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# Measuring Asymmetric Price Transmission in the U.S. Hog/Pork Markets: A Dynamic Conditional Copula Approach

by

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**Measuring Asymmetric Price Transmission in the U.S. Hog/Pork Markets:**

**A Dynamic Conditional Copula Approach**

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## Abstract

This paper introduces the application of copula models to the empirical study of price transmission, with an empirical application to the U.S. hog/pork markets. Our copula approach corrects the potential bias in estimation that results from ignoring the volatility by modeling the marginal distribution of price changes through GARCH models. We also develop and apply a flexible time-varying copula framework to estimate dynamic transmission coefficients /elasticicities. The model results confirm the existence of time-varying and asymmetric behaviour in price co-movements between the farm and retail markets. Positive upper and zero lower tail dependences provide evidence that big increases in farm prices are matched at the retail level whereas negative shocks at the farm level are less likely to be passed on to consumers. The application of copula techniques provides multiple, useful extension and generalizations of conventional approaches for modeling asymmetric transmissions processes on the degree of market integration and its response to price shocks under the extreme market conditions.
Keywords: asymmetric price transmission, copula, time-varying copula

## Introduction

Vertical price transmission links input prices to output prices and often investigates the extent to which retail commodity markets are impacted by changes at the raw material level. The degree to which market shocks are transmitted up and down the marketing chain has long been considered to be an important indicator of the performance of the market. Much of the motivation underlying this line of research has involved concerns about market power and potential effects that increased market concentration may have on price adjustment processes.

A wide variety of empirical research has been focused on the asymmetry of price transmission (APT). Meyer and von Cramon-Taubadel (2004) and Frey and Manera (2007) provided comprehensive reviews of the theoretical and empirical issues underlying this literature. Early work in asymmetric adjustments usually divided price changes in input prices into two groups conditioned on the direction or magnitude of changes, and then investigated transmission coefficients of each case (e.g., Houck 1977). Recent empirical research realized the nonstationary feature of time series data and applied cointegration techniques while focusing on asymmetric adjustments using regime-switching models (e.g., Serra and Goodwin 2003) or asymmetric long run price linkage (e.g., Gervais 2011 and Abbassi et al. 2012).

Several concerns are associated with the existing approaches. First, almost all of the existing empirical studies in price transmission have assumed constant variance, though price and price change data are often quite volatile. Ignoring volatility in empirical analysis can lead to bias estimation of the transmission and adjustment coefficients. Second, although these modern empirical tools (e.g., threshold and smooth transition models) have provided some convenience in modeling APT, they are not flexible enough to represent constantly changing market conditions, especially short run dynamics. For example, a three regime threshold or smooth transition error correction model allows price adjustment to have three different reactions based on the magnitude and/or direction of previous deviation from the long run price equilibrium. However, the adjustment speeds or transmission coefficients are still assumed to be linear and constant within each regime. In reality, even given the similar levels of deviation, the adjustments can still differ based on other forces such as policy intervention and market power.

Another important feature in market integration is price co-movements under extreme market conditions. For instance, we are interested in investigating the probability that one will observe an extremely large adjustment of output price given an extremely large increase of input price. In statistics, we call this "tail dependence." Goodwin et al. (2011) argued that many regime-switching models (e.g., threshold and smooth transition error correction models) allow price adjustments to vary as the market situation changes. When the deviation serves as the forcing variable, the transmission coefficient in the regime that changes beyond (below) the upper (lower) threshold is intuitively equivalent to a reflection of upper (lower) tail dependence. This argument, however, is questionable as it ignores the fact that regime switching models require the threshold to lie between the maximum and minimum values of the series. A congenital practice is between 15th and 85th quintiles of the observations. That said, the highest and lowest 15% of the values are excluded from the search so as to ensure an adequate number of observations on each side of the threshold/regime. Therefore, these regime switching models cannot provide such close information as tail dependence.

These limitations motivate the search for more flexible alternative measures of co-movements (or more broadly speaking, dependence structure). A flexible modeling technique, which 1) controls the volatility issue and 2) allows for a more flexible interrelationship (such as nonlinear, time-varying, multi-variable driven, and handles tail dependence) to exist, will be helpful in better understanding price transmission and market integration issues. Copula models separate marginals and dependence structures and allow more flexibility in modeling the dependence/relationship structures of price co-adjustments. The copula approach thus serves as a promising candidate.

The objective of this study is to introduce the application of copula models to the empirical study of APT, with an empirical application to the U.S. hog/pork markets. Our contributions are threefold. First, we correct the potential bias in estimation that results from ignoring the volatility by modeling the marginal distribution of price changes through GARCH models. Second, we extend Patton's (2006) conditional copula concepts and adopt Patton (2012) and Creal's *et al.* (2011) time varying concepts to allow the price co-movements to be dynamic. This provides more flexibility as it allows for the possibility of both asymmetric adjustments and structural changes in price transmission.

**Copula Approach**

What is a copula? Copula means join, couple, tie, and bond. A copula is a multivariate distribution whose marginals are all uniform over (0, 1). Given the fact that any continuous random variable can be transformed to be uniform over (0, 1) by its probability integral transformation, $U_i \equiv F_i(Y) \sim Unif(0,1)$, copulas can be used to provide multivariate dependence structure separately from the marginal distributions. For example, a two-dimensional joint distribution can be decomposed into two marginal distributions and a two-dimensional copula:

$$\text{Let } Y \equiv [Y_1, Y_2]' \sim F(y_1, y_2), \text{ with } \mathrm{Y}_1 \sim F_1 \text{ and } \mathrm{Y}_2 \sim F_2$$

$$\text{then } \exists \text{ C: } [0,1]^2 \rightarrow [0,1]$$

$$\text{s.t. } F(y_1, y_2) = C(F_1(y_1), F_2(y_2)) \ \forall (y_1, y_2) \in R^2 \tag{1}$$

Patton (2006; 2012) extended the concept of standard copulas to conditional copulas:

$$\text{Let } Y \equiv [Y_1, Y_2 \mid M_{t-1}]' \sim F(y_1, y_2), \text{ with } \mathrm{Y}_1 \mid M_{t-1} \sim F_1 \text{ and } \mathrm{Y}_2 \mid M_{t-1} \sim F_2$$

$$\text{then } \exists \text{ C: } [0,1]^2 \rightarrow [0,1]$$

$$\text{s.t. } F(y_1, y_2 \mid M_{t-1}) = C(F_1(y_1 \mid M_{t-1}), F_2(y_2 \mid M_{t-1})) \ \forall (y_1, y_2) \in R^2 \tag{2}$$

where $M_{t-1}$ is the information set.

A copula function contains all the information about the dependence between random variables. In the price transmission case, if we know the specific copula of the two price adjustments, then we shall be able to obtain all the relevant information regarding the co-movements and transmission between the two prices. However, numerous different copulas exist and each is associated with different dependence attributes (e.g., asymmetry or symmetry, tail dependence or no tail dependence, both upper and lower tail dependence or just one side tail dependence).

For example, the Normal copula allows a symmetric dependence structure and does not allow the tail dependence; the Student's t copula allows for joint extreme events in both tails. Assume a positive shock occurs in one market, and that prices are more likely to be co-adjusted when an extremely big price change has been observed, but price shocks would not be transmitted to one another when the changes are very small. Then the Gumbel copula, which is an asymmetric copula, exhibiting greater dependence in the upper tail than in the lower, might be an appropriate choice. The Clayton copula is also an asymmetric copula, but it exhibits greater dependence in the lower tail than in the upper. For more detailed discussions regarding the dependence attributes associated with different copulas, we recommend readers to Joe (1997) and Nelsen (2006), among many others.

Given a wide range of copulas, how one should choose the most appropriate copula is an essential issue in real applications. It is important to first investigate the summary dependence attributes of the interested variables before the choice of potential copula models. Careful pre-estimation explanatory analysis and post-estimation model selection and comparison tests will help to find the most appropriate copula models.

The empirical procedure for the copula application in the price transmission analysis can be divided into 4 steps. First, model the conditional marginal distribution functions for the two price adjustments. Second, estimate the parameters for selected copula models based on the estimation of the marginal distributions from the first step and preliminary dependence investigation. Third, compare and select the appropriate copula(s) using certain selection criteria. Fourth, interpret the copula results and apply them to the analysis of APT.

*Model Marginal Distributions*

We denote the retail, wholesale, and farm prices as $P^R, P^W$ and $P^F$, respectively, and log-differences as $p^R, p^W$ and $p^F$ correspondingly, where $p_t^i = \log(P_t^i) - \log(P_{t-1}^i)$ is the difference of natural logarithm prices.

The first step is to model the marginal distribution for each price changes, which is equivalent to modeling the distribution of standardized residuals. Before we proceed to the marginal distribution modeling, we first need to model the conditional mean and variance to obtain the standardized residuals. We specify the conditional means and variances for log-difference of the prices using an autoregressive and GARCH framework, and Cross-equation effects are also included in the conditional mean models when applied:

$$\begin{cases} p_t^{input} = \alpha_1 + \sum_{i=1} \beta_{1i} p_{t-i}^{input} + \sum_{j=1} \gamma_{1j} p_{t-j}^{output} + \sigma_{1t}\varepsilon_{1t}, \quad \text{and } \varepsilon_{1t} \sim F_1(0,1) \\ p_t^{output} = \alpha_2 + \sum_{i=1} \beta_{2i} p_{t-i}^{input} + \sum_{j=1} \gamma_{2j} p_{t-j}^{output} + \sigma_{2t}\ \varepsilon_{2t}, \quad \text{and } \varepsilon_{2t} \sim F_2(0,1) \end{cases} \tag{3}$$

where

$p^{input}$ =retail price changes and $p^{output}$ = wholesale price changes, for the retail-wholesale pair
$p^{input}$ =retail price changes and $p^{output}$ = farm price changes, for the retail-farm pair
$p^{input}$ =wholesale price changes and $p^{output}$ = farm price changes, for the wholesale-farm pair

After the estimation of AR-GARCH models for the price adjustments, we construct the standardized residuals as:

$$\hat{\varepsilon}_k = \frac{p_t^{\,k} - \left( \hat{\alpha}_k + \sum_{i=1} \hat{\beta}_{ki}\, p_{t-i}^{input} + \sum_{j=1} \hat{\gamma}_{kj}\, p_{t-j}^{output} \right)}{\hat{\sigma}_{kt}}, \quad k = output, input \tag{4}$$

Many choices are possible for the parametric model for marginal distributions for the standardized residuals, including Normal, standardized t, skewed t (as in Patton 2012) and others. In this study, we test and estimate the skewed t, which allows Normal (when the degree of freedom is close to infinite) and standardized t (when the skewness parameter equals zero) as two special cases. The Cramer-von Mises (CvM) test can be utilized to test the null of skew t distribution.

*Pre-Copula Measurement of Sample Dependence*

By far the most familiar dependence concept is the correlation coefficient. Correlation coefficient has important applications in price transmission studies. For the two variable case, the estimated transmission (elasticity) coefficient $\hat{\beta}$ is simply a product of Pearson correlation coefficient and the ratio of standard deviations of prices, i.e. $\hat{\beta} = \hat{\rho} * \hat{\sigma}_y / \hat{\sigma}_x$. Constant variance (as usual in the existing literature) means asymmetric response or speed of adjustment $\hat{\beta}$ will be determined by the correlation coefficient alone. The dependence structure of elliptical copula family is fully determined by the correlation coefficient (bivariate case) or correlation matrix (multivariate case).

Person correlation has certain unpleasant limitations as a way to measure the dependence structure such as it is only valid under strict linear transformations. When applied to the price transmission study, the transmission or adjust coefficient changes when one uses the logarithm of the prices. As a remedy, the rank correlation is invariant under strictly increasing transformations. Mimicking the familiar approach of Pearson to the measurement of dependence, a natural idea is to compute the correlation between the ranks.

In some cases, the concordance between tail (extreme) values of random variables is of interest. For example, one may be interested in the probability that price adjustments in two markets exceed or fall below given levels. This requires a dependence measure for the upper or lower tails of the distribution. Such a dependence measure is essentially related to the conditional probability that one price change exceeds some value, given that another exceeds some extreme value. The coefficients of upper and lower tail dependence of (X,Y) are defined as:

$$\lambda_U(Y_1, Y_2) = \lim_{h \to 1^-} P(Y_2 > F_2^{-1}(h) \mid Y_1 > F_1^{-1}(h)),$$
$$\lambda_L(Y_1, Y_2) = \lim_{h \to 0^-} P(Y_2 < F_2^{-1}(h) \mid Y_1 < F_1^{-1}(h)), ,$$

Tail dependence is a measure of the dependence between extreme events, and population tail dependence can be obtained as the limit of population quantile dependence as h $\to 0$ or h $\to 1$.

*Copula Estimation and Model Selection*

After exploring the summarized dependence statistics of the sample data, the next step would be to choose the potential appropriate copulas for estimation. The most commonly used estimation method is the maximum likelihood. Simultaneous estimation of all parameters using the full maximum likelihood (FML) approach is the most direct estimation method. Although estimating all of the coefficients simultaneously yields the most efficient estimates, the large number of parameters can make numerical maximization of the likelihood function difficult.

An alternative method would be a sequential 2-step maximum likelihood method (TSML) in which the marginals are estimated in the first step and the dependence parameter is estimated in the second step, using the copula after the estimated marginal distributions have been substituted into it. This method exploits an attractive feature of copulas for which the dependence structure is independent of the marginal distributions. This second method has additional variants depending upon whether the first step is implemented parametrically or non-parametrically, and on the method used to estimate the variance of the dependence parameter(s) at the second stage. Under standard conditions, the estimates obtained from TSML are consistent and asymptotically normal (Patton 2006).

We adopt the TSML method in this study. Estimate the marginal distributions first and then use the estimated parameters to estimate the copulas using the maximum likelihood function. In addition to the constant copulas, we also test and estimate the time-varying copula as discussed in Creal *et al* (2011). The specification allows the dependence parameters to be a function of the lagged copula parameter and a “forcing variable” that is related to the standardized score of the copula log-likelihood.

Our model selection is based on the goodness of fit tests and in-sample model comparison discussed in Patton (2012). The former determine whether the proposed copula model is different from the (unknown) true copula. The latter seeks to determine which model in a given set of competing copula models is the “best”, according to some measure.

**Data**

Monthly data on hog and pork prices from January 1970 to March 2003 are collected from USDA. Prices are deflated to the real price level using the CPI (1982-1984=100). Figure 1 displays the logarithm farm, wholesale and retail price series. We are interested in investigating the dependence structure between any pair-wise price adjustments/co-movements. The farm price reached a historical minimum in November 1994 and dropped to the lowest level in December 1998, the so called “hog crisis”. The wholesale price and farm price are relatively correlated to each other as shown in this graph. In the early days, two series are seemed to be more correlated to each other. However, the margin becomes larger as time goes by and as the real price declined. Figure 2 present the pair-wise price and price changes time series plots.

**Results**

All analyses are conducted based on the data series in logarithms. We begin by assessing the time series properties of price series using the standard Augmented Dickey-Fuller (ADF) test and the Phillips–Perron test. Both unit root tests fail to reject the unit root hypothesis for the price series, but are not able to reject stationarity for the price change series. Thus, the price change series may be considered as stationary processes. Summary statistics of three price change series are presented in Table 1.

*Marginal Distributions*

Based on the AIC or BIC, the results of the conditional means and variances as well as the cross-equation effects for each pair-wised price change using Equations (3) are presented in Table 2. For the farm-whole case, the optimal models were found to be an AR(2) for the farm price changes and an AR(1) for the wholesale price changes. Testing for the significance of three lags of the "other series", conditional on these models, finds no evidence of significant cross-equation effects in the conditional mean. For the wholesale-retail and farm-retail cases, we find two and one lag cross-equation effects respectively.

Using the estimated results of the conditional mean and volatility, we obtain the standardized residuals via Equation (4). Results from modeling the marginal distribution of skewed t distribution and the Cramer-von Mises (CvM) test results are presented in Table 3. For the standardized residuals obtained from farm price changes, the skewness parameters are close to zero, which indicate a standard t distribution with no skews. For those standardized residuals from the wholesale and retail price changes, the positive skewness parameter means the distributions are asymmetric positively skewed. CvM test results fail to reject the null hypothesis that skew t is an appropriate distribution for modeling all of the six standardized residuals. Figure 3 visualizes the goodness of fit.

*Pre-Copula Dependency Investigation*

We then obtain the standardized residuals for dependence analysis. Figure 3 shows the pair-wise scatter plots of price changes and standardized residuals to visualize the dependency between different markets. Before we move to the copula modeling, it is necessary and helpful to explore some summary statistics of dependence to help choose the appropriate copula model(s). Pre-Copula dependency investigation results using nonparametric methods are summarized in Table 4. Pearson and Spearman correlation coefficients indicate that the farm level and wholesale level prices are more linked to each other and potentially more likely to be co-adjusted. The tail dependence presented in Table 4 utilized the nonparametric method proposed by Frahm (2005). All three pairs present positive upper and lower tail dependence. Farm-wholesale price changes exhibit stronger tail dependence than the farm-retail and wholesale-retail cases. These indicate that under the market extremes, farm and wholesale market prices are more likely to adjust/move together. Under each price pair, the upper tail dependence is higher than the lower tail dependence. This indicates that price co-adjustments are more likely to be observed when there are extremely large price increases, compared to the extremely large price decrease situations. However for the wholesale-retail and the farm-retail cases, the 90% bootstrapping confidence intervals include the zero (or close to zero), which means it is possible for these price changes to have no/zero dependence.

Based on the above results, we may narrow down the copula options which allow one-direction dependence structure (positive); copulas with and without tail dependence; and we don't limit the candidates to have asymmetric tail dependence only. Thus we narrow down our potential copula to the following eight models: Normal, Clayton, Rotated Clayton, Plackett, Frank, Gumbel, Rotated Gumbel and Student t.[1]

*Constant Copulas*

The estimate results from eight constant copulas are listed in Table 5. Based on the log likelihood (LL) values, we picked the two best-fit copula models for each pair of price adjustments. For the farm-wholesale and farm-retail cases, the two best fit copulas are Gumbel and Student t. The Gumbel copula allows for upper tail dependence and no lower dependence; while the Student t copula indicates both upper and lower tail dependences exist. For the wholesale-retail case, the two best fit copulas are Normal and Student t. The Normal copula indicates no tail dependence, which in the price co-movement case means market do not integrated to each other when there are extremely large shocks in the market price. Tail dependences from the two best-fit copulas for each case are presented in Table 6. This is just a preliminary procedure of the model selection to narrow down the final options. We will need some formal tests to help us decide the best choice based on the information we have.

Based on our estimations, we have two potential copula models available for each pair of markets. Since different copulas could have very different interpretations of dependence structure, we need to be very careful in the model selection. We adopt the

[1] For more detailed information regarding the associated attributes for these commonly used copulas, see Nelsen (2006).

CvM and Kolmogorov-Smirnov (KS) goodness of fit tests (Patton 2012) to see if the estimated models have the same distribution as the empirical distribution functions. The results of goodness of fit tests are presented in Table 7. All tests cannot reject the null that the selected copulas have the same family as the empirical copula. The selection ranks are based on the in-sample model comparison discussed by Patton (2012). Model comparison indicates that the student t copula fits the best for the farm-wholesale and wholesale-retail cases, but the Gumbel copula fits the best.

*Time-Varying Copulas*

As previously mentioned, the dependence structure may also exhibit time-varying attributes because of factors like the structural change of the industry, new policy regime, improvement in infrastructural facility and unexpected market shocks. We thus test the time-varying correlation to see if the dependence structure changes dynamically. We adopt Patton's (2006) test for time-varying dependence that allows for a break in the rank correlation coefficient at some unknown date. The results are showed in Table 7. For the farm-wholesale and wholesale-retail cases, the results are not able to reject the null hypothesis of constant dependence structure. However, for the farm-retail case, the test rejects the constant rank correlation hypothesis. We therefore proceed to the time-varying copula estimation procedure for the farm-retail case. The model specification follows the Creal suggestion. The estimate results (Table 8) indicate that the time-varying copulas have higher AIC compare to its corresponding constant copula cases.

For the tail dependence of the time-varying copula models, the t copula suggests a close to zero dependence and the Gumbel indicates declining positive upper tail dependence and zero lower tail dependence. Consider the situations near the two very extreme conditions, the 1994 and 1998 crisis. The two markets had very limited linkage when the prices were dramatically declining. This provides some evidence for the market power APT hypothesis, which argues the retailers have more market power. When there is a huge positive shock in the farm level price, the retail price will increase correspondingly; however, if there is a negative price adjustment (i.e., decrease in prices), the retailers might not lower the price accordingly.

*Time-Varying Pearson Correlation Coefficients*

Though the Pearson correlation coefficient is associated with many limitations as a measurement of dependency, it is still the most widely used tool when measuring the relationship between two prices and price adjustments. More specifically, the linear correlation coefficient has important implications in the price transmission literature. The transmission coefficient (or elasticity, or adjust speed) is a product of the Pearson correlation coefficient and the ratio of standard deviations. The widely adopted regime-switching models allow the transmission coefficient or speed to be different in each regime. However, within the same regime, it is still just a product of linear correlation coefficient and ratio of standard deviations. Time-varying linear correlation coefficient can be derived from the time-varying copulas. Given the specification for our price change time series model in equation (2), the time-varying correlations of the two variables can be expressed as:

$$\begin{aligned}\rho_{t-1} &= Corr_{t-1}(Y_1, Y_2) = Corr_{t-1}(\varepsilon_{1t-1}, \varepsilon_{2t-1}) \\ &= E_{t-1}(\varepsilon_{1t-1}, \varepsilon_{2t-1}), \text{ where } \varepsilon_{it-1} \mid M_{t-1} \sim F_i(0,1) \\ &= E_{t-1}[F_1^{-1}(U_1), F_2^{-1}(U_2)]\end{aligned}$$

The expression usually cannot be obtained analytically, however this can be solved by using the two-dimensional numerical integration as suggested by Patton (2012):

$$E_{t-1}[F_1^{-1}(U_1), F_2^{-1}(U_2)] = \int_0^1 \int_0^1 F_1^{-1}(u_1) F_2^{-1}(u_2) c(u_1, u_2; \theta(t)) du_1 du_2 \qquad (5)$$

where c is the probability density function of the copula. The results of the numerical integrated dynamic Pearson correlation coefficients from the time-varying Gumbel and t copula are plotted in Figure 5.[2]

As a summary, these results from copula models indicate that farm and wholesale markets are more closely related to each other. Retail price adjustment is less dependent on the other two markets. Farm-retail and retail-wholesale price adjustments have relatively constant dependence structures, but farm-retail price adjustments exhibit a dynamic, time-varying relationship. The dynamic linear correlation coefficients decrease as time goes by (as real prices decrease). This relationship may reflect the market power of retailers.

[2] Dynamic price transmission coefficients can be obtained by using the time-varying correlation coefficients and the time-varying standard deviation obtained from the marginal distribution estimation. This is an ongoing work and shall provide more informative data regarding the asymmetric transmission or adjustment.

In terms of price co-movements under market extremes for the farm-wholesale and wholesale-retail situations, constant tail dependence indicates that markets are linked to each other under extreme market conditions. Shocks, both positive and negative, in one market would transfer to the other market. For the farm-retail case, dependency under extreme market conditions is decreasing dynamically. Under very extreme conditions (i.e., in December 1994 when hog prices reach the historical low, and the 1998 hog crisis), lower tail dependence reached a very low (close to zero) level. This provides evidence that a retail price does not respond to a dramatic reduction in a farm level price.

## Conclusions

Copulas are useful extensions and generalizations of approaches for modeling joint distributions and dependency that have appeared in the literature. Their applications on price transmission (e.g., long-run equilibrium, short-run adjustment and price linkage among relevant markets or along the supply chain), when allowing time-varying transmission coefficients, shall offer valuable information for understanding the price transmission and draw significant attention at the meeting section discussion.

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Table 1. Summary Statistics of Log Price Changes

| | Farm | Wholesale | Retail |
|---|---|---|---|
| Mean | -0.003 | -0.003 | -0.001 |
| Std dev | 0.088 | 0.048 | 0.025 |
| Skewness | 0.481 | 0.441 | 1.325 |
| Kurtosis | 7.074 | 4.151 | 11.798 |

Table 2. Models for Conditional Mean and Variance

| Farm and wholesale | Wholesale and retail | Farm and retail |
|---|---|---|
| F: AR(2)-GARCH(1,1) | W: AR(1)-CE(2)-GARCH(1,1) | F: AR(2)-CE(1)-GARCH(1,1) |
| W: AR(1)-GARCH(1,1) | R: AR(1)-CE(2)-GARCH(1,1) | R: AR(1)-CE(1)-GARCH(1,1) |

Table 3. Skew t Density Parameters and Tests

| | Farm | Wholesale | Wholesale | Retail | Farm | Retail |
|---|---|---|---|---|---|---|
| Degree of Freedom | 14.389 | 15.738 | 17.774 | 4.149 | 17.231 | 3.893 |
| Skewness | 0.024 | 0.173 | 0.158 | 0.158 | 0.038 | 0.130 |
| CvM p value | 0.380 | 0.460 | 0.720 | 1.000 | 0.200 | 0.580 |

Table 4. Pre-Copula Dependency Summary

| | Farm and wholesale | Wholesale and retail | Farm and retail |
|---|---|---|---|
| Pearson | 0.87 | 0.55 | 0.42 |
| Spearman<br>(90% bootstrapping CI) | 0.87<br>(0.83, 0.89) | 0.48<br>(0.41, 0.54) | 0.41<br>(0.34, 0.48) |
| Lower tail | 0.46<br>(0.14, 0.83) | 0.26<br>(0.02, 0.65) | 0.12<br>(0.00, 0.54) |
| Upper tail | 0.67<br>(0.31, 0.95) | 0.31<br>(0.05, 0.71) | 0.23<br>(0.02, 0.66) |

Table 5. Estimate some constant copulas

| **Farm & wholesale** | **param1** | **param2** | **LL** |
|---|---|---|---|
| Normal | 0.874 | | 288.5 |
| Clayton | 2.321 | | 197.9 |
| Rot Clayton | 3.016 | | 255.1 |
| Plackett | 32.630 | | 280.1 |
| Frank | 9.000 | | 266.5 |
| Gumbel | 3.040 | | 292.1 |
| | (0.122) | | |
| Rot Gumbel | 2.804 | | 258.0 |
| Student's t | 0.877 | 0.110 | 292.1 |
| | (0.011) | (0.052) | |
| **Wholesale & retail** | **param1** | **param2** | **LL** |
| Normal | 0.506 | | 58.9 |
| | (0.060) | | |
| Clayton | 0.695 | | 43.9 |
| Rot Clayton | 0.732 | | 48.7 |
| Plackett | 4.686 | | 53.6 |
| Frank | 3.310 | | 51.9 |
| Gumbel | 1.465 | | 56.7 |
| Rot Gumbel | 1.449 | | 54.2 |
| Student's t | 0.505 | 0.107 | 61.2 |
| | (0.060) | (0.062) | |
| **Farm & retail** | **param1** | **param2** | **LL** |
| Normal | 0.433 | | 41.3 |
| Clayton | 0.502 | | 24.8 |
| Rot Clayton | 0.611 | | 38.4 |
| Plackett | 3.646 | | 37.6 |
| Frank | 2.761 | | 37.2 |
| Gumbel | 1.367 | | 41.5 |
| | (0.061) | | |
| Rot Gumbel | 1.333 | | 32.6 |
| Student's t | 0.436 | 0.050 | 41.8 |
| | (0.046) | (0.044) | |

Note: bootstrap standard errors in parentheses.

Table 6. Tail dependence from the best two copulas

| **Farm & wholesale** | Upper tail | Lower tail |
|---|---|---|
| Gumbel | 0.795 | 0 |
| Student's t | 0.829 | 0.829 |
| **Wholesale & retail** | | |
| Normal | 0 | 0 |
| Student's t | 0.646 | 0.646 |
| **Farm & retail** | | |
| Gumbel | 0.322 | 0 |
| Student's t | 0.632 | 0.632 |

Table 7. Goodness of Fit Tests

| | KS_R | CvM_R | Rank |
|---|---|---|---|
| Farm & wholesale | | | |
| Normal | 0.5 | 0.5 | 3 |
| Gumbel | 1 | 1 | 2 |
| Student t | 0.5 | 0 | 1 |
| Wholesale & retail | | | |
| Normal | 0.4 | 0.4 | 2 |
| Gumbel | 0.4 | 0.4 | 3 |
| Student t | 0.95 | 1 | 1 |
| Farm & retail | | | |
| Normal | 0.95 | 0.95 | 3 |
| Gumbel | 0.85 | 1 | 2 |
| Stud t | 0.9 | 0.9 | 1 |
| Time-Varying Gumbel | 0.35 | 0.2 | NA |
| Time-Varying-Student t | 0.15 | 0.35 | NA |

Table 8. Tests for Time-Varying Dependence

| | p-value |
|---|---|
| Farm & wholesale | 0.74 |
| Wholesale & retail | 0.19 |
| Farm & retail | 0.05 |

Table 9. Estimate Time-Varying Copulas for Farm-Retail Price Changes

| | | Parametric |
|---|---|---|
| Gumbel | Omega | -0.0067 |
| | | (0.0652) |
| | Alpha | 0.0646 |
| | | (0.1066) |
| | Beta | 0.9990 |
| | | (0.1106) |
| | Log L | 50.3323 |
| | | |
| Student *t* | Omega | -0.0022 |
| | | (0.0344) |
| | Alpha | 0.0693 |
| | | (0.0523) |
| | Beta | 0.9982 |
| | | (0.0294) |
| | V_1 | 0.0101 |
| | | (0.0021) |
| | Log L | 56.3352 |

Table 9. Goodness of Fit Tests

| | KS_R | CvM_R | Rank |
|---|---|---|---|
| Farm & wholesale | | | |
| Normal | 0.5 | 0.5 | 3 |
| Gumbel | 1 | 1 | 2 |
| Student t | 0.5 | 0 | 1 |
| Wholesale & retail | | | |
| Normal | 0.4 | 0.4 | 2 |
| Gumbel | 0.4 | 0.4 | 3 |
| Student t | 0.95 | 1 | 1 |
| Farm & retail | | | |
| Normal | 0.95 | 0.95 | 3 |
| Gumbel | 0.85 | 1 | 1 |
| Stud t | 0.9 | 0.9 | 2 |
| Time-Varying Gumbel | 0.35 | 0.2 | NA |
| Time-Varying-Student t | 0.15 | 0.35 | NA |

Note: the rank is based on the in-sample model comparison method proposed by Patton (2012).

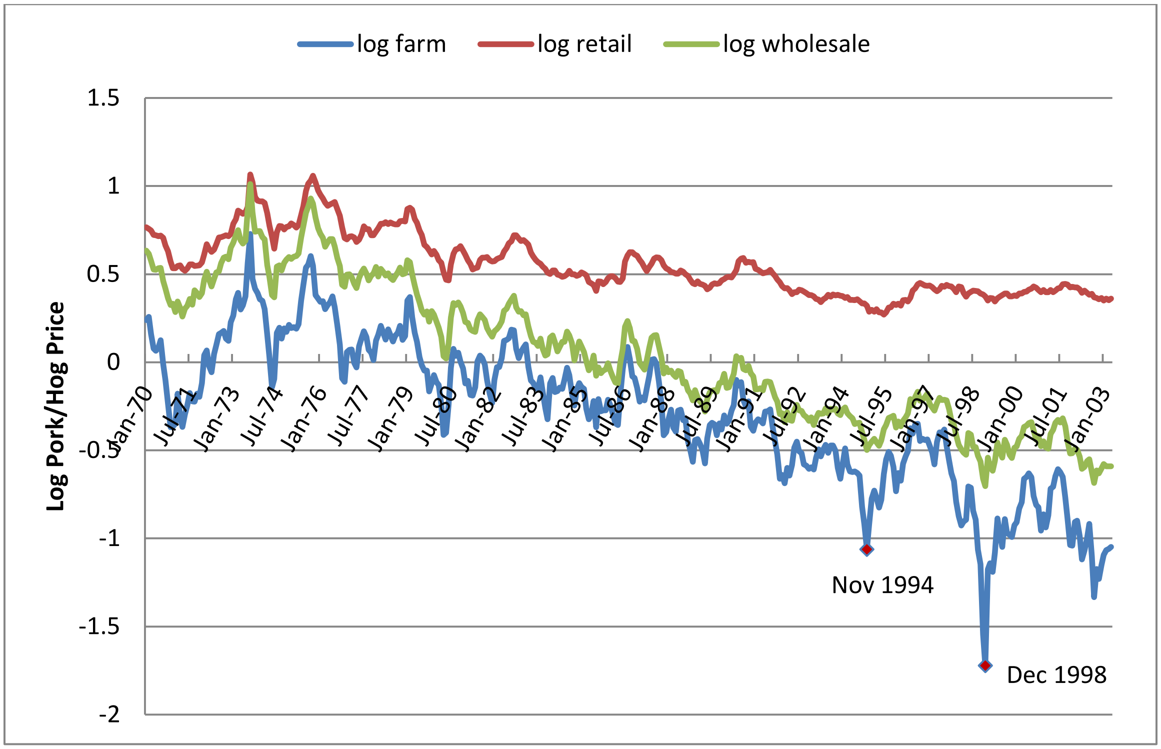


Figure 1. Monthly Pork/Hog (Log) Real Prices: Jan 1970-Mar 2003


Figure 2. Pair-Wise Monthly Pork/Hog (Log) Prices and Price Changes: 1970-2003

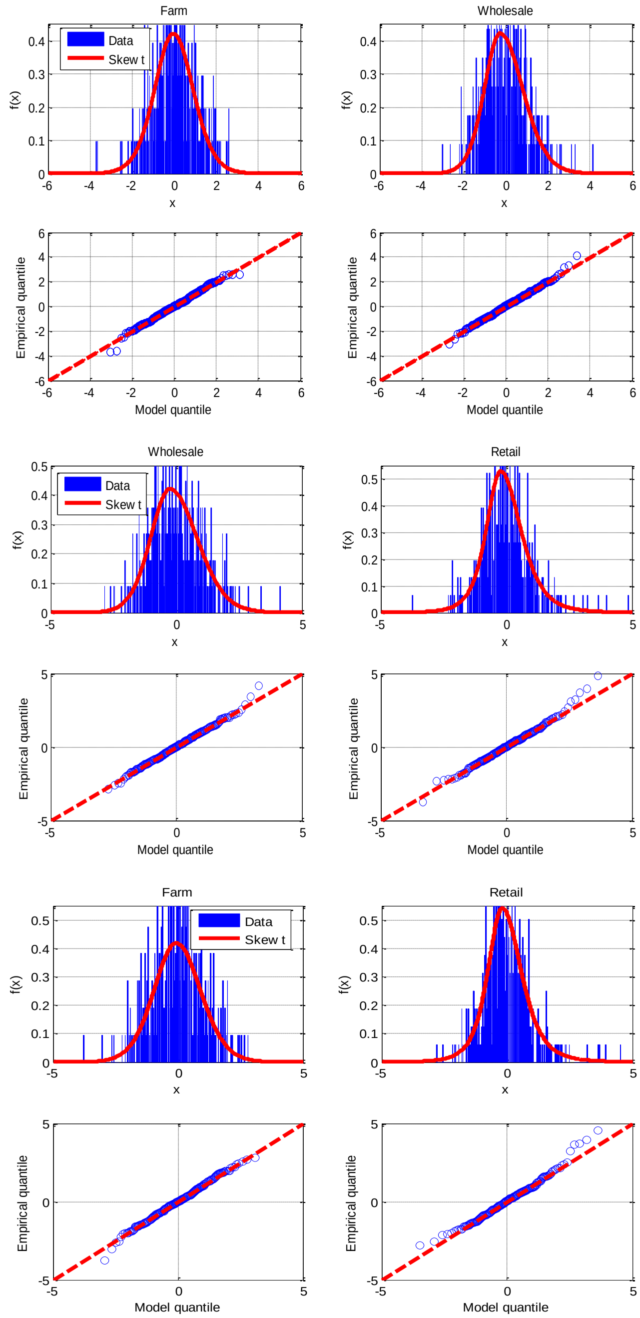


Figure 3. Fit Skew t for Standardized Residuals.

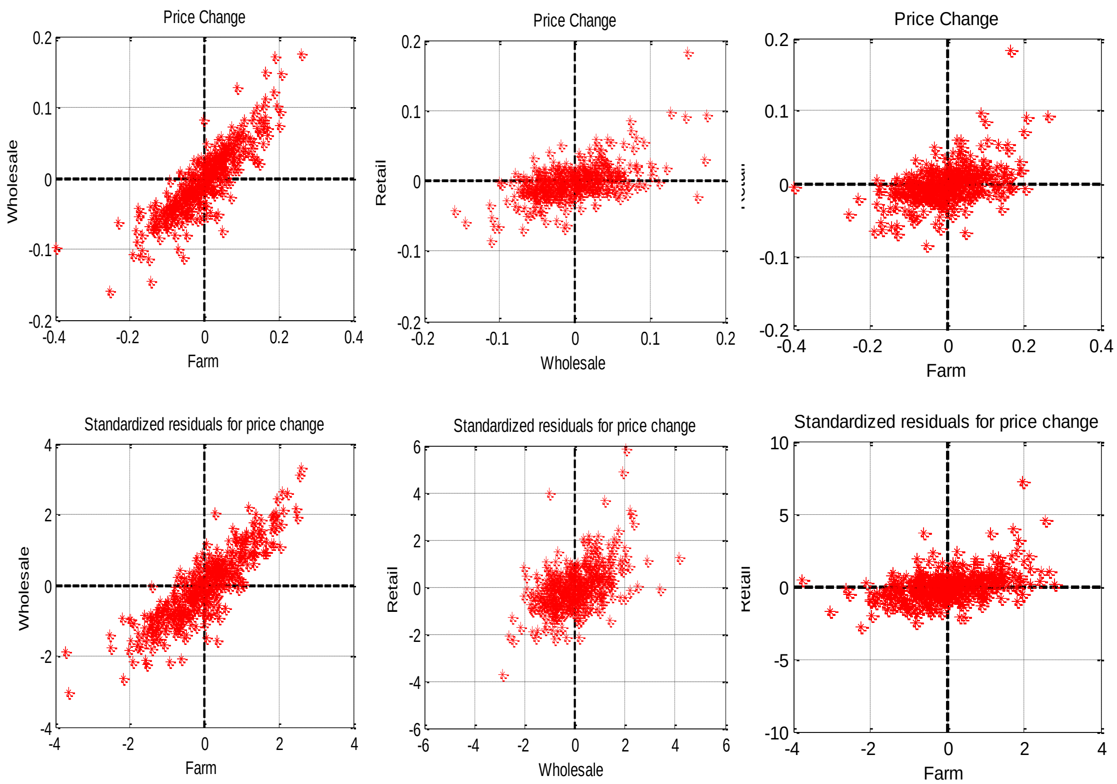


Figure 4. Pair-Wise Scatter Plots of Price Changes and Standardized Residuals

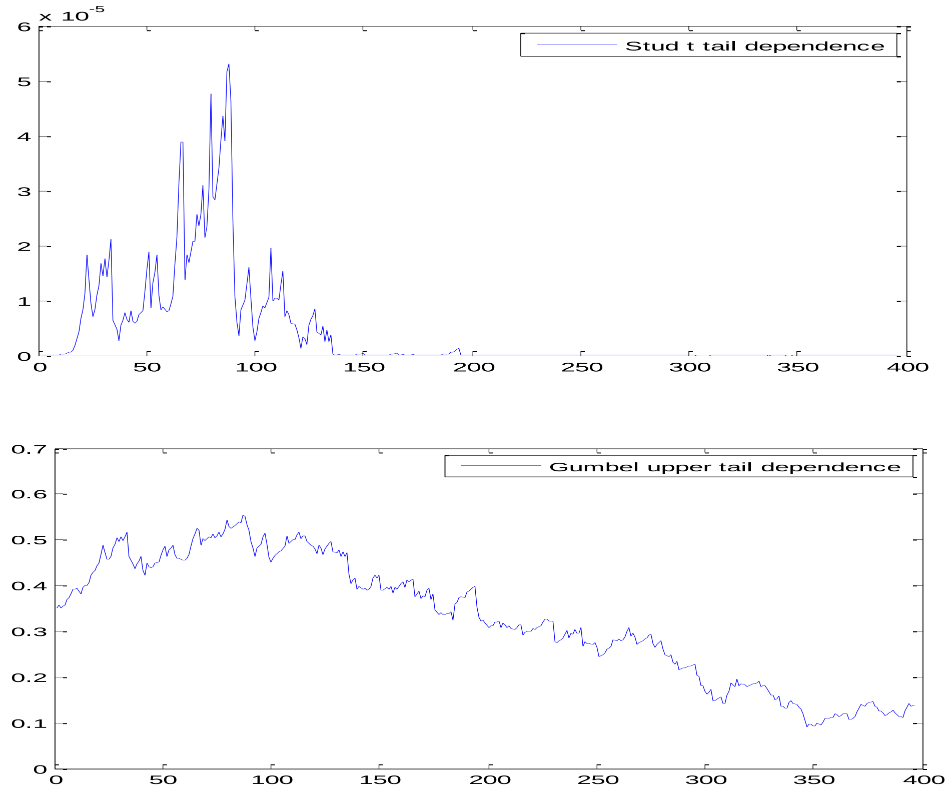


Figure 5. Tail Dependence from Time-Varying Copulas

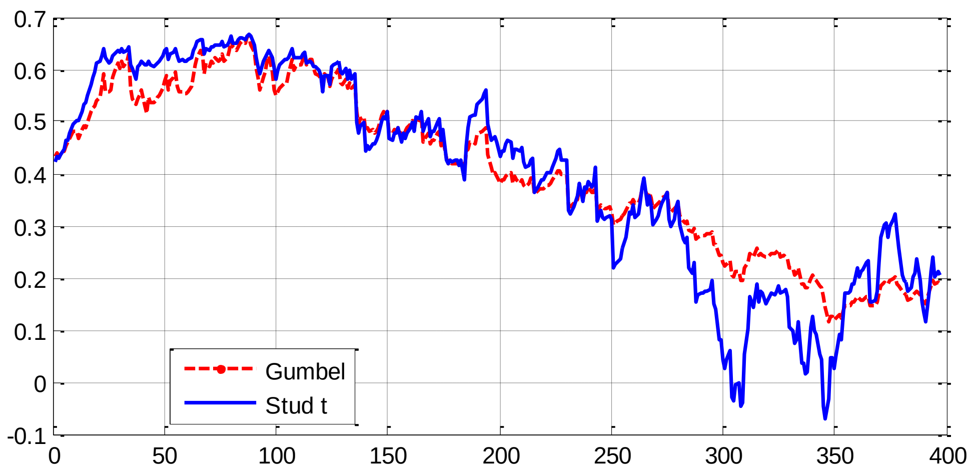


Figure 6. Linear Correlation Coefficient Derived from the Time-Varying Copulas