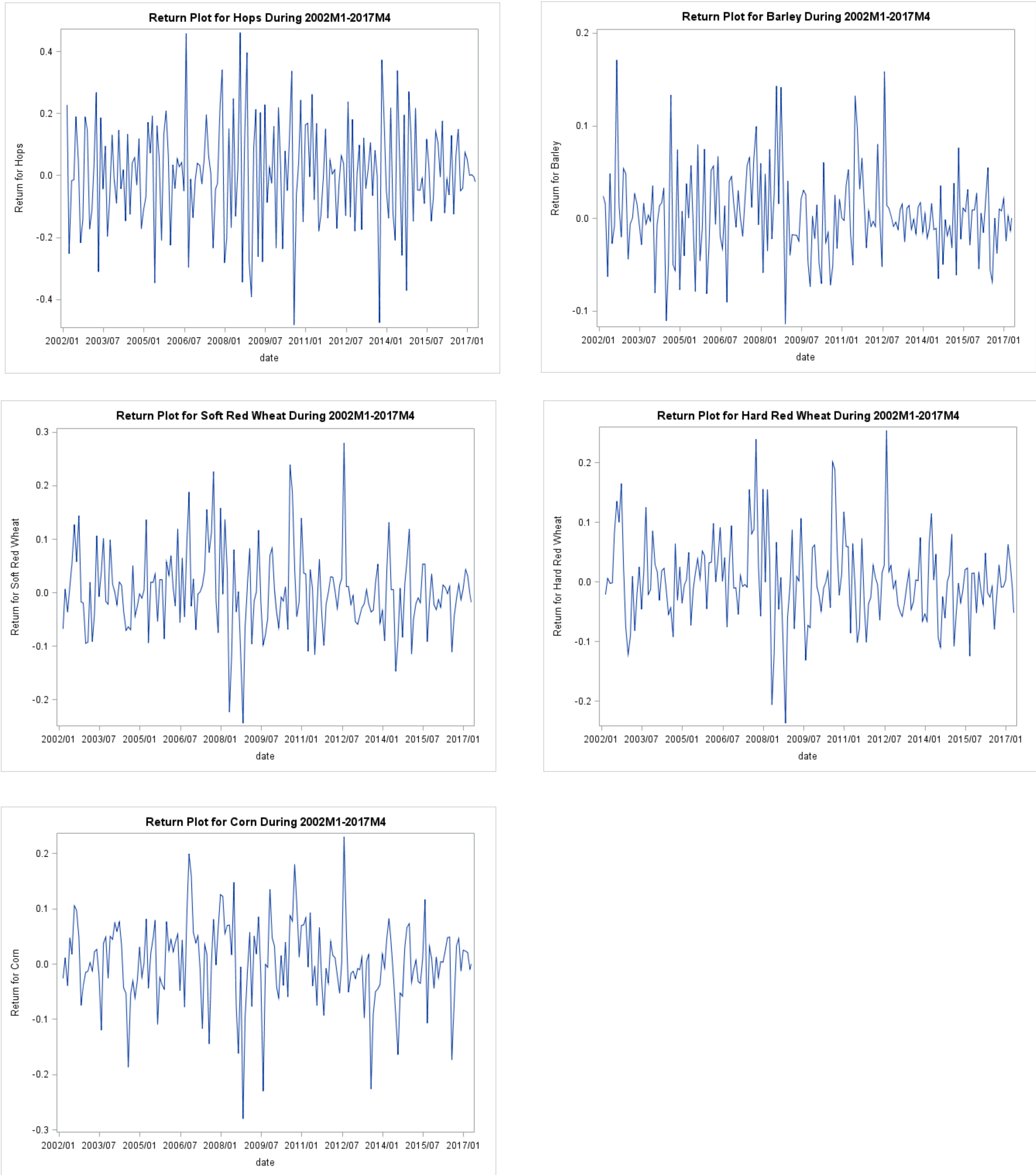

Figure 3: The Plots of Prediction and Confidence Interval for Hops under VAR and VEC Model

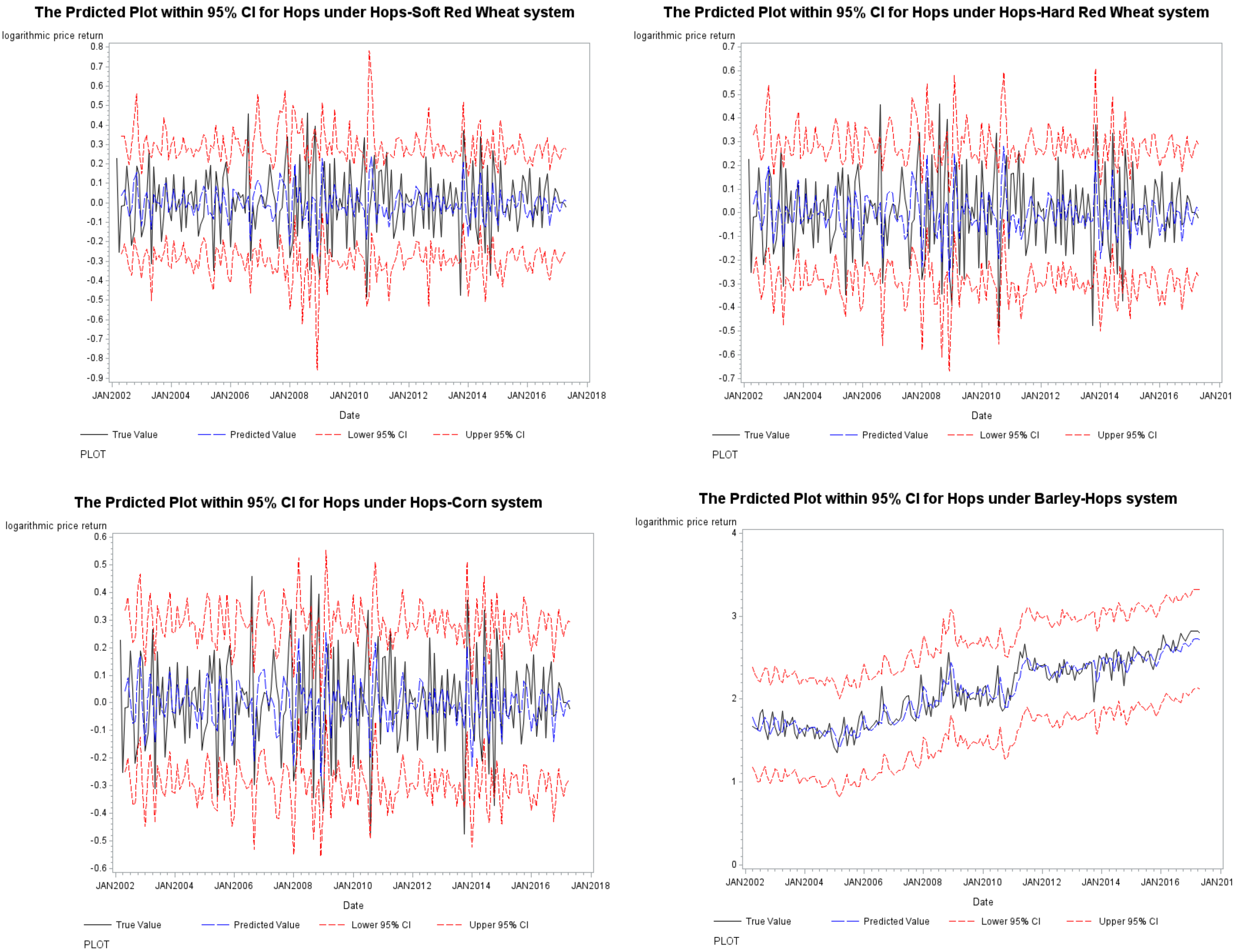

Figure 4: The Predicted VS. Real Logarithmic Price for Barley under VECM Model