Price Dependence between Different Beef Cuts and Quality Grades: A Copula Approach at the Retail Level for the U.S. Beef Industry

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Abstract

The objective of this study is to assess the degree and the structure of price dependence between different cuts of the beef industry in the USA. This is pursued using the statistical tool of copulas. To this end, it utilizes retail monthly data of beef cuts, within and between the quality grades of Choice and Select, over the period 2000–2014. For the Choice quality grade, there was evidence of asymmetric price co-movements between all six pairs of beef cuts under consideration. No evidence of asymmetric price co-movements was found between the three pairs of beef cuts for the Select quality grade. For the pairs of beef cuts formed between the Choice and Select quality grades, the empirical results point to the existence of price asymmetry only for the case of the chuck roast cut.

JEL codes: Q11, C13, L66

1 Introduction

Overwhelming evidence suggests that consumers perceive beef as a differentiated product. Physical intrinsic qualities like color, shape, appearance, tenderness, juiciness, flavor as well as its nutritional properties (fatty acid composition) appear to influence consumers' decisions when purchasing beef. Data from Leick, Behrends, Schmidt, and Schilling (2012), indicate that consumers may select cuts from the beef carcass that display certain quality attributes, even if there is a considerable price difference.

Despite this fact, most of the studies on price dependence and asymmetric price response in the U.S. beef industry have been carried out considering aggregate commodity prices. The quantitative tools utilized range from simple correlation analysis and regression models to recently developed econometric approaches such as the linear error correction model (ECM), the asymmetric non-linear ECM, the threshold vector ECM, the smooth transition cointegration model, the Markov-switching ECM, and the copulas. Goodwin and Holt (1999), estimate a full vector error correction model (VECM) of beef price relationships at the farm, wholesale and retail levels. The authors found evidence of asymmetric price adjustment towards the equilibrium. Pozo, Schroeder, and Bachmeier (2013), with the use of a threshold asymmetric error-correction model (TAECM), find no evidence of asymmetric price transmissions (APT) in the response of retail beef prices to changes in upstream prices. Emmanouilides and Fousekis (2014) assess the degree and the structure of price dependence along the U.S. beef supply chain utilizing the statistical tool of copulas. Their empirical findings point to the existence of price transmission asymmetry, which is more important for the pair wholesale–retail.

The USDA (United States Department of Agriculture (2014)) certifies and awards grades based on different attributes of the beef carcass. In terms of quality, USDA awards three grades. USDA Prime is the superior grade with amazing tenderness, juiciness, flavor and fine texture. It has the highest degree of fat marbling and is derived from the younger beef. Prime is generally featured at the most exclusive upscale steakhouse restaurants. USDA Choice is the second highest graded beef. It has less fat marbling than Prime. Choice is a quality steak particularly if it is a cut that is derived from the loin and rib areas of the beef such as a tenderloin filet or rib steak. Generally

USDA Choice will be less tender, juicy and flavorful with a slightly more coarse texture versus Prime. USDA Select is generally the lowest grade of steak available at a supermarket or restaurant. It is tougher, less juicy and less flavorful since it is leaner than Prime and Choice with very little marbling. The texture of Select is generally more coarse[1]. In general, Prime (higher quality grade) receives a higher price than Choice (lower quality grade), and Choice receives a higher price than Select (lowest quality grade), both at retail and wholesale levels. Currently, about 3% of carcasses grade as Prime, and 57% as Choice[2].

Quality grades do not constitute the only beef attribute to determine consumers' willingness to pay. Consumers' selections of ribeye, top loin, and sirloin steaks are impacted more by their perception of thickness, marbling, and color than by price Leick et al. (2012). Different beef cuts exhibit different prices. In general, cuts like ribs, loin, and sirloin are usually priced higher than round or briskets, and cuts from the middle part of the animal are priced higher than cuts from the ends of the carcass.

Against this background, the objective of this paper is to investigate if the existence of product differentiation could be a source of asymmetric price comovements within certain beef quality grades and beef cuts. Preference for specific quality attributes and cuts implies that consumers have different marginal willingness to pay for these "different" beef products. Consequently, their response might be different when prices change. At the same time, retailers can price discriminate based on the different attributes of the commodity. This means that sellers might adopt different pricing strategies, depending on the quality grade and cut, when market conditions change. Conclusively, estimating price dependence while considering beef as a non-differentiated product, would ignore differential responses. Empirical results may not capture the actual pricing behavior. In our study, we estimate empirically price dependence between beef products differentiated by quality and by cuts, at the retail level, with the use of the statistical tool of copulas. Copulas offer an alternative way to analyze price co-movements, particularly during extreme market events. A

[1] For more details of exactly how a beef certifier measures marbling, maturity of the beef, the color of beef and its texture to determine an accurate USDA Grade, we can go to the United States Standards for Grades of Carcass Beef established by the United States Department of Agriculture – Agricultural Marketing Service (1997)

[2] Wholesale cutout beef data available from USDA-Agricultural Marketing Service(AMS)

significant advantage of copulas is that they allow the joint behavior of random processes to be modeled independently of the marginal distributions, providing this way considerable flexibility in empirical research (Patton (2012)). Thus, copulas are a valuable tool for modeling the joint behavior of random variables during extreme market events making it possible to assess whether prices move with the same intensity during market upswings and downswings.

There are a few empirical studies, in agricultural economics, which have investigated market dependence using copulas. Emmanouilides, Fousekis, and Grigoriadis (2013), assessed price dependence in the olive oil market of the Mediterranean (Greece, Spain, and Italy). Reboredo (2012) examined co-movement between international food (corn, soya beans and wheat) and oil prices. Qiu and Goodwin (2012), estimated APT in the hog supply chain (case of vertical price dependence).

To the best of our knowledge, there has been no published work which has examined price co-movements between different cuts and quality grades of beef with the use of copulas.

The present work is structured as follows: Section 2 contains the theoretical framework. Section 3 presents the data, the empirical models and the results. Section 4 offers conclusions.

2 Theoretical framework

2.1 Copulas and dependence measurement

Copula theory dates back to Sklar (1959), but only recently copula models have realized widespread application in empirical models of joint probability distributions, see Nelsen (2007). Sklar proved that a joint distribution can be factored into the marginals and a dependence function, which he called "copula". Thus, he created a new class of functions (copulas) that tie together two marginal probability functions that may be related to one another. Sklar showed that if G is a bivariate distribution function with margins $G_1(x)$ and $G_2(y)$, where (X,Y) are random processes, then there exists a copula function C:$[0,1]^2$ to [0,1] such that for every (x,y) $\in$ R^2 we have[3]

$$G(x,y) = C(G_1(x), G_2(y)) \tag{1}$$

Given that the marginal distributions are continuous, C, $G_1(x)$, and $G_2(y)$ are uniquely determined by $G(x,y)$. Conversely, for any pair (G_1, G_2) and for any copula C, the function G, written in equation (1), defines a joint cdf for (X,Y) with margins G_1 and G_2. The copula can be obtained from equation (1) in the following way:

$$C(u_1, u_2) = G(G_1^{-1}(u_1), G_2^{-1}(u_2)) \tag{2}$$

where G_i^{-1}, for i=(1,2), represent the marginal quantile functions, and u_i represent quantiles on $U[0,1]$. The joint pdf associated with the C copula function is obtained as:

$$c(u_1, u_2) = \frac{\partial C^2}{\partial u_1 \partial u_2} = \frac{g(G_1^{-1}(u_1), G_2^{-1}(u_2))}{g_1(G_1^{-1}(u_1)) g_2(G_2^{-1}(u_2))} = \frac{g(x,y)}{g_1(x) g_2(y)} \tag{3}$$

where g is the joint pdf associated with G, and g_1 and g_2 are the marginals pdfs of X and Y respectively. From equation (3) it follows

$$g(x,y) = c(G_1(x), G_2(y)) g_1(x) g_2(y) \tag{4}$$

From the equation above we can observe that the joint pdf contains information on the marginal behavior of each random variable as well as on the dependence betwen them. The fact that the marginal distributions become uniform means that the influences of the original marginal distributions have been removed from the data. The only remaining feature is the way the transformed random processes are paired, and the dependence between them is captured by the copula function, which describes the way this "coupling" is done. It is evident from equation (4) that the copula function fully describes the dependence of the random variables by capturing the information missing from the marginal distributions to complete the joint distribution, see Meucci (2011).

[3]For simplicity we consider the bivariate case. The analysis, however, can be extended to a m-variate case with m>2.

Copulas are used to describe dependence (linear and non-linear) between random variables, allowing the joint behavior of random processes to be modeled independently of the marginal distributions. At the same time copulas link joint distribution functions to their one-dimensional margins.

A rank based test of functional dependence is $Kendall's\ tau$. It provides information on co-movement across the entire joint distribution function, both at the center and at the tails of it. It is calculated from the number of concordant and discondordant pairs of observations in the following way:

$$\tau_N = \frac{P_N - Q_N}{\binom{N}{2}} = \frac{4P_N}{N(N-1)} - 1, \tag{5}$$

where N represents the number of observations, and P_N and Q_N denote the number of concordant and discondordant pairs, respectively.[4] Kendall's *tau* captures co-movement across the entire joint distribution function (center and tails).

Often though, information concerning dependence at the tails (at the lowest and the highest ranks) is extremely useful for economists, managers and policy makers. Tail (extreme) co-movement is measured by the upper, λ_U, and the lower, λ_L, dependence coefficients defined as

$$\lambda_U = \lim_{u \uparrow 1} prob(U_1 > u | U_2 > u) = \lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1-u} \in [0,1], \tag{6}$$

$$\lambda_L = \lim_{u \downarrow 0} prob(U_1 < u | U_2 < u) = \lim_{u \to 0} \frac{C(u,u)}{u} \in [0,1], \tag{7}$$

where λ_U measures the probability that X is above a high quantile given that Y is also above that high quantile, while λ_L measures the probability that X is below a low quantile given that Y is also below that low quantile. In order to have upper or lower tail dependence, λ_U or λ_L need to be positive. Otherwise, there is upper or lower tail independence. Hence, the two measures of tail dependence provide information about the likelihood for the two random variables to boom

[4]Two pairs (x_j, y_j), (x_k, y_k), $j,k = 1,2,\ldots,N$, are defined as concordant (discocordant) when $(x_j – x_k)$,$(y_j – y_k) > 0$ (< 0).

and to crash together. It is worth noticing that since the tail coefficients are expressed via copulas in equations (6) and (7) , certain properties of copulas apply to λ_U and λ_L (*e.g.* invariance to monotonically increasing transformations of the variables).

Using copulas to describe dependence between random variables is very advantageous for the researcher. First of all, copulas can model co-movement between these random processes independently of the marginal distributions. Secondly, copulas allow for more flexible functional forms of dependence, with linear dependence being a special case. This means that copulas provide information on the degree as well as on the structure of dependence. Third, copulas are invariant to increasing and continuous transformations. This last property is useful because dependence is the same for prices of beef cuts as for their logarithmic transformations.

2.2 Parameters and dependence structures of commonly used families of bivariate copulas

Given that dependence between random processes can be quite complicated, Durante and Sempi (2010), define a "good" family of copulas as: (a) interpretable, meaning that its members have a probabilistic interpretation; (b) flexible, meaning that its members are capable of representing many possible types and degrees of dependence; (c) easy-to-handle, meaning that the family members are expressed in a closed form or, at least, can be easily simulated by means of some known algorithm. Further research on the topic has led to a quite considerable number of copula families with desirable properties. This study presents and discusses eight of them, which are typically employed in economics and finance, see Patton (2012).

The Gaussian (or Normal) and the Student-t are members in the family of elliptical copulas. The Gaussian involves a single dependence parameter, θ, which is the linear correlation coefficient corresponding to the bivariate normal distribution. The student-t involves two parameters, the correlation coefficient and the degrees of freedom (ν). When $\nu \geq 30$ the Student-t copula becomes indistinguishable from the Gaussian one. Members of the family of Archimedean copulas are the Clayton, the Gumbel, the Frank, the Joe, the Gumbel-Clayton, and the Joe-Clayton. The first four contain a single dependence parameter denoted as θ, while the last two involve two dependence parameters, denoted as θ_1 and θ_2. The key advantages of the Archimedean copulas over the elliptical ones are: (a) they can be written in explicit forms and (b) they are not restricted to radial symmetry, thus offering a great flexibility in modeling different kinds of dependence. The key advantages of the elliptical over the Archimedean ones are: (a) they are more suitable in modeling high-dimensional dependence structures and (b) they can specify different levels of correlation between marginal distributions, see Savu and Trede (2010).

Table 1 presents the copulas under consideration in our study, their respective dependence parameters, their relationship to $Kendall's\ tau$ as well as to λ_U and λ_L (upper and lower dependence coefficients). As we can see, the Gaussian copula is symmetric and exhibits zero tail dependence. Thus, irrespective of the degree of the overall dependence, extreme changes in one random variable are not associated with extreme changes in the other random variable. The t-copula exhibits symmetric non-zero tail dependence (joint booms and crashes have the same probability of occurrence). The Clayton copula exhibits only left co-movement (lower tail dependence). The Gumbel and the Joe copulas exhibit only right co-movement (upper tail dependence). The Frank copula has zero tail dependence. The Gumbel-Clayton and the Joe-Clayton copulas allow for, potentially asymmetric, both upper and lower co-movement.

3 The data, the empirical models and the results

The data for the empirical analysis are monthly retail beef prices on certain cuts, for the quality grades of choice and select. We use certain cuts for two reasons. The first one is for data availability. The second one is for comparison between grades. Observations refer to the period 2000:1 to 2014:5, and have been obtained from the Bureau of Labor Statistics (2014) as well as from United States Department of Agriculture – Economic Research Service (2014)[5]. For the higher quality grade (Choice) the cuts are: chuck roast, steak round, sirloin steak and round roast. For the lower

[5] We consider the BLS description "graded and ungraded, excluding USDA Prime and Choice" as representative of Select quality grade.

quality grade (Select) the cuts are: chuck roast, steak round and sirloin steak. The Prime quality grade has not been taken into account in our study because it comprises a negligible share. Our final data have 173 observations for each of the cuts considered in this study[6].

Figure 1(A) presents the price series at the retail level for the different cuts of the choice quality grade. Figure 1(B) presents the price series at the retail level for the different cuts of the select quality grade. We observe that in both quality grades retail prices follow the same trend.

For the empirical part of the study, we use the semi-parametric approach proposed by Chen and Fan (2006) which involves three steps: (i) an Autoregressive Moving Average – Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) model is fit to the rates of price change for each of the series (called innovation series) (ii) The obtained residuals are standardized (filtered data) and then used to calculate the respective empirical distribution functions (copula data and meaning data on (0,1)). (iii) The estimation of copula models is conducted by applying the maximum likelihood (ML) estimator to the copula data (Canonical ML). The semi-parametric approach exploits the fact that the copula and the margins can be estimated separately using potentially different methods. The Canonical ML copula estimator is consistent but less efficient relative to the fully parametric one. Hence, the asymptotic distributions of the copula parameters and the dependence measures, such as the Kendall's tau and the tail coefficients, should be approximated using resampling methods (Choroś, Ibragimov, and Permiakova (2010), Gaißer, Ruppert, and Schmid (2010)). All estimations, testing, and resampling in this study have been carried out using R (version 3.1.2, R Core Team (2014)).

To obtain the filtered rates of price change, an ARMA(p,q)–GARCH(1,1) model has been fit to the raw data[7]. Model selection was based on the Akaike Information Criterion. Table 2 presents the selection of the best fitted ARMA(p,q)-GARCH(1,1) model for each of the series of beef cuts, for the quality grades of choice and select.

ARMA with GARCH errors were estimated with rugrach package Ghalanos (2014). The obtained residuals from each of the ARMA(p,q)-GARCH(1,1) model were standardized (filtered

[6]For the sirloin steak cut of the Select quality grade there are 165 observations since data are available up to 2013:8.
[7]Rates of price change.

data) and used to calculate the copula data on (0,1). Figure 2 presents the scatterplots of the copula data for all pairs of beef cuts within and between quality grades.

Copula function selection was performed with CDVine package (Brechmann and Schepsmeier, 2013a) based on AIC/BIC criteria (Jordanger and Tjøstheim (2014), Dißmann, Brechmann, Czado, and Kurowicka (2013), Manner (2007)). The same colula families were selected for all pairs/cases in both criteria. Goodness of fit was performed using the Cramér–von Mises(CvM) procedure (Genest, Rémillard, and Beaudoin (2009), Genest and Huang (2012), Kojadinovic, Yan, Holmes et al. (2011), Berg (2009)). The copula package in R was used for the CvM procedure (Hofert, Kojadinovic, Maechler, and Yan (2014), Jun Yan (2007)). We performed 50,000 repetitions. Results were obtained with the maximum pseudo-likelihood (mpl) estimation method, and the dependence parameters were estimated using the L-BFGS-B optimization algorithm (Byrd, Lu, Nocedal, and Zhu (1995), Nash and Varadhan (2011), Nash (2014)), while allowing up to 100,000 iterations to achieve convergence.

The Cramer-von-Mises (CvM) procedure was decisive in our final decision regarding the selection of the copula family. Once the copula family was selected, the asymptotic distributions of the copula parameters and the dependence measures (Kendall's tau, tail coefficients) were approximated using resampling methods. We performed 50,000 repetations. Figure 3 presents the parametric and non-parametric density plots from the bootstrap method.

The selected copula functions with their associated parameters are presented in Tables 3, 4, and 5. We report standard errors produced from the non-parametric bootstrap. The p-values of the CvM test, for each copula family selected, are also reported in the above mentioned tables. As a general comment, p-values are quite high – ranging from 0.363 to 0.977– eliminating any ambiguity regarding the selection of the appropriate copula family.

Table 3 presents the selected copula functions for the six pairs of beef cuts, for the choice quality grade. The Joe copula is selected four times and the Gumbel copula is selected two times. Kendall's τ ranges from 0.082 to 0.240, and is statistically significant at any reasonable level. The estimates from Kendall's τ indicate that overall dependence is not that strong. In all six cases, the estimate of the lower tail dependence coefficient (λ_L) is equal to zero. This means, when the price of one of the selected beef cuts crashes, the possibility for the price of a different beef cut to crash is zero. Thus, a price crash at one cut is not associated with a price crash at a different cut for the choice quality grade (specific cuts considered in this study). The estimates of the upper tail dependence coefficient (λ_U) range from 0.133 (for the pair steak round - sirloin steak) to 0.409 (for the pair chuck roast - round roast). For the latter, the value of λ_U implies that with probability 40.9%, a price boom for the retail price of the chuck roast cut, will be associated with a price boom for the retail price of the round roast cut. All of the tail dependence coefficients are statistically significant at the one percent level of significance. Thus, for the case of the choice quality grade, and for all pairs of beef cuts considered in this work, there is evidence of asymmetric price dependence: price increases in one cut will be transmitted (with the estimated probabilities) to the other cut, but price decreases in one cut will not be transmitted to the other cut.

Table 4 presents the selected copula functions for the three pairs of beef cuts for the case of the select quality grade. For the pair chuck roast – steak round the copula selected is the Gaussian, implying that both estimates of the tail dependence coefficients (λ_L,λ_U) are equal to zero. This means that a retail price crash (boom) for the chuck roast cut will not be associated with a retail price crash (boom) for the round roast cut. The overall dependence parameter (Kendall's τ) is 0.243 and is statistically significant. The Frank copula is selected for the pair chuck roast – sirloin steak, implying that both estimates of the tail dependence coefficients (λ_L,λ_U) are equal to zero. This means that a retail price crash (boom) for the chuck roast cut will not be associated with a retail price crash (boom) for the sirloin steak cut. The overall dependence parameter (Kendall's τ) is 0.115 and is statistically significant. The Frank copula is also selected for the pair steak round – sirloin steak. This means that a retail price crash (boom) for the steak round cut will not be associated with a retail price crash (boom) for the sirloin steak cut. The overall dependence parameter (Kendall's τ) is quite low with a value of 0.095. Hence, for all the pairs of the select quality grade, there is no evidence of asymmetric price dependence.

Table 5 presents the selected copulas for the pairs of the same cuts between quality grades. For the pair Choice/chuck roast – Select/chuck roast the estimated Kendall's τ parameter is 0.173, indicating a not so strong overall dependence. The estimates of the tail dependence coefficients are zero for λ_L, and 0.341 for λ_U. This means that with probability 34.1% a retail price boom for the chuck roast cut of the quality grade choice will be associated with a retail price boom of the same cut for the select quality grade. There is no association between choice and select quality grade, in the case of a crash in the retail price of the chuck roast cut. Thus, there is evidence of asymmetric price dependence between choice and select quality grade for the chuck roast cut. For the pair Choice/steak round – Select/steak round the copula selected is the Gaussian, implying that both tail dependence coefficients (λ_L,λ_U) are equal to zero. This means that a retail price crash (boom) for the steak round cut for the choice quality grade will not be associated with a retail price crash (boom) for the steak round cut for the select quality grade. The overall dependence parameter (Kendall's τ) is 0.172, and is statistically significant. For the pair Choice/sirloin steak - Select/sirloin steak the Gaussian copula was selected, implying that both tail dependence coefficients (λ_L,λ_U) equal to zero. This means that a retail price crash (boom) for the sirloin steak cut for the choice quality grade will not be associated with a retail price crash (boom) for the sirloin steak cut for the select quality grade. The overall dependence parameter (Kendall's τ) is 0.174, and is statistically significant.

4 Conclusions

The existence of asymmetric price co-movements in the food industry has attracted the interest of many researchers for quite a long time. In the case of the U.S. beef industry, most of the studies on price dependence and asymmetric price response have been carried out considering aggregate commodity prices. The objective of this paper is to investigate if the existence of product differentiation could be a source of asymmetric price co-movements within certain beef quality grades and beef cuts. This objective has been carried out using monthly retail price data and the statistical tool of copulas. The summary of our results follows.

For the Choice quality grade, there is evidence of asymmetric price dependence in all six pairs of beef cuts considered in this study. For all pairs, the estimated upper tail dependence coefficients (λ_U) are statistically significant, while the lower tail dependence coefficients (λ_L) are zero. Strongly positive retail price shocks in one cut are matched, with probability ranging from

0.133 to 0.409, with comparably strong positive retail price changes in the other cut.

For the Select quality grade, there is no evidence of asymmetric price responses between the cuts under consideration. All three pairs of beef cuts exhibit zero estimated lower tail and upper tail dependence coefficients (λ_L ,λ_U). This indicates that retail price booms (crashes) in one cut will not be associated with retail booms (crashes) in a different cut.

For the pairs of same cuts between Choice and Select quality grades, the selected copulas differ for each of the three pairs. For the steak round cut as well as the sirloin steak cut (pairs between Choice and Select), the estimated lower tail and upper tail dependence coefficients are zero, indicating zero extreme right and left co-movements. For the chuck roast cut there is evidence of asymmetric price dependence. A price boom at the retail price of the chuck roast cut for the Choice quality grade will be associated with probability 34.1% with a price boom at the retail price of the chuck roast cut for the Select quality grade. On the other hand, a price crash for the chuck roast cut in either quality grade will not be associated with a price crash for the chuck roast cut of the other quality grade.

One interpretation of our results is that sellers adopt different pricing strategies when market conditions change, depending on the quality grade. For the choice quality grade, there is evidence of asymmetric price dependence between different cuts. This means that retailers respond differently to price increases than they do to price decreases. For the select quality grade, there is no evidence of asymmetric price dependence between all different pairs of cuts considered in this study. Hence, there is no evidence of asymmetric price response from the retailers for the case of the select quality grade.

Future works can include observations from different cuts of the Prime quality grade. Additionally, more cuts from the Choice and Select quality grades can be used for comparisons.

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Figures and Tables

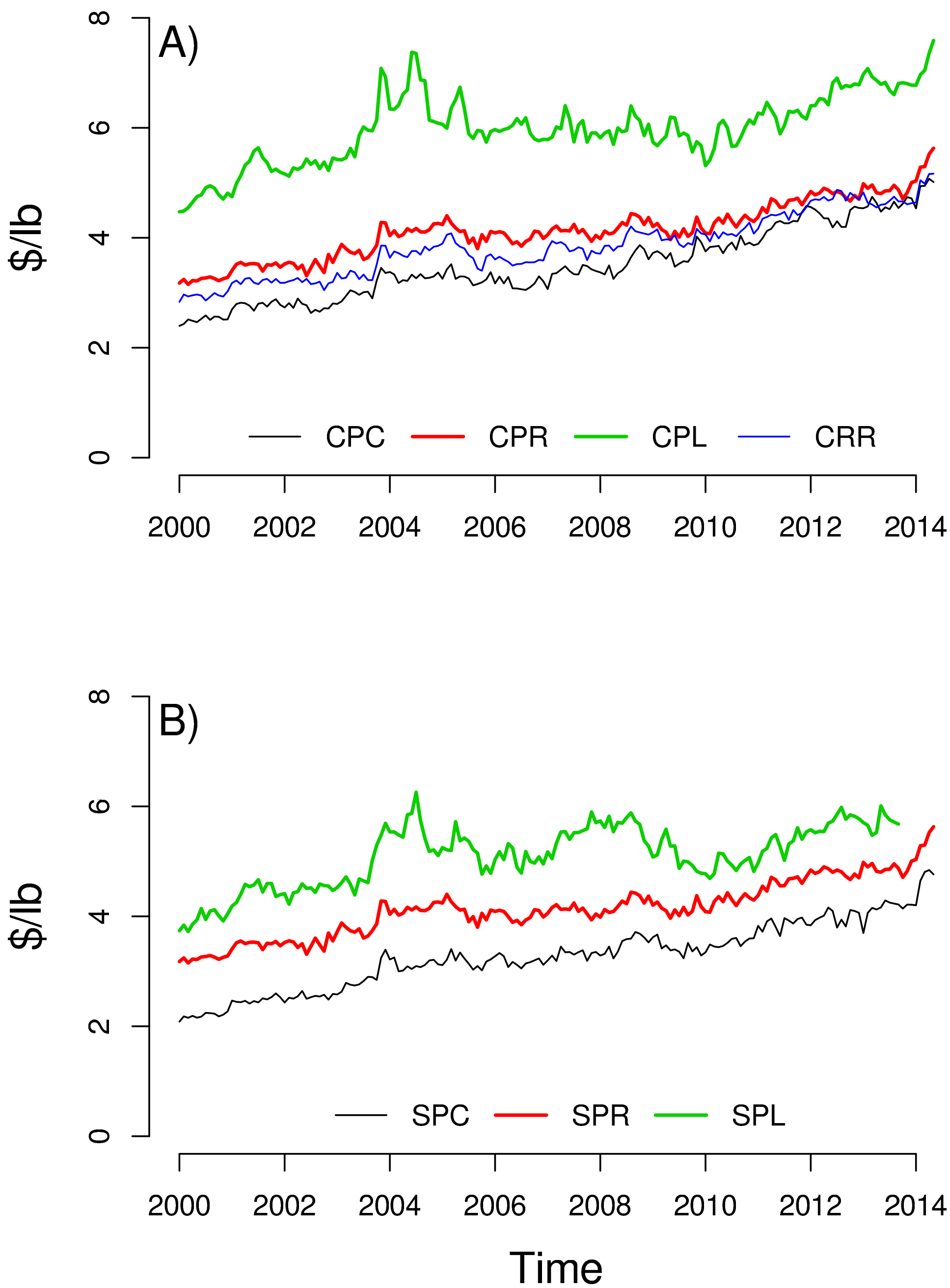

Figure 1: A) Retail price series for different beef cuts of the choice grade; B) Retail price series for different beef cuts of the select grade. Both series are measured in dollars per lb.

Notation of beef cuts time series: CPC=choise chuck roast, CPL=choise sirloin steak, CPR=choise steak round, CRR=choise round roast, SPC=select chuck roast, SPL=select sirloin steak, SPR=select steak round.

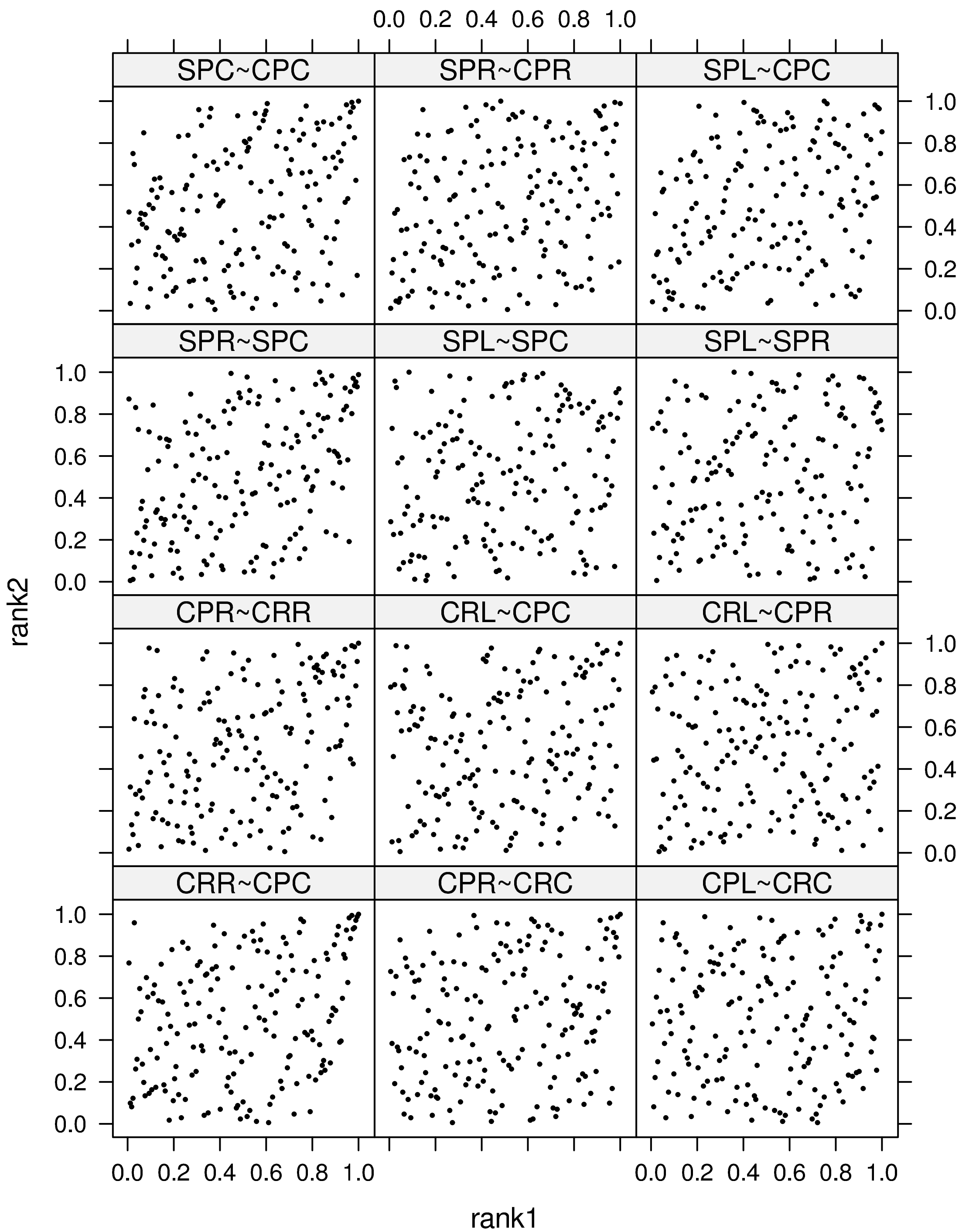

Figure 2: Scatterplots for the beef cuts of the copula data (ranks).

Notation of copula data: CPC=choise chuck roast, CPL=choise sirloin steak, CPR=choise steak round, CRR=choise round roast, SPC=select chuck roast, SPL=select sirloin steak, SPR=select steak round.

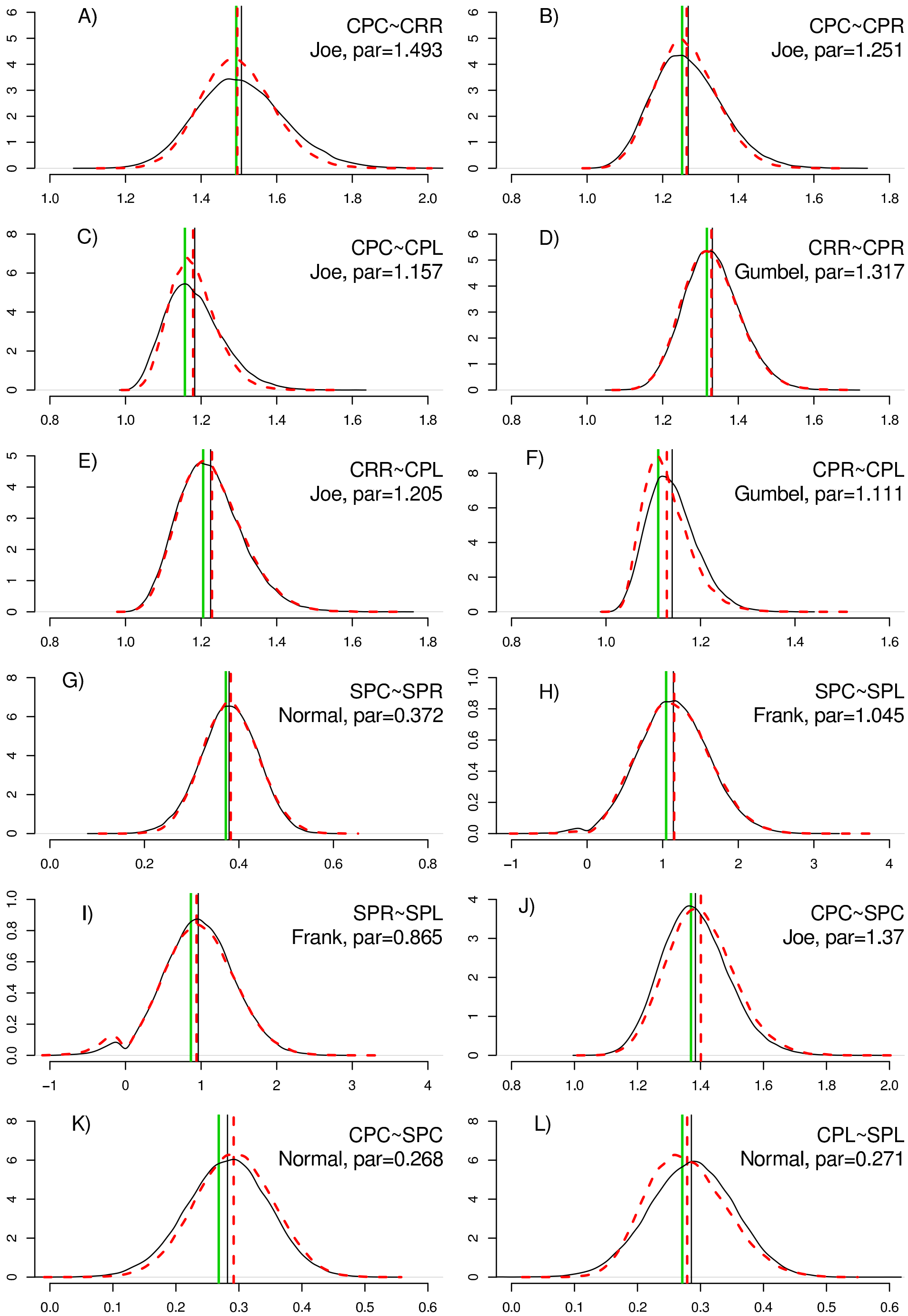

Figure 3: Density plots of parameter estimation from parametric and non-parametric 50,000 bootstrap repetitions.

Notation of graphs: continuous black curve = parametric bootstrap, dashed read curve = non-parametric bootstrap, green vertical line = estimated parameter of the original sample, black vertical line = mean of parametric bootstrap, dashed vertical red line = mean of non-parametric bootstrap.

Notation of copula data: CPC=choise chuck roast, CPL=choise sirloin steak, CPR=choise steak round, CRR=choise round roast, SPC=select chuck roast, SPL=select sirloin steak, SPR=select

Table 1: Copulas functions, parameters, Kendall's τ, and tail dependence $^{(*)}$

Copulas	**Parameters**	**Kendall's τ**	**Tail dependence** (λ_L, λ_U)
Gaussian	$\theta \in (-1,1)$	$\frac{2}{\pi}\text{arcsin}(\theta)$	(0,0)
Student − t	$\theta \in (-1,1)$ v>2	$\frac{2}{\pi}\text{arcsin}(\theta)$	$2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$, $2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$
Clayton	$\theta > 0$	$\frac{\theta}{\theta+2}$	$(2^{\frac{-1}{\theta}}, 0)$
Gumbel	$\theta \geq 1$	1- $\frac{1}{\theta}$	$(0, 2 - 2^{\frac{1}{\theta}})$
Frank	$\theta \in R\backslash\{0\}$	1 -$\frac{4}{\theta} + 4\frac{D(\theta)}{\theta}$	(0,0)
Joe	$\theta \geq 1$	$1+\frac{4}{\theta^2}\int_0^1 tlog(t)(1-t)^{2(1-\theta)/\theta}\,dt$	$(0, 2 - 2^{\frac{1}{\theta}})$
Gumbel − Clayton	$\theta_1 > 0,\ \theta_2 \geq 1$	1 - $\frac{2}{\theta_2(\theta_1+2)}$	$(2^{\frac{-1}{\theta_1\theta_2}}, 2 - 2^{\frac{1}{\theta_2}})$
Joe − Clayton	$\theta_1 \geq 1,\ \theta_2 > 0$	$1+\frac{4}{\theta_1\theta_2}\int_0^1(-(1-(1-t)^{\theta_1})^{\theta_2+1} * \frac{(1-(1-t)^{\theta_1})^{-\theta_2}-1}{(1-t)^{\theta_2-1}})dt$	$(2^{\frac{-1}{\theta_2}}, 2 - 2^{\frac{1}{\theta_1}})$

$^{(*)}$ Table from Brechmann and Schepsmeier (2013b).

Table 2: Best fitted ARMA(p,q)–GARCH(1,1) models (*)

Beef Cuts	**ARMA(p,q)**
	Choice quality grade
Chuck roast	(1,2)
Round roast	(2,2)
Steak round	(2,2)
Steak sirloin	(1,1)
	Select quality grade
Chuck roast	(2,2)
Steak round	(2,2)
Steak sirloin	(1,2)

(*)Application of the Box–Pierce and the autoregressive conditional heteroskedasticity–Lagrange multiplier (ARCH–LM) tests at various lag lengths showed that residuals are free from autocorrelation and from ARCH effects.

Table 3: Choice quality grade. Copula parameter estimates [1]

Beef cuts pairs	Selected Copula	CvM p–value	Parameters	Kendall's τ	λ_L	λ_U
Chuck roast /Round roast	Joe	0.364	$\hat{\theta}$=1.493***	0.217***	0	0.409***
			(0.095)	(0.032)	-	(0.047)
Chuck roast /Steak round	Joe	0.460	$\hat{\theta}$=1.251***	0.125***	0	0.260***
			(0.081)	(0.034)	-	(0.061)
Chuck roast /Sirloin steak	Joe	0.655	$\hat{\theta}$=1.157***	0.082***	0	0.179***
			(0.062)	(0.028)	-	(0.054)
Round roast /Steak round	Gumbel	0.9745	$\hat{\theta}$=1.317***	0.240***	0	0.307***
			(0.076)	(0.043)	-	(0.050)
Round roast /Sirloin steak	Joe	0.414	$\hat{\theta}$=1.205***	0.105***	0	0.222***
			(0.085)	(0.037)	-	(0.067)
Steak round /Sirloin steak	Gumbel	0.789	$\hat{\theta}$=1.110***	0.099***	0	0.133***
			(0.050)	(0.038)	-	(0.048)

(1) The Kendall's τ and the tail dependence coefficients with their respective standard errors (in parentheses) as well as the standard errors of the copula parameters have been obtained using i.i.d. bootstrap with 50,000 replications.
*** Statistical significance at the 1% level or less.

Table 4: Select quality grade. Copula parameter estimates [1]

Beef cuts pairs	**Selected Copula**	**CvM p–value**	**Parameters**	**Kendall's τ**	λ_L	λ_U
Chuck roast /Steak round	Gaussian	0.363	$\hat{\theta}$=0.372***	0.243***	0	0
			(0.059)	(0.041)	-	-
Chuck roast /Sirloin steak	Frank	0.672	$\hat{\theta}$=1.045**	0.115**	0	0
			(0.463)	(0.049)	-	-
Steak round/Sirloin steak	Frank	0.534	$\hat{\theta}$=0.864*	0.095*	0	0
			(0.511)	(0.055)	-	-

[1] The Kendall's τ and the tail dependence coefficients with their respective standard errors (in parentheses) as well as the standard errors of the copula parameters have been obtained using i.i.d. bootstrap with 50,000 replications.

*** Statistical significance at the 1% level or less.

** Statistical significance at the 5% level.

* Statistical significance at the 10% level.

Table 5: Choice and Select quality grades. Copula parameter estimates [(1)]

Pairs between	**Selected Copula**	**CvM p–value**	**Parameters**	**Kendall's τ**	λ_L	λ_U
Chuck roast	Joe	0.450	$\hat{\theta}$=1.370***	0.173***	0	0.341***
			(0.108)	(0.039)	-	(0.063)
Steak round	Gaussian	0.977	$\hat{\theta}$=0.268***	0.172***	0	0
			(0.062)	(0.042)	-	-
Steak sirloin	Gaussian	0.938	$\hat{\theta}$=0.271***	0.174***	0	0
			(0.063)	(0.042)	-	-

[(1)] The Kendall's τ and the tail dependence coefficients with their respective standard errors (in parentheses) as well as the standard errors of the copula parameters have been obtained using i.i.d. bootstrap with 50,000 replications.
*** Statistical significance at the 1% level or less.