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Abstract

The present article offers an empirical assessment of the degree and the structure of price dependence between wholesale and retail market levels in the U.S. beef industry, while accounting for product differentiation. This is pursued using the statistical tool of copulas and monthly rates of price changes for different cuts and quality grades of the beef product for the time period 2002–2016. Six wholesale–retail pairs were formed based on different cuts and quality grades. The empirical results suggest that prices at retail level respond differently to extreme negative and positive wholesale price shocks. More specifically, extreme price increases at the wholesale level are transmitted to the retail level in five out of six pairs whereas extreme price decreases are not passed from the wholesale to the retail market level in five out of six pairs. Based on these findings, there is evidence of asymmetric price relationships between wholesale–retail market levels in the U.S. beef marketing channel, when quality differences in cuts and grades is considered.

1 Introduction

Asymmetric price relationships is an increasingly disputed issue in agricultural and food economics. Increases in farm prices are believed to be transmitted faster at the retail level, whereas negative price shocks at the farm level take more time to be passed on to consumers. Downward price stickiness in agri–food supply chains can be considered as evidence of problems in the flow of information through the markets, and an indicator of inefficiency. For these reasons it attracts the attention of researchers and policy makers.

There exists a widespread belief that price transmission in the U.S. beef industry is asymmetric. These concerns have been validated to some extent in the literature. Recent evidence by Kuhns and Volpe (2014) for the United States Department of Agriculture-Economic Research Service reveals that retail beef prices rise rapidly, but fall slowly in response to price changes in upstream markets. Emmanouilides and Fousekis (2015) assessed the degree and the structure of price dependence along the U.S. beef supply chain with the use of the statistical tool of copulas. Their findings reveal the existence of asymmetric price dependence between wholesale–retail levels. Goodwin and Holt (1999), estimated a full vector error correction model (VECM) of beef price relationships at the farm, wholesale and retail levels. The authors found evidence that the adjustment path towards the equilibrium is asymmetric. On the other hand, Pozo et al. (2013) with the use of a threshold asymmetric error-correction model (TAECM) found no evidence of asymmetric price transmissions (APT) in the response of retail beef prices to changes in upstream prices.

In the majority of the studies, increased concentration in downstream markets and input manufacturing has been often pointed out to explain why decreases in upstream prices are not accompanied by proportional decreases in downstream markets. The beef packing industry has concentrated a lot of concern over the years since firms started to concentrate market power due to mergers and acquisitions (Cai et al., 2009; Love et al., 2009). At wholesale level, the four-firm concentration ratio (CR4) reached the level of 85 percent in 2010, dropped to 84 percent in 2011, and raised again to 85 percent in 2012.[1] In general, the four-firm concentration ratio has remained around 80 percent in the last ten years (USDA, Packers and Stockyards program 2013 Annual Report). At the same time, there are high levels of concentration at the retail level of the beef industry. At this last stage of the beef supply chain we find retail grocers, food service providers and restaurants with significant name recognition and potentially high degree of market power as well (e.g. McDonald's, Kroger, Safeway, Costco, Compass Group PLG, etc.).

However, there are other possible explanations for asymmetric price dependence besides market power. Adjustment costs, inventory management, increasing returns to scale, exchange rates, transportation costs, menu costs of changing prices and product differentiation are identified in the literature as some of the sources responsible for the existence of asymmetries in price transmission (Meyer and Cramon-Taubadel, 2004; Conforti, 2004).

This work investigates if product differentiation could be a source of asymmetric price relationships between wholesale–retail market levels in the US beef industry. Beef is sold to consumers as cuts. Different beef cuts exhibit different prices. Cuts

[1]The top four beef packing operations are: Tyson Foods Inc., Cargill Meat Solutions Corp., JBS USA, National Beef Packing Co.,LLC.

from the middle part of the animal are priced higher than cuts from the ends. Cuts like ribs, loin, and sirloin are usually priced higher than cuts like round or briskets. Different cuts do not constitute the only beef attribute to determine consumers' willingness to pay. Physical intrinsic qualities like tenderness, texture, juiciness, fat composition, appear to influence consumers' decisions when purchasing beef (Leick et al., 2012).

Beef is being inspected and graded before it reaches the retail market. The U.S. Department of Agriculture (USDA) offers this service since the day the system was established.[2] Till today, no system has proven more reliable operating without bias under actual commercial conditions (Morris, 1999). There are eight types of quality grades, but the ones commonly available at the retail level are: i) Prime (highest in quality and intramuscular fat, amazing tenderness, juiciness, flavor and fine texture, limited supply, featured at the most exclusive upscale steakhouse restaurants), ii) Choice (high quality, widely available in food service industry and retail), and iii) Select (acceptable quality, commonly sold at supermarkets, less juicy and less tender due to leanness).[3] About 3% of carcasses grade as Prime, more than 50% grade as Choice, and 40% grade as Select. Most of the graded beef sold in supermarkets is USDA Choice or USDA Select.

In the light of the preceding, there is plenty of evidence suggesting that consumers perceive beef as a differentiated product. At the same time, the U.S. beef industry vertically differentiates its product through the USDA grading system. Despite this

[2]Organized grading of beef dates back to 1923.

[3]Lower grades are U.S. Standard (lower quality, yet economical, lacking marbling), U.S. Commercial (low quality, lacking tenderness, produced from older animals), U.S. Utility, U.S. Cutter and U.S. Canner.

fact, the majority of studies on price transmission along the US beef supply chain have been carried out considering aggregate commodity prices. This means that the literature treats beef as an aggregate product when overwhelming evidence suggests otherwise. As a consequence, potential differences in price adjustments between different beef cuts and beef quality grades are averaged out when using aggregate data.

The objective of this study is to empirically examine if the existence of product differentiation could be a source of asymmetric price dependence between the wholesale and the retail levels of the U.S. beef industry, for certain cuts and quality grades of the beef product. The statistical tool utilized in this study is that of copulas. Copulas are used 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. Panagiotou and Stavrakoudis (2015) used the statistical tool of copulas in order to assess the degree and the structure of price dependence between different cuts and quality grades at of the U.S. beef industry at retail level. Results indicated that, depending on the cuts and the grades, there was evidence of asymmetric and non-asymmetric price co-movements. Fousekis and Grigoriadis (2016) used nonparametric copulas in order to examine the intensity and the mode of price linkages for quality differentiated coffee beans. The empirical findings suggested that there is symmetric price co-movement under positive and negative price shocks; that means, shocks of the same absolute magnitude but of different sign are transmitted from one coffee market to another with the same intensity. The transmission of shocks, however, of the same sign but of different magnitude is asymmetric. Fousekis et al. (2016) assessed the degree of integration of the international skim milk powder between the three the EU, the U.S. and Oceania markets (principal producing regions), with the employment of nonparametric kernel-based time-varying copulas. Their empirical results indicate a strong and increasing degree of overall price co-movement along with statistically significant probabilities for joint price crashes and booms.

Copulas have a wide range of applications in the area of economics. Aloui and Aïssa (2016) employed a vine copula approach to investigate the dynamic relationship between energy, stock and currency markets. Vine copulas offers a greater flexibility when modeling complex dependency patterns for high-dimensional distributions. The authors find evidence of a significant and symmetric relationship between the three variables. Pérez-Rodríguez et al. (2015) used a copula-based GARCH approach in order to describe the dependence structure between GDP and tourism receipts growth rates. Two developed economies, United Kingdom and Spain, and an emerging economy such as Croatia were considered. Empirical findings indicated that there is a significant, asymmetric and positive dependence between tourism and GDP growth rates for the three countries studied.

With regard to vertical price relationships along marketing channels, copulas can reveal the nature of price dependence under extreme price changes (Emmanouilides and Fousekis, 2015). If prices in different market levels boom and crash together with the same intensity, there is no evidence of asymmetric price dependence, and this is an indicator of a well functioning market. If prices in different market levels do not boom but crash together (and vice versa), then there is evidence of asymmetric price relationships. A 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; Fan and Patton, 2014).

In the most recent related study, Surathkal et al. (2014) examined the relationship between wholesale and retail beef prices while accounting for product differentiation in cuts and quality grades. The authors estimated threshold autoregressive (TAR) and momentum-TAR (MTAR) models while testing for the statistical significance of threshold effects. The TAR model was a better fit, and the threshold F test showed that there are significant thresholds effects. Their results revealed the existence of asymmetric effects, indicating that a decrease or an increase in wholesale beef prices tend to have different effects on the retail beef prices. Additionally, these effects were found to vary across quality grades: superior quality beef tend to show longer persistence to increase in prices and adjusts at a slower rate than relatively inferior quality beef.

In conclusion, Panagiotou and Stavrakoudis (2015) used the statistical tool of copulas in order to assess the degree and the structure of price dependence between different beef cuts and quality grades, but they focused only at the retail level of the US beef supply chain. Emmanouilides and Fousekis (2015) employed copulas in order to assess the structure of price dependence in the U.S. beef marketing channel during extreme market upswings and downswings, but they used aggregate commodity prices for the empirical implementation of their study. Lastly, Surathkal et al. (2014) accounted for product differentiation in cuts and quality grades and investigated the nature of vertical price transmission along the US beef supply chain. The estimation method was a threshold autoregressive model.

To the best of our knowledge, there has been no published work which has used the statistical tool of copulas in order to examine empirically the existence of asymmetric price dependence between wholesale–retail levels of the U.S. beef industry with the use of data on different beef cuts and quality grades.

The present work is structured as follows: Section 2 contains the methodology. Section 3 presents the data and empirical models, and Section 4 the results and discussion. Section 5 offers conclusions.

2 Copula theory

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) for more details). The models use a copula function to tie together two marginal probability functions that may or may not be related to one another.

A two–dimensional copula, $C(u_1, u_2)$, is a multivariate distribution function in the unit hypercube $[0, 1]^2$ with uniform U(0,1) marginal distributions Nelsen (2007).[4] As long as the marginal distributions are continuous, a unique copula is associated with the joint distribution, H, and is described in equation (1). This function constitutes a form of the principal result of copula theory (Sklar's theorem). It is obtained as:

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

$$C(u_1, u_2) = H(H_1^{-1}(u_1), H_2^{-1}(u_2)) \tag{1}$$

Similarly, given a two-dimensional copula, $C(u_1, u_2)$, and two univariate distributions, $H_1(x)$ and $H_2(x)$, equation 1 is a two-variate distribution function with marginals $H_1(x)$ and $H_2(x)$, whose corresponding density function can be written as:

$$h(x, y) = c(H_1(x), H_2(y))h_1(x)h_2(y), \tag{2}$$

where the functions h_1 and h_2 are the densities of the distribution functions H_1 and H_2 respectively.

The density function of the copula, c, given its existence, can be derived using equation 1 and marginal density functions, h_i:

$$c(u_1, u_2) = \frac{h(H_1^{-1}(u_1), H_2^{-1}(u_2))}{h_1(H_1^{-1}(u_1))h_2(H_2^{-1}(u_2))} \tag{3}$$

A rank based test of functional dependence is $Kendall'stau$. 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 (P_N) and disconcordant (Q_N) pairs of observations in the following way:

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

If a copula function (C) is known then τ can be calculated as:

$$\tau = 1 - 4 \int\int_{[0,1]^2} \frac{\partial C}{\partial u_1}\frac{\partial C}{\partial u_2}\,\mathrm{d}u_1\,\mathrm{u}_2 \tag{5}$$

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, such that λ_U, $\lambda_L \in [0,1]$, which are defined as

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

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

where, given the random vector (X,Y) with marginal distribution, U_1 for X and U_2 for Y, 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 strictly 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 and to crash together. For example, in our work, positive upper and zero lower tail dependence estimates would provide evidence that big increases in wholesale prices are matched at the retail level, whereas extreme negative shocks at the wholesale level are less likely to be transmitted to the retail level.

This study considers a range of bivariate copula specifications. All of them are members of the elliptical copulas and Archimedean copulas, since they permit considerable flexibility in capturing price dependence between different cuts of beef between wholesale and retail level in the US beef industry. Elliptical and Archimedean copulas are the two of the most commonly used copula families. The elliptical copulas that we evaluate are the Gaussian (or Normal) and Student–t. Among the one parameter Archimedean copulas we consider there are the Clayton, Gumbel, Frank, and Joe. Clayton-Gumbel, Joe-Gumbel, Joe-Clayton and the Joe-Frank are among the two-parameter Archimedean copulas we examine.

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). From the elliptical copulas, 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). From the one parameter Archimedean copulas, 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. From the two- parameter Archimedean copulas, the Gumbel-Clayton and the Joe-Clayton allow for potentially asymmetric upper and lower co-movement. The Joe-Gumbel exhibits only right co-movement while the Joe-Frank exhibits zero tail dependence.

Table 1: Copula functions, parameters, Kendall's tau, tail dependence $^{(*)}$

Copulas	**Parameters**	**Kendall's tau**	**Tail dependence** $(\lambda_L,\ \lambda_U)$
1) Gaussian (N)	$\theta \in (-1, 1)$	$\frac{2}{\pi}\arcsin(\theta)$	(0,0)
2) Student-t (t)	$\theta \in (-1, 1)$ $\nu > 2$	$\frac{2}{\pi}\arcsin(\theta)$	$2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$, $2t_{\nu+1}(-\sqrt{\nu+1}\sqrt{\frac{1-\theta}{1+\theta}})$
3) Clayton (C)	$\theta > 0$	$\frac{\theta}{\theta+2}$	$(2^{\frac{-1}{\theta}},\ 0)$
4) Gumbel (G)	$\theta \geq 1$	1- $\frac{1}{\theta}$	(0, 2 - $2^{\frac{1}{\theta}}$)
5) Frank (F)	$\theta \in R\backslash\{0\}$	$1 - \frac{4}{\theta} + 4\frac{D(\theta)}{\theta}$ with $D(\theta) = \int_0^\theta \dfrac{x/\theta}{\exp(x)-1}\mathrm{d}\,x$	(0,0)
6) Joe (J)	$\theta \geq 1$	$1+\frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{2(1-\theta)/\theta}\,\mathrm{d}t$	(0, 2 - $2^{\frac{1}{\theta}}$)
7) Clayton-Gumbel (BB1)	$\theta_1 > 0,\ \theta_2 \geq 1$	1 - $\frac{2}{\theta_2(\theta_1+2)}$	$(2^{\frac{-1}{\theta_1\theta_2}}$, 2 - $2^{\frac{1}{\theta_2}})$
8) Joe-Gumbel (BB6)	$\theta_1 \geq 1,\ \theta_2 \geq 1$	$1+\frac{4}{\theta_1\theta_2}\int_0^1(-\log(1-(1-t)^{\theta_1})$ $\times(1-t)(1-(1-t)^{-\theta_1}))\,\mathrm{d}t$	(0, 2 - $2^{\frac{1}{\theta_1\theta_2}}$)
9) Joe-Clayton (BB7)	$\theta_1 \geq 1,\ \theta_2 > 0$	$1+\frac{4}{\theta_1\theta_2}\int_0^1(-(1-(1-t)^{\theta_1})^{\theta_2+1}$ $\times\frac{(1-(1-t)^{\theta_1})^{-\theta_2}-1}{(1-t)^{\theta_2-1}})\mathrm{d}t$	$(2^{\frac{-1}{\theta_2}}$, 2 - $2^{\frac{1}{\theta_1}})$
10) Joe-Frank (BB8)	$\theta_1 \geq 1,\ \theta_2 \in (0, 1]$	$1+\frac{4}{\theta_1\theta_2}\int_0^1(-\log(\frac{(1-t\theta_2)^{\theta_1}-1}{(1-\theta_2)^{\theta_1}-1})$ $\times(1-t\theta_2)(1-(1-t\theta_2)^{-\theta_1}))\,\mathrm{d}t$	(0, 0)

$^{(*)}$ Table adapted from Joe (2014) and Schepsmeier et al. (2016).

3 Data and Empirical Models

3.1 Data

The data for the empirical analysis are monthly wholesale and retail beef prices on certain cuts for the quality grades of choice and select.[5] Prime quality grade has not been taken into account in our study because it comprises a negligible share. The cuts examined are: chuck roast, steak round and sirloin steak. We use specific cuts for two reasons. The first one is for data availability. The second one is for comparison between the two quality grades as well as between the wholesale and retail market levels. Observations refer to the period 2002:1–2016:8. Wholesale data were collected from the USDA-AMS Weekly Beef Archive (United States Department of Agriculture-Agricultural Marketing Service, 2016). Retail level data were collected from the Bureau of Labor Statistics (2016) and from the United States Department of Agriculture-Economic Research Service (2016). Our final data consist of twelve time series (beef cuts) with 176 observations in each one.[6] At retail level we have three time series (one for each cut) for the choice quality grade and three time series (one for each cut) for the select quality grade. The same holds for the data on quality grades and cuts at wholesale level. Summary statistics for the different cuts of choice and select quality grades are provided in Table 2. Figure 1 presents the price series for each one of the different cuts of choice and select quality grades, at wholesale and retail levels, respectively. As we can observe, it both market levels the

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

[6] For the sirloin steak cut of the select quality grade at the retail level, the last observation reported is August 2013.

higher quality grade, Choice, receives a higher price than the lower quality grade, Select.

In what follows, we describe the procedure in order to estimate the nature of price dependence for the six wholesale–retail pairs of beef cuts of choice and select quality grades.

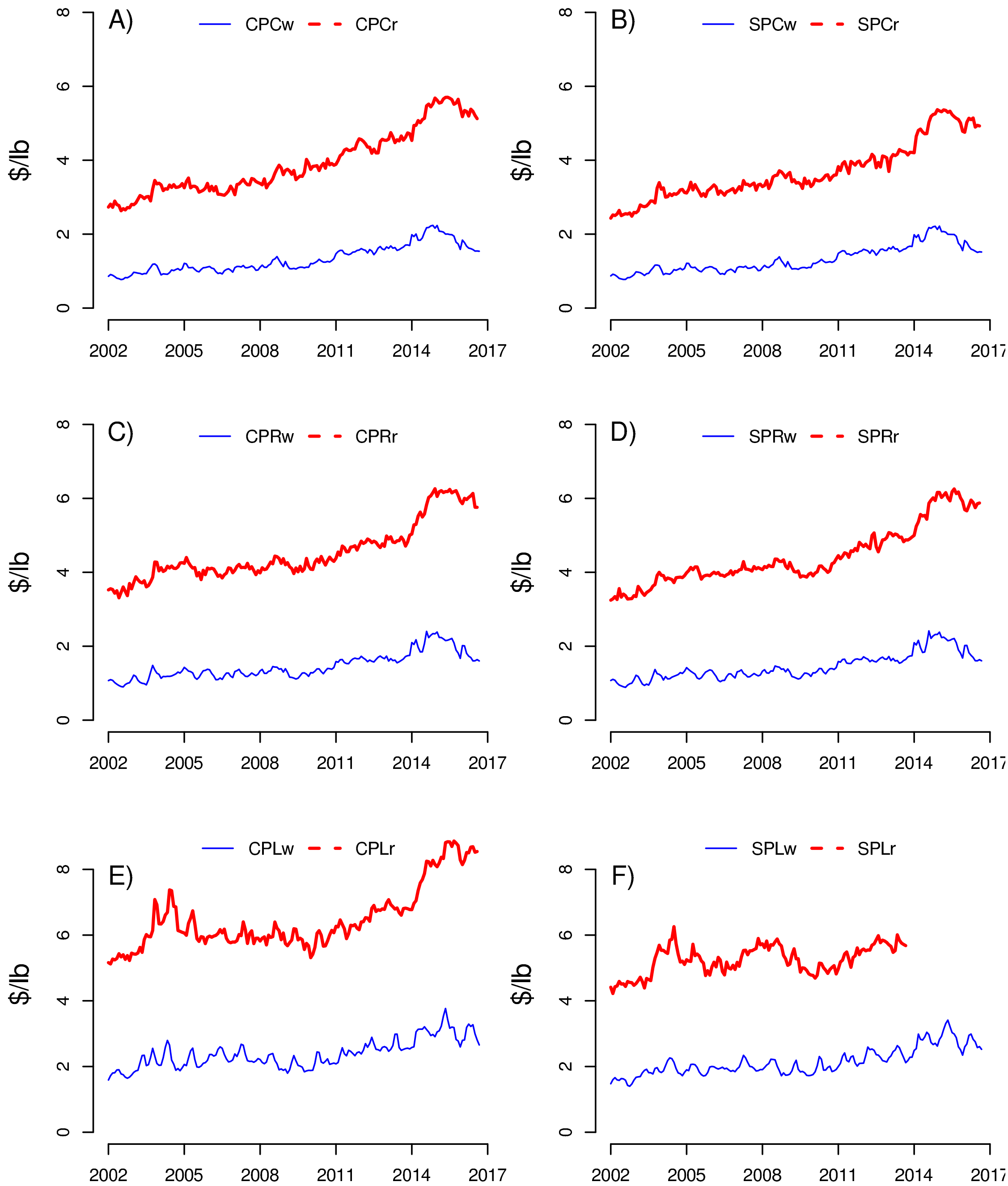

Figure 1: Time series of beef cuts prices. Notation of price series data: w=wholesale, r=retail, CPC=choice chuck roast, CPR=choice steak round, CPL=choice sirloin steak, SPC=select chuck roast, SPR=select steak round, SPL=select sirloin steak.

Table 2: Summary statistics of beef cuts prices. Notation of price series data: w=wholesale, r=retail, CPC=choice chuck roast, CPR=choice steak round, CPL=choice sirloin steak, SPC=select chuck roast, SPR=select steak round, SPL=select sirloin steak.

	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis
CPCw	1.327	0.369	0.770	2.237	0.707	2.543
CPCr	3.923	0.861	2.632	5.704	0.610	2.242
CPRw	1.459	0.348	0.899	2.402	0.886	3.154
CPRr	4.527	0.761	3.309	6.261	0.975	2.993
CPLw	2.383	0.432	1.589	3.766	0.634	2.951
CPLr	6.488	0.958	5.121	8.864	1.104	3.276
SPCw	1.317	0.362	0.774	2.217	0.742	2.642
SPCr	3.685	0.770	2.432	5.368	0.699	2.640
SPRw	1.448	0.352	0.887	2.415	0.867	3.105
SPRr	4.435	0.797	3.246	6.256	0.812	2.684
SPLw	2.142	0.411	1.399	3.412	0.836	3.160
SPLr	5.244	0.434	4.221	6.257	-0.244	2.214

3.2 ARMA–GARCH filtering and residual analysis

In order to obtain the copula data which will be employed for the empirical analysis of the study, we follow the semi-parametric approach proposed by Chen and Fan (2006). The approach involves three steps:

1. An ARMA–GARCH model is fit to the rates of price change for each of the series.
2. The obtained residuals are standardized (filtered data), creating this way the copula data on (0,1). Copula data are then used to calculate the respective empirical distribution functions.
3. The estimation of copula models is conducted by applying the maximum likelihood (ML) estimator to the copula data (Canonical ML).

Table 3 presents the p-values resulting from the application of the Lung-Box and the auto-regressive conditional heteroskedasticity–Lagrange multiplier (ARCH–LM) tests to the filtered data at various lag lengths. Lag order is indicated in parenthesis. Following the literature (Emmanouilides and Fousekis, 2015), in order to obtain the filtered rates of price change an ARMA(2,1)–GARCH(1,1) model has been fitted to each of the innovation series. Results in Table 2 indicate that the filtered data are free from autocorrelation and from ARCH effects.

Table 3: Residual diagnostics test results. Notation of price series data: w=wholesale, r=retail, CPC=choice chuck roast, CPR=choice steak round, CPL=choice sirloin steak, SPC=select chuck roast, SPR=select steak round, SPL=select sirloin steak.

	Mean	Var	Kurt.	Skew.	KS	CvM	LB(1)	LB(5)	LB(9)	AR(3)	AR(5)	AR(7)
CPCw	-0.001	1.005	3.756	0.453	0.000	0.000	0.800	0.965	0.383	0.685	0.842	0.942
CPCr	0.017	1.038	4.347	0.226	0.000	0.000	0.821	0.993	0.844	0.105	0.310	0.490
CPRw	0.023	0.996	4.362	0.636	0.000	0.000	0.724	1.000	0.347	0.841	0.676	0.630
CPRr	0.016	1.033	3.441	0.271	0.000	0.000	0.877	1.000	0.998	0.644	0.775	0.884
CPLw	-0.014	1.067	2.770	0.009	0.000	0.000	0.843	0.052	0.001	0.922	0.217	0.315
CPLr	0.029	1.058	4.922	0.350	0.000	0.000	0.474	1.000	0.903	0.964	0.766	0.616
SPCw	-0.013	1.003	3.855	0.479	0.000	0.000	0.826	1.000	0.654	0.588	0.751	0.880
SPCr	-0.094	1.034	3.221	0.091	0.000	0.000	0.514	1.000	0.994	0.795	0.922	0.796
SPRw	-0.007	1.003	4.396	0.803	0.000	0.000	0.653	1.000	0.266	0.976	0.802	0.722
SPRr	0.012	1.086	4.060	0.408	0.000	0.000	0.893	0.852	0.774	0.697	0.921	0.932
SPLw	0.014	1.012	2.881	-0.056	0.000	0.000	0.642	0.979	0.015	0.891	0.492	0.446
SPLr	0.057	0.980	3.121	0.270	0.000	0.000	0.541	1.000	0.928	0.420	0.580	0.652

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, are approximated using resampling methods ((Choroś et al., 2010; Gaißer et al., 2010)). All estimations, testing, and resampling in this study have been carried out using R (version 3.1.2, R Core Team (2014)).

3.3 Copula stability

Random processes can be influenced by the presence of extreme market conditions. Thus, before selecting the appropriate functional form for a copula, we need to test for time–varying dependence. If the copula parameters are constant over the period of time examined in this study then we can proceed with the selection of the empirical copula. On the other hand, if the parameters are influenced by breaks and/or persistent shifts, then it is possible that more than one copula families might be selected in order to describe the nature of price dependence between the two market levels. Copula stability was tested with the employment of the Busetti–Harvey test. Table 4 presents the values of the constancy test for the three quantiles of the bivariate empirical copulas (0.25, 0.5 and 0.75). The values of the statistics are in all cases below the 5 per cent critical value (0.461), suggesting that the null hypothesis of constancy is consistent with the data. Hence, there is not sufficient statistical evidence for breaks and/or persistent shifts in the empirical copulas examined in this study.

Table 4: Buseti-Harvey test statistics.

	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$
CPC	0.081	0.055	0.133
CPR	0.105	0.134	0.061
CPL	0.199	0.332	0.068
SPC	0.075	0.056	0.135
SPR	0.180	0.167	0.208
SPL	0.293	0.334	0.203

(*) Critical values are 0.743, 0.461 and 0.347 for the 1, 5 and 10 per cent levels of significance, respectively.

3.4 Copula selection procedure

We applied the Clarke (2007) and Vuong (1989) tests for copula selection. Clarke and Vuong tests are nested tests that compare two models in order to find which one is the best. If two models (model1 and model2 for example) are compared, then a score is assigned:

1. +1, if model1 is better than model2
2. -1, if model2 is better than model1
3. 0, if the test cannot discriminate between two models.

If one has to choose between N copula families then each family is tested against all remaining (N-1) families. We tested all possible combinations with Akaike and with Schwarz corrections. This procedure produced four possible combinations of test scores. The scores among all pairs were summed up. The copula with the highest combined score was selected as the best fitted copula family. The final scores are reported in Table 5. Appendix A presents all the scores produced from testing each copula family against the remaining nine copula families, for each wholesale–retail pair of different cuts and quality grades.

Although the Clarke and the Vuong tests are easy to implement and quite straightforward, there are two main problems when someone compares a large set of copula families (10 in this work):

- In some cases the same score might be assigned in two or more than two models.
- One model (m1) can actually have a higher score than another model (m2), but when directly comparing these two models the test cannot distinguish between them. Thus the results depend on the family set that has been used and not on the direct comparison between two models.

In both cases one needs to use other options as well, such as goodness of fit procedures, log likelihood, AIC or BIC. Various goodness of fit tests have been applied in order to select the right copula family (Genest et al., 2009; Kojadinovic et al., 2011; Berg, 2009; Okhrin et al., 2016).

In order to obtain to obtain p-values we used the bootstrap method. We performed 1000 repetitions.

Table 5 lists the results obtained by applying Vuong and Clarke tests. For each pair of variables (wholesale and retail) we applied the Vuong and Clarke tests using three variations of correction: a) no correction, b) Akaike and c) Schwarz, for the ten copula families reported in Table 1. The test result is an integer number stating how many times a specific copula scores better than all the remaining others. Possible outcomes (for 10 copula families) can be in the range of [-9,9]. Although Table 5 lists results with no correction for comparison with other cases, we did not took in consideration these results. Scores taken with Akaike (AIC) or Schwarz (BIC) correction from both Vuong and Clarke tests were summed up and this total score (Sum row at Table 5) was used as final selection criterion: the copula family with the highest score was selected as most suitable.

Tables A1–A6 in Appendix A present analytically the Vuong and Clarke test scores for each one of the six wholesale–retail beef cuts examined in this work.

Appendix B offers a comparison of the Vuong and Clarke selection criterion with some of the most commonly used copula selection criteria (logL, AIC, BIC).

4 Results and discussion

There is considerable empirical evidence in favor of uni–directional causality from upstream to downstream market levels in the US beef industry.[7] A research report by the United States Department of Agriculture-Economic Research Service (2011) under the title “How Retail Beef and Bread Prices Respond to Changes in Ingredient and Input Costs”, summarizes the findings of these studies. Results indicate that it takes on average one to two months for prices to transmit from wholesale level to retail level. The empirical results of this study were obtained while accounting for the existence of one lag in price transmission between wholesale and retail levels in the US beef industry.

Table 6 presents the parameter(s), Kendall’s tau (τ) and the lower and upper tail dependence coefficients (λ_L, λ_U) for the selected copula families for each one of the six wholesale–retail pairs of the choice and select quality grades. The selection procedure was described in section 3. Standard errors (in parentheses) were obtained with the bootstrap method. We performed 1000 repetitions. All estimates are statistically significant at the 1% level of significance or lower.[8]

In the case of the Choice quality grade three different copula families were selected for each cut. The Student–t copula was selected for the chuck roast cut (CPC), suggesting that price booms and price crashes at wholesale level will be transmitted at retail level with the same probability (10.3%), since the lower and upper tail

[7]The nature of direction has been examined using Granger causality tests as well as tests of weak exogenecity (Emmanouilides and Fousekis, 2015).

[8]Parameters τ, λ_L and λ_U are also significantly different than zero, since their values are produced from the statistically significant estimates of the family parameter θ (Table 1).

dependence coefficients assume the same value ($\lambda_L = \lambda_U = 0.103$). The degrees of freedom are approximately 7.2 (well below 30), suggesting a strong departure from normality.

The Normal copula was selected for the steak round cut (CPR). The value of the upper tail dependence coefficient (λ_U) is 0.323, indicating that with a probability of 32.3% a strongly positive rate of price change at the wholesale level will be matched with a strongly positive rate of price change at the retail level. On the other hand,the value of the lower tail dependence coefficient (λ_L) is zero, suggesting that extreme price decreases at wholesale level will not be transmitted at retail level.

The Normal copula was selected for the sirloin steak cut (CPL). The specific copula family suggests that both tail dependence coefficients (λ_L,λ_U) are no different than zero. Accordingly, a price crash (boom) at the wholesale level will not be associated with a price crash (boom) at the retail level, since the probability of transmission is no different than zero.

Kendall's tau (τ) estimates are 0.276, 0.254, and 0.279, for the chuck roast, the steak round and the sirloin steak cuts, respectively. The low values for the Kendall's τ indicate that overall dependence is not that strong in all three pairs of the higher quality grade.

The Gumbel copula was selected for all three different cuts of the Select quality grade (SPC, SPR and SPL). The Gumbel copula suggests that prices booms are transmitted between wholesale–retail levels whereas price crashes are not. More specifically, in all three cuts, the lower tail dependence coefficients are no different than zero, indicating that extreme price decreases at wholesale level are not matched by extreme price decreases at retail level. On the other hand, the upper tail dependence coefficients are statistically different than zero, providing this way evidence that price booms at the wholesale market level will be associated with price booms at the retail market level with a probability of 24.8%, 29.1% and 22.4%, for the chuck roast, the steak round and the sirloin steak cuts, respectively. A comparison of the values of the lower and upper tail dependence coefficients, for all six different pairs of Choice and Select quality grades, reveals that extreme positive price increases are more likely to be transmitted from wholesale to retail market level in the case of the inferior quality grade than they are in the case of the superior quality grade. The latter verifies, to a certain extent, the findings by Surathkal et al. (2014). In their study the authors concluded that the superior beef quality tends to show longer persistence to increase in prices and adjusts at a slower rate than the relatively inferior beef quality.

Kendall's tau (τ) estimates for the Select quality grade assume values between 0.171 and 0.227, indicating that overall dependence is not very strong. As one can observe, overall dependence between the three pairs of the Choise quality grade is (a little) stronger than overall dependence between the three pairs of the Select quality grade. This finding suggests that price changes (not booms or crashes) at wholesale level are more likely to be passed to the retail level in the case of the higher quality grade than it is for the lower quality grade. In general, the low values for the estimates of the overall dependence (Kendall's τ) in both the superior and the inferior quality grades, suggest that there is rather a very weak tendency of price changes (not extreme ones) to co-move between wholesale and retail levels.

The empirical findings of zero values for the lower tail dependence coefficients and non–zero values for the upper tail dependence coefficients, in five out of six pairs in this study, could be an indication of asymmetric price dependence between wholesale–retail market levels in the U.S. beef marketing channel. Asymmetric price relationships between the two market levels could suggest that retailers adopt different pricing strategies when extreme market conditions occur at the wholesale level: retailers' reaction is different under extreme price increases than it is under extreme price decreases. Results indicate that retailers do not respond to price crashes at the wholesale level in five out of six pairs examined in this study. The only exception is the chuck roast cut of the Choice quality grade, where extreme positive and extreme negative price changes at wholesale level are equally likely to be passed to the retail level. On the other hand, retailers respond to price booms at wholesale level and with a statistical significant probability this extreme price increase will be passed to the retail market level as well. The only exception is the sirloin cut of the choice quality grade where extreme price changes at wholesale level are not transmitted to the retail level.

The findings of this work could be another indication that in last stage of the beef supply chain there are firms (retail grocers, food service providers, restaurants) with some significant degree of market power. Under perfect competition, price changes upstream (wholesale in this study) would be transmitted downstream (retail). The findings of this work do not point towards that direction, but suggest in most of the cases extreme price decreases at wholesale level are not transmitted to retail level.

We should note here that the findings of (a)symmetric price dependence based on the values of the tail dependence coefficients of two price series (residuals) are not equivalent to (a)symmetric price changes. Although these two are intuitively linked, they are quite different concepts because: i) price dependence is on the distribution level, transmission is for specific price levels, and ii) price transmission can take place not only at low and high prices (tails), but also intermediate levels of prices.

Finally, it is worth noting that the observations we have at our disposal are at a national level and not at a local level. As Richards and Pofahl (2010) point out, the CR4 for retail food markets is about 50% at national level but rises to 80% at local level, since most food markets are local.

Estimation parameters and the values of different selection criteria are reported analytically in appendix B for each one of the six pairs investigated in this study.

5 Conclusions

There exists a growing literature on the structure of price relationships in agricultural and food economics. The ability of the vertical market structure to transmit price signals up and down the distribution system is a reflection of market performance. Evidence of downward price stickiness in agri–food supply chains can be considered as an indicator of inefficiency, and as such they attract the attention of economists and policy makers.

In the U.S. beef industry, there is a widespread belief that vertical price relationships are asymmetric. Empirical investigation on this issue has been conducted with a variety of quantitative tools such as copulas, VECM and threshold asymmetric vector correction models. As a rule, price increases upstream have been found to be transmitted downstream faster and/or more fully than price decreases. However, the majority of studies on price transmission in the US beef industry have been carried out considering aggregate commodity prices, when there is overwhelming evidence that beef should be examined as a differentiated product.

In this context, this study empirically examined if product differentiation could be a source of asymmetric price dependence along the U.S. beef marketing channel. The statistical tool used is that of copulas, since copula techniques provides us with useful extensions of conventional approaches for modeling asymmetric transmissions processes on the degree of market integration as well as evaluating responses to price shocks in the presence of extreme market conditions.

Results indicate that there is evidence of asymmetric price dependence between wholesale and retail market levels, for the different beef cuts of superior and inferior quality grades. We arrived at this conclusion because, in five out of six pairs, price booms are transmitted from wholesale to retail market level with a statistically significant probability whereas the transmission probability of a price crash from wholesale to retail level is zero.

The findings of this work verify, to a certain extent, the results of the studies by Emmanouilides and Fousekis (2015) and by Surathkal et al. (2014). The empirical results in both articles indicated that a decrease or an increase in wholesale beef prices tend to have different effects on the retail beef prices. The main difference is that the former study employed aggregate beef data while the latter work used different beef cuts and quality grades for the empirical analysis.

Asymmetric price relationships between the two market levels could suggest that retailers adopt different pricing strategies when extreme market conditions occur at the wholesale level: their reaction is different under extreme price increases than it is under extreme price decreases. This might be another indication that in the last stage of the beef supply chain there are firms with some significant degree of market power.

Lastly, asymmetric price dependence based on the values of the tail dependence coefficients are not equivalent to asymmetric price transmission. Price transmission can take place at not only low and high prices (tails), but also intermediate levels of prices. The findings of this study refer to the degree and the structure of price dependence between wholesale–retail levels when price booms and/or price crashes take place at wholesale level.

One would like to examine for the existence of asymmetries in price transmission from farm level to retail level, while accounting for product differentiation. Unfortunately, data on cuts and quality grades at farm level don't exist. Meat inspection and grading starts at wholesale level. A possible avenue for future research can include data from prime quality grade and/or more cuts from choice and select quality grades.

Table 5: Vuong and Clarke test results with Akaike and Schwarz corrections. Notation of pair series data (wholesale/retail): CPC=choice chuck roast, CPR=choice steak round, CPL=choice sirloin steak, SPC=select chuck roast, SPR=select steak round, SPL=select sirloin steak.

pair	correction	test	1	2	3	4	5	6	7	8	9	10
CPC	none	Vuong	0	0	0	1	0	-2	0	1	0	0
		Clarke	-4	8	-5	0	2	-8	5	-2	4	0
	Akaike	Vuong	1	0	0	2	1	-1	0	-1	0	-2
		Clarke	-3	7	-4	1	3	-8	5	-3	3	-1
	Schwarz	Vuong	1	0	0	3	1	-1	0	-1	0	-3
		Clarke	0	6	-4	3	4	-8	3	-4	2	-2
	Sum		-1	**13**	-8	9	9	-18	8	-9	5	-8
CPR	none	Vuong	2	2	-5	2	-5	0	2	0	2	0
		Clarke	-5	-4	-9	4	-5	2	4	4	5	4
	Akaike	Vuong	3	0	-3	3	-2	0	-1	0	0	0
		Clarke	-4	-6	-9	6	-5	4	3	3	4	4
	Schwarz	Vuong	3	-2	-2	6	-2	1	-1	-1	-1	-1
		Clarke	-4	-6	-9	8	-4	7	2	2	3	1
	Sum		-2	-14	-23	**23**	-13	12	3	4	6	4
CPL	none	Vuong	5	5	0	0	-2	-6	1	-2	1	-2
		Clarke	0	5	-5	1	-1	-7	7	-1	4	-3
	Akaike	Vuong	6	2	0	1	0	-3	0	-3	0	-3
		Clarke	3	2	-3	3	2	-7	4	-2	3	-5
	Schwarz	Vuong	7	1	0	1	0	-2	-1	-3	0	-3
		Clarke	4	1	-2	5	3	-6	3	-5	3	-6
	Sum		**20**	6	-5	10	5	-19	6	-13	7	-17
SPC	FALSE	Vuong	1	1	0	0	-2	0	0	0	0	0
	FALSE	Clarke	-2	-1	-6	5	-4	-4	4	5	5	-2
	Akaike	Vuong	2	-1	0	1	-1	1	0	-1	0	-1
	Akaike	Clarke	2	-3	-6	6	-1	0	2	2	2	-4
	Schwarz	Vuong	2	-1	0	2	-1	1	0	-1	0	-2
	Schwarz	Clarke	4	-4	-3	8	-1	0	-1	1	1	-5
	Sum		10	-7	-9	**17**	-4	2	1	-1	3	-12
SPR	FALSE	Vuong	0	0	0	1	0	-2	0	1	0	0
	FALSE	Clarke	-5	7	-5	2	-2	-5	3	2	4	-1
	Akaike	Vuong	0	0	0	2	1	-1	0	-1	0	-1
	Akaike	Clarke	-4	5	-5	4	0	-4	3	1	2	-2
	Schwarz	Vuong	2	0	0	2	1	-1	0	-2	0	-2
	Schwarz	Clarke	0	4	-5	6	1	-2	0	-1	1	-4
	Sum		-2	9	-10	**15**	3	-8	3	-3	2	-9
SPL	FALSE	Vuong	0	0	0	0	0	0	0	0	0	0
	FALSE	Clarke	-5	6	-3	1	-2	-4	4	1	5	-3
	Akaike	Vuong	0	0	0	1	1	0	0	-1	0	-1
	Akaike	Clarke	-1	3	-1	4	0	-2	1	-1	3	-6
	Schwarz	Vuong	1	0	0	2	1	0	0	-1	0	-3
	Schwarz	Clarke	0	3	1	4	0	-1	0	-2	2	-7
	Sum		0	6	0	**11**	2	-3	1	-5	5	-17

Table 6: Copula estimation results and test statistics

pair	family	θ	θ_2	τ	λ_L	λ_U	p-val	logL	AIC	BIC
CPC	t	0.420	ν=7.249	0.276	0.103	0.103	0.718	17.115	-30.23	-23.912
		(0.068)	(5.724)							
CPR	G	1.341		0.254	0.000	0.323	0.720	15.877	-29.754	-26.595
		(0.077)								
CPL	N	0.425		0.279	0.000	0.000	0.290	15.974	-29.947	-26.788
		(0.059)								
SPC	G	1.237		0.191	0.000	0.248	0.240	9.699	-17.398	-14.238
		(0.068)								
SPR	G	1.294		0.227	0.000	0.291	0.020	11.278	-20.556	-17.397
		(0.075)								
SPL	G	1.206		0.171	0.000	0.224	0.200	5.814	-9.628	-6.693
		(0.077)								

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Appendices

Appendix A Vuong and Clarke test results

Each table below has two parts. The upper triangle shows the results of Vuong test (index number of selected copula) between each pair of copula families (1 to 10). The last column shows the total score of the corresponding copula. The copula with the highest score is selected as the best. The lower triangle shows the results of Clarke test (index number of selected copula) between each pair of copula families (1 to 10). The last row shows the total score of the corresponding copula. The copula the highest score is selected as the best.

For the calculation of the total score a value of -1, 0, 1 is assigned to each pair comparison and subsequently these values are summed up. For N copula families the total score is in the range of [-N+1, N-1], for example if N=10 as in this case the total score can be between -9 and 9.

We performed this type of calculation twice, one time with the Akaike correction and another time with the Schwarz correction. The combined results using both tests and both correction methods (four scores) were used in order to select the best fitted copula family.

Table A1: CPC Vuong/Clarke test results with Akaike correction

	1	2	3	4	5	6	7	8	9	10	Vuong
1		0	0	0	0	0	0	0	0	1	1
2	2		0	0	0	0	0	0	0	0	0
3	0	2		0	0	0	0	0	0	0	0
4	4	2	0		0	4	0	4	0	0	2
5	0	0	5	0		0	0	0	0	5	1
6	1	2	0	4	5		0	0	0	0	-1
7	7	0	7	7	0	7		0	0	0	0
8	0	2	0	4	0	8	7		0	0	-1
9	9	2	9	0	0	9	0	9		0	0
10	0	2	0	0	5	10	0	0	0		-2
Clarke	-3	7	-4	1	3	-8	5	-3	3	-1	

Table A2: CPC Vuong/Clarke test results with Schwarz correction

	1	2	3	4	5	6	7	8	9	10	Vuong
1		0	0	0	0	0	0	0	0	1	1
2	0		0	0	0	0	0	0	0	0	0
3	0	2		0	0	0	0	0	0	0	0
4	4	2	0		0	4	0	4	0	4	3
5	0	0	5	0		0	0	0	0	5	1
6	1	2	0	4	5		0	0	0	0	-1
7	0	0	7	0	0	7		0	0	0	0
8	0	2	0	4	5	8	7		0	0	-1
9	0	2	9	0	0	9	0	9		0	0
10	0	2	0	4	5	10	0	0	0		-3
Clarke	0	6	-4	3	4	-8	3	-4	2	-2	

Table A3: CPR Vuong/Clarke test results with Akaike correction

	1	2	3	4	5	6	7	8	9	10	Vuong
1		1	1	0	1	0	0	0	0	0	3
2	1		2	0	0	0	0	0	0	0	0
3	1	2		4	0	0	0	0	0	0	-3
4	4	4	4		4	0	4	0	0	0	3
5	0	0	5	4		0	0	0	0	0	-2
6	6	6	6	0	6		0	0	0	0	0
7	7	7	7	4	7	0		0	0	0	-1
8	8	8	8	4	8	0	0		0	0	0
9	9	9	9	0	9	0	0	0		0	0
10	10	10	10	0	10	0	0	0	0		0
Clarke	-4	-6	-9	6	-5	4	3	3	4	4	

Table A4: CPR Vuong/Clarke test results with Schwarz correction

	1	2	3	4	5	6	7	8	9	10	Vuong
1		1	1	0	1	0	0	0	0	0	3
2	1		0	4	0	0	0	0	0	0	-2
3	1	2		4	0	0	0	0	0	0	-2
4	4	4	4		4	0	4	4	4	0	6
5	0	0	5	4		0	0	0	0	0	-2
6	6	6	6	0	6		0	0	0	6	1
7	7	7	7	4	7	6		0	0	0	-1
8	8	8	8	4	8	6	0		0	0	-1
9	9	9	9	4	9	0	0	0		0	-1
10	10	10	10	4	0	6	0	0	0		-1
Clarke	-4	-6	-9	8	-4	7	2	2	3	1	

Table A5: CPL Vuong/Clarke test results with Akaike correction

	1	2	3	4	5	6	7	8	9	10	Vuong
1		1	0	1	1	1	0	1	0	1	6
2	1		0	0	0	2	0	2	0	2	2
3	0	0		0	0	0	0	0	0	0	0
4	0	0	4		0	4	0	4	0	0	1
5	0	0	0	0		0	0	0	0	5	0
6	1	2	0	4	5		0	0	9	0	-4
7	0	0	7	0	0	7		0	0	0	0
8	0	2	0	4	0	8	7		0	0	-3
9	0	0	9	0	0	9	0	0		0	1
10	1	2	0	0	5	0	7	0	9		-3
Clarke	3	2	-3	3	2	-7	4	-2	3	-5	

Table A6: CPL Vuong/Clarke test results with Schwarz correction

	1	2	3	4	5	6	7	8	9	10	Vuong
1		1	0	1	1	1	1	1	0	1	7
2	1		0	0	0	0	0	2	0	2	1
3	0	0		0	0	0	0	0	0	0	0
4	0	4	4		0	4	0	4	0	0	1
5	0	0	0	0		0	0	0	0	5	0
6	1	2	0	4	5		0	0	0	0	-2
7	0	0	0	0	0	7		0	0	0	-1
8	1	2	0	4	5	0	7		0	0	-3
9	0	0	9	0	0	9	0	0		0	0
10	1	2	0	4	5	0	7	0	9		-3
Clarke	4	1	-2	5	3	-6	3	-5	3	-6	

Appendices

Appendix B Copula estimation results

Tables B1 to B6 report the parameter estimates for each one of the ten copula families for each wholesale-retail pair. The estimated p-values are from the Cramer von Mises goodness of fit test. Log Likehood, Akaike and Bayesean criteria statistics are also provided.

Asterisk in the first column denotes the selected copula family according to Clarke/Vuong procedure, as presented in the main body of this article. Maximum (p-value, logL) or minimum (AIC, BIC) values of respective criteria are also denoted with column asterisks for comparison.

Tables B1–B3 report the results for the different cuts of the choice quality grade between wholesale–retail market levels.

For the chuck roast cut (CPC), the Log Likehood test and the AIC selected the Joe-Clayton (BB7) as the best fitted copula indicating that price booms and price crashes are passed with different probabities from wholesale level to retail level. The Cramer von Mises goodness of fit test picked the Joe copula family suggesting that only extreme price increases transmit between the two market levels. In the first column, the Clarke/Vuong procedure selected the Student–t copula. Hence, four out of five copula selection criteria indicate that price booms are transmitted between wholesale–retail market levels and three out five criteria indicate that both price booms and price crashes are passed between the two market levels.

For the streak round cut (CPR), the AIC and the BIC selected the Gumbel copula family, as the Clarke/Vuong procedure in the main body of the study did, suggesting this way that only price booms, with a probability of 32.3%, are passed from wholesale to retail level. The Cramer von Mises and the Log Likehood tests picked the Joe-Clayton(BB7) as the best fitted copula indicating that price booms and price crashes are passed between the two market levels, but with different probabities.

Lastly, for the sirloin cut of the higher quality grade (CPL), the Log Likehood test, the Akaike and the Bayesean information criteria selected the Normal family of copulas. The Clarke/Vuong procedure in the main body of this article selected the Normal copula as well, suggesting this way that price booms and price crashes are not transmitted between wholesale–retail market levels. The Cramer von Mises test picked the Joe as the best fitted copula, indicating that only price booms are transmitted. Thus, five out of five copula selection criteria indicate that price crashes do not transmit from the wholesale level to the retail level and four out five criteria indicate that price booms are not passed between the two market levels. These results are another indication that for the sirloin cut of the choice quality grade price booms and price crashes at the wholesale level of the beef supply chain are not transmitted to the retail level, as it was presented in the main body of the text.

Tables B4–B6 report the results for the different cuts of the select quality grade between wholesale–retail market levels.

For the chuck roast cut (SPC), the Clarke/Vuong procedure selected the Gumbel copula suggesting that only price booms transmit from wholesale level to retail level. The Cramer von Mises goodness of fit test and the Log Likehood test selected the

Joe-Clayton (BB7) as the best fitted copula indicating that price booms and price crashes are passed, with different probabities, from wholesale level to retail level. The probalities are 24.3% and 6.3% for extreme price increases and extreme price decreases, respectively. Lastly, the AIC and the BIC picked the Normal copula suggesting that price booms and prices crashes do not tranmit from the wholesale lelel to the retail level. Thus, three out of five copula selection criteria indicate that price crashes are not transmitted between wholesale–retail market levels. The remaining two copula selection criteria indicate that price crashes are passed from the wholesale level to the retail level, but with a very low probability (6.3%). On the other hand, price booms are transmitted from the wholesale level to the retail level according to four out of five selection criteria, with almost the same probability of transmission (24%). These findings are an indication that the Gumbel copula, as selected by the Clarke/Vuong procedure in the main body of this work, describes quite well the nature of price dependence between the two market levels for the case of the chuck roast cut of the lower quality grade.

For the round roast cut (SPR), the Clarke/Vuong procedure selected the Gumbel copula and the Cramer von Mises goodness of fit test selected the Joey copula. These two copula families indicate that only extreme price increases are passed from wholesale to retail level while extreme price decreases are not. The AIC and the Log Likehood test selected the Joe-Clayton (BB7) as the best fitted copula suggesting this way that price booms and price crashes are passed with different probabities from wholesale level to retail level. Lastly, the BIC picked the Normal copula suggesting that price booms and prices crashes do not tranmit from the wholesale lelel to the retail level. Hence, three out of five copula selection criteria indicate that price crashes are not transmitted between wholesale and retail market levels. The remaining two copula selection criteria indicate that price crashes are passed between the two market levels but with a relatively low probability (12.8%). On the other hand, price booms are transmitted between the two market levels according to four out of five selection criteria. These findings are an indication that the Gumbel copula, as selected by the Clarke/Vuong procedure in the main body of this work, captures quite well the nature of price dependence between the two market levels for the chuck roast cut of the select quality grade.

Lastly, in the case of the sirloin cut (SPL), the Clarke/Vuong procedure selected the Gumbel copula indicating that only extreme price increases are passed from wholesale level to retail level. The Cramer von Mises goodness of fit test selected the Joe-Clayton (BB7) as the best fitted copula suggesting this way that price booms and price crashes are transmitted with different probabities between the two market levels. The AIC and the Log Likehood test selected the Student–t copula which indicates that price booms and price crashes are passed with the same probability from wholesale level to retail level. Lastly, the BIC picked the Clayton copula indicating that only price crashes are transmitted between the two market levels. Thus, in the case of the sirloin cut of the select quality grade, price booms and price crashes appear to trasmit between the two market levels. More specifically, four out of five copula selection criteria indicate that price booms are transmitted between wholesale and retail market levels and only one selection criterion suggests that price booms do not trasmit (or the probability of trasnmission is zero). Four out five selection criteria also suggest that price crashes are passed between the two market levels with probabilities ranging from 0.126 to 0.186. The fact that price crashes tranmit between wholesale–retail market levels is in contrast with the zero probability of tranmission as suggested by the Clarke/Vuong procedure in the main body of the article, even though these probabilities are not particularly high.

Table B1: CPC copula estimation (empirical $\tau = 0.276$)

family	θ	θ_2	τ	λ_L	λ_U	p-value	logL	AIC	BIC
1 - N	0.427		0.281		0.000	0.566	16.166	−30.331	−27.172*
2 - t *	0.420	7.249	0.276	0.103	0.103	0.682	17.115	−30.230	−23.912
3 - C	0.591		0.228	0.310	0.000	0.563	13.925	−25.850	−22.691
4 - G	1.348		0.258		0.327	0.035	15.349	−28.698	−25.539
5 - F	2.610		0.272		0.000	0.159	14.253	−26.507	−23.348
6 - J	1.433		0.196		0.378	0.951*	11.640	−21.280	−18.121
7 - BB1	0.298	1.207	0.279	0.145	0.224	0.610	17.460	−30.920	−24.602
8 - BB6	1.001	1.347	0.258	0.000	0.328	0.031	15.343	−26.686	−20.368
9 - BB7	1.270	0.456	0.273	0.219	0.274	0.594	17.644*	−31.289*	−24.971
10 - BB8	6.000	0.379	0.265	0.000	0.000	0.065	13.867	−23.734	−17.416

Table B2: CPR copula estimation (empirical $\tau = 0.260$)

family	θ	θ_2	τ	λ_L	λ_U	p-value	logL	AIC	BIC
1 - N	0.402		0.263	0.000	0.000	0.349	14.097	−26.193	−23.034
2 - t	0.396	30.000	0.260	0.001	0.001	0.182	14.073	−24.146	−17.828
3 - C	0.417		0.172	0.189	0.000	0.144	7.713	−13.426	−10.267
4 - G *	1.341	0.000	0.254	0.000	0.323	0.726	15.877	−29.754*	−26.595*
5 - F	2.214		0.235	0.000	0.000	0.191	10.711	−19.423	−16.264
6 - J	1.509		0.222	0.000	0.417	0.565	15.493	−28.985	−25.826
7 - BB1	0.023	1.329	0.256	0.000	0.315	0.625	15.897	−27.794	−21.476
8 - BB6	1.159	1.218	0.247	0.000	0.366	0.709	16.000	−28.000	−21.682
9 - BB7	1.449	0.175	0.253	0.019	0.387	0.879*	16.669*	−29.339	−23.021
10 - BB8	1.628	0.980	0.237	0.000	0.000	0.353	15.899	−27.798	−21.480

Table B3: CPL copula estimation (empirical $\tau = 0.275$)

family	θ	θ_2	τ	λ_L	λ_U	p-value	logL	AIC	BIC
1 - N *	0.427		0.281	0.000	0.000	0.265	16.126*	−30.252*	−27.093*
2 - t	0.420	30.000	0.276	0.001	0.001	0.391	15.883	−27.766	−21.447
3 - C	0.584		0.226	0.305	0.000	0.701	14.570	−27.140	−23.981
4 - G	1.302		0.232	0.000	0.297	0.012	11.985	−21.970	−18.811
5 - F	2.391		0.252	0.000	0.000	0.012	12.435	−22.871	−19.711
6 - J	1.356		0.168	0.000	0.333	0.929*	7.979	−13.958	−10.799
7 - BB1	0.396	1.126	0.259	0.211	0.150	0.574	15.843	−27.686	−21.368
8 - BB6	1.001	1.302	0.232	0.000	0.298	0.009	11.977	−19.953	−13.635
9 - BB7	1.175	0.495	0.256	0.247	0.196	0.678	15.873	−27.746	−21.428
10 - BB8	6.000	0.352	0.244	0.000	0.000	0.010	12.044	−20.089	−13.771

Table B4: SPC copula estimation (empirical $\tau = 0.217$)

family	θ	θ_2	τ	λ_L	λ_U	p-value	logL	AIC	BIC
1 - N	0.344		0.224	0.000	0.000	0.589	10.057	−18.114*	−14.955*
2 - t	0.334	30.000	0.217	0.000	0.000	0.423	9.774	−15.547	−9.229
3 - C	0.375		0.158	0.157	0.000		6.692	−11.385	−8.226
4 - G *	1.235		0.191	0.000	0.247	0.283	9.582	−17.163	−14.004
5 - F	1.686		0.182	0.000	0.000	0.216	6.619	−11.238	−8.079
6 - J	1.317		0.153	0.000	0.308		8.246	−14.491	−11.332
7 - BB1	0.147	1.170	0.203	0.018	0.191	0.600	10.252	−16.504	−10.186
8 - BB6	1.001	1.235	0.190	0.000	0.248	0.274	9.579	−15.159	−8.841
9 - BB7	1.229	0.251	0.203	0.063	0.243	0.704*	10.623*	−17.246	−10.928
10 - BB8	1.317	1.000	0.153	0.000	0.308	0.027	8.246	−12.491	−6.173

Table B5: SPR copula estimation (empirical $\tau = 0.246$)

family	θ	θ_2	τ	λ_L	λ_U	p-value	logL	AIC	BIC
1 - N	0.374		0.244	0.000	0.000	0.136	12.049	−22.098	−18.939*
2 - t	0.377	8.167	0.246	0.072	0.072	0.319	13.055	−22.110	−15.792
3 - C	0.516		0.205	0.261	0.000	0.162	11.309	−20.618	−17.459
4 - G *	1.294		0.227	0.000	0.291	0.019	11.259	−20.518	−17.359
5 - F	2.280		0.241	0.000	0.000	0.012	11.239	−20.478	−17.319
6 - J	1.364		0.171	0.000	0.338	0.883*	8.089	−14.179	−11.020
7 - BB1	0.291	1.158	0.246	0.128	0.180	0.139	13.296*	−22.591*	−16.273
8 - BB6	1.001	1.293	0.227	0.000	0.291	0.017	11.253	−18.506	−12.188
9 - BB7	1.205	0.409	0.241	0.183	0.223	0.188	13.279	−22.559	−16.241
10 - BB8	6.000	0.342	0.236	0.000	0.000	0.012	11.004	−18.007	−11.689

Table B6: SPL copula estimation ($\tau = 0.162$)

family	θ	θ_2	τ	λ_L	λ_U	p-value	logL	AIC	BIC
1 - N	0.290		0.187	0.000	0.000	0.638	5.461	−8.922	−5.988
2 - t	0.250	3.529	0.161	0.166	0.166	0.440	8.032*	−12.064*	−6.195
3 - C	0.413		0.171	0.186	0.000		6.084	−10.169	−7.234*
4 - G *	1.206		0.171	0.000	0.224	0.211	5.814	−9.628	−6.693
5 - F	1.526		0.166	0.000	0.000	0.219	4.031	−6.063	−3.128
6 - J	1.253		0.126	0.000	0.261		4.485	−6.970	−4.035
7 - BB1	0.266	1.102	0.199	0.094	0.124	0.758	7.501	−11.002	−5.134
8 - BB6	1.001	1.206	0.171	0.000	0.224	0.197	5.810	−7.621	−1.752
9 - BB7	1.151	0.334	0.201	0.126	0.174	0.791*	7.834	−11.668	−5.799
10 - BB8	6.000	0.247	0.162	0.000	0.000	0.173	3.936	−3.872	1.997

Appendices

Appendix C Copula plots

Left panel

Plots in the left on the panel displays the copula data (dark gray) on the $[0, 1]^2$ space, as well as contour lines of the corresponding copula family. Moreover 1000 simulated data of the same family and estimated parameters (Table 6) are also displayed with light gray.

Right panel

Right plot on the panel displays the $\chi-$plot, which is based on the following two quantities:

$$\chi_i = \frac{\hat{F}_{U_1,U_2}(u_{i,1}, u_{i,2}) - \hat{F}_{U_1}(u_{i,1})\hat{F}_{U_2}(u_{i,2})}{\hat{F}_{U_1}(u_{i,1})(1 - \hat{F}_{U_1}(u_{i,1}))\hat{F}_{U_2}(u_{i,2})(1 - \hat{F}_{U_2}(u_{i,2}))}$$

$$\lambda_i = 4\text{sgn}(\tilde{F}_{U_1}(u_{i,1}), \tilde{F}_{U_2}(u_{i,2})) \cdot max(\tilde{F}_{U_1}(u_{i,1})^2, \tilde{F}_{U_2}(u_{i,2})^2)$$

where:

- $\hat{F}$, empirical distribution function.
- λ_i is a measure of the distance between a data point $(u_{i,1}, u_{i,2})$ and the center of the bivariate data set.

- χ corresponds to correlation coefficient between U_1 and U_2.

- Under independence:

$$\chi_i \sim \mathcal{N}(0, 1/N)$$

$$\lambda_i \sim \mathcal{U}[-1, 1]$$

Points colored in blue represent pairs of u_1, u_2 with values less than the mean of u_1, u_2 respectively, where points colored in red represent pairs of u_1, u_2 with values bigger than the mean of u_1, u_2 respectively.

Under independence, points on the $\chi-$plot are scattered relatively horizontally, otherwise they follow a different pattern depending on the copula family and parameters.

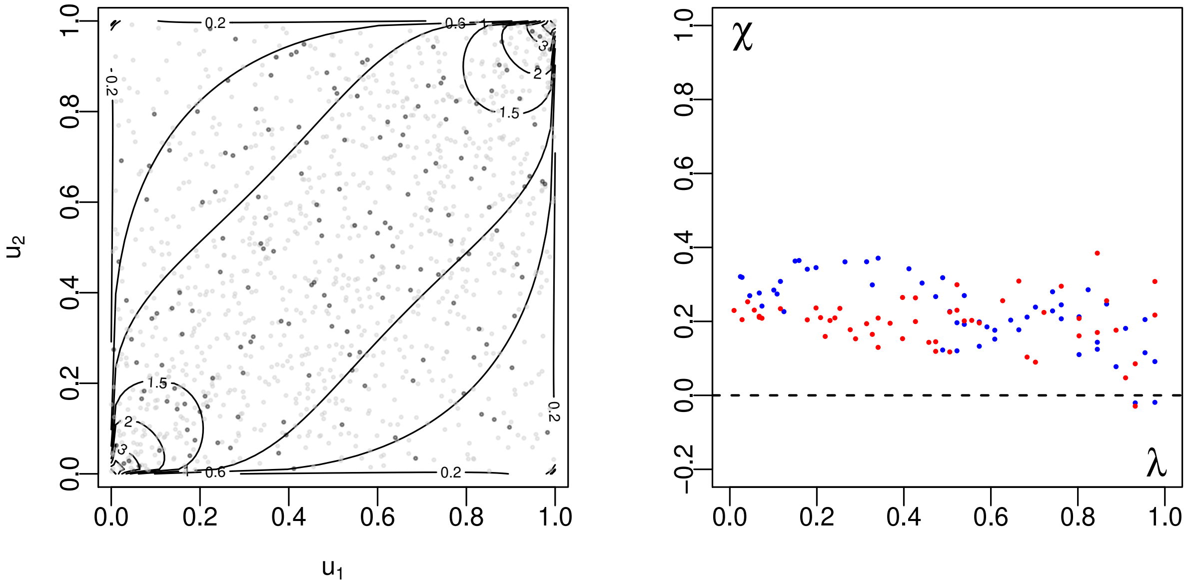

Figure C1: CPC copula plot

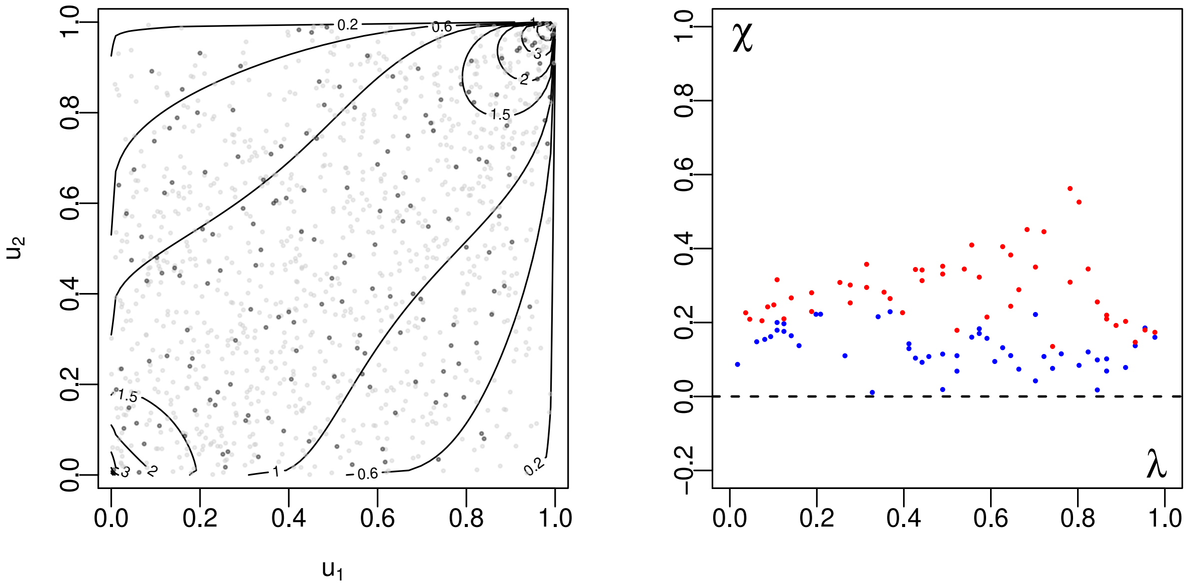

Figure C2: CPR copula plot

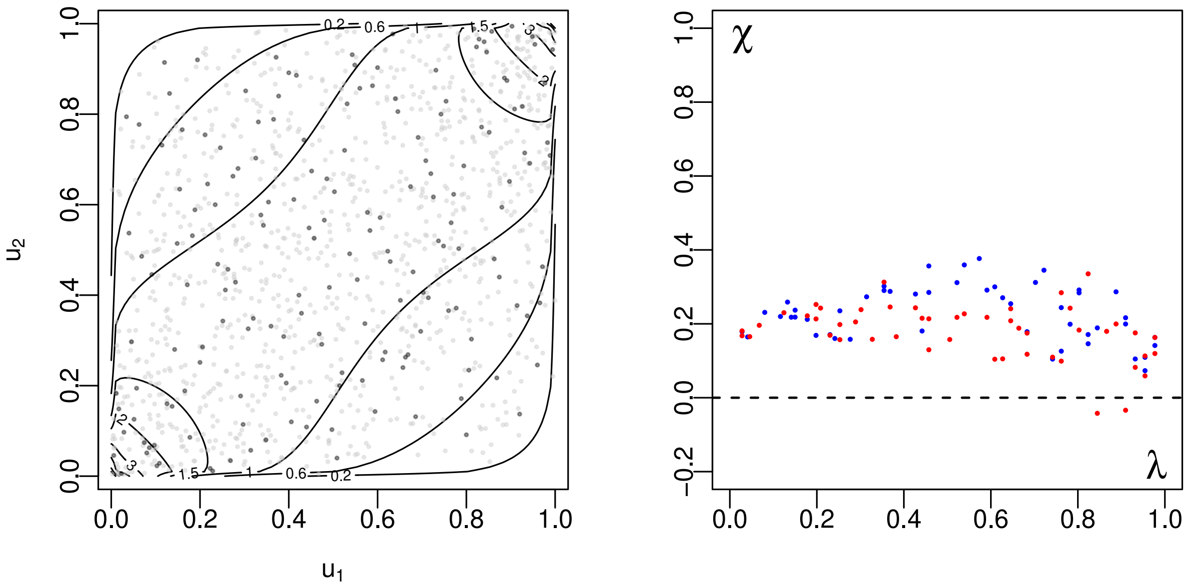

Figure C3: CPL copula plot

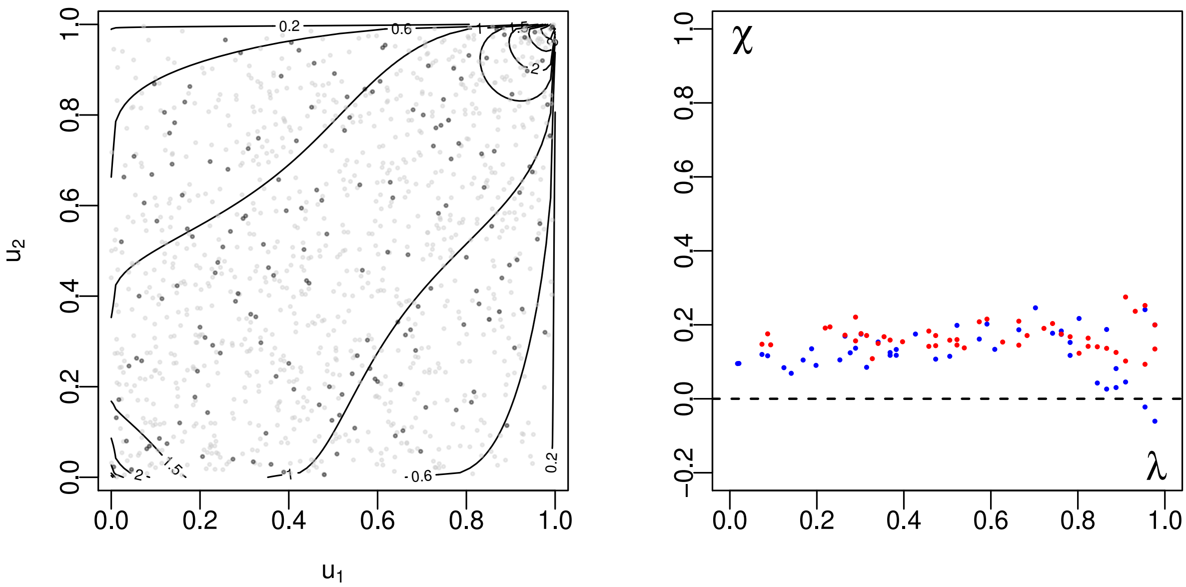

Figure C4: SPC copula plot

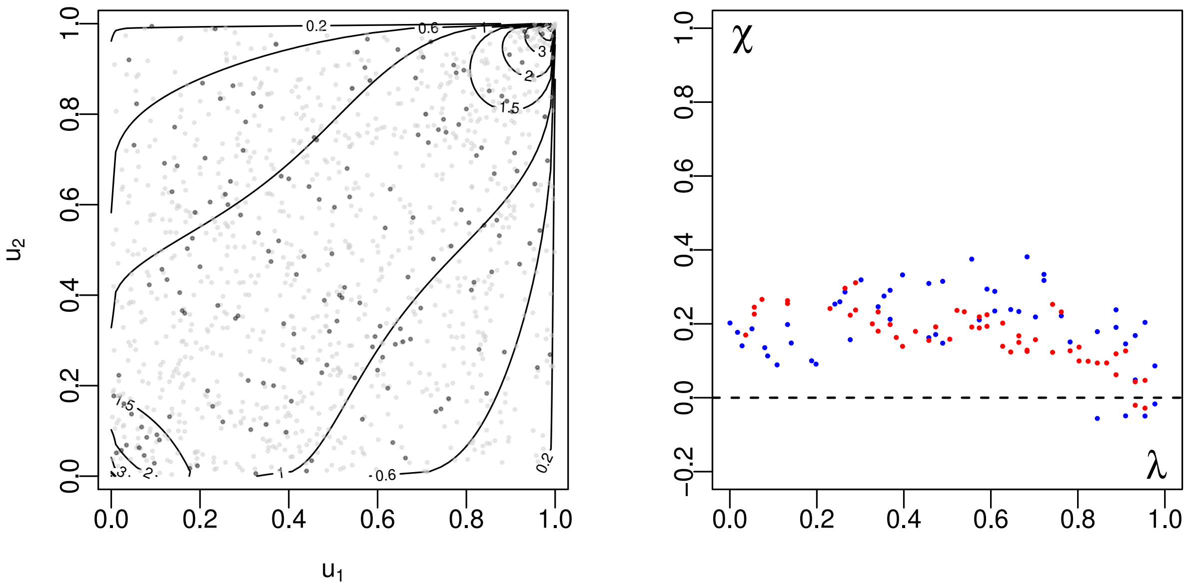

Figure C5: SPR copula plot

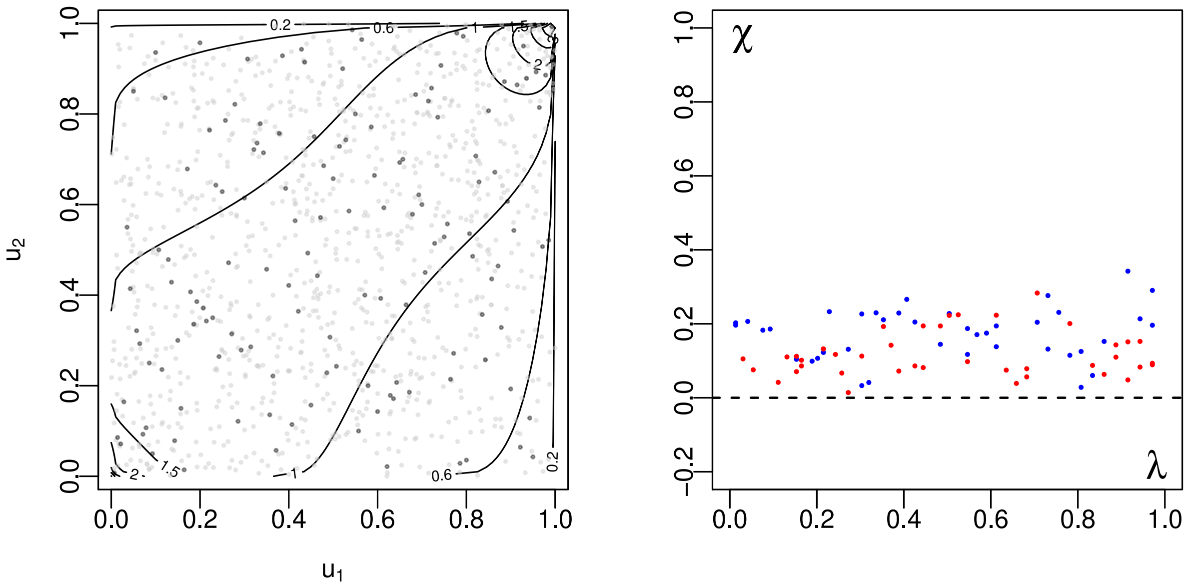

Figure C6: SPL copula plot