

An Examination of Tail Dependence in Bordeaux Futures Prices and Parker Ratings*

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Abstract

This paper explores the nonlinearities of the bivariate distribution of Bordeaux *en primeur*, or wine futures, prices and Parker “barrel ratings” for the period of 2004 through 2010. In particular, copula-function methodology is introduced and employed to examine the nature of the bivariate distribution. Our results show a significant nonlinear relationship between Parker ratings and wine prices, characterized by significant positive tail dependence and higher correlation between high ratings and high prices. Marginal distributions for Parker ratings and wine prices are then identified and Monte Carlo simulation is employed to operationalize the relationship for risk-management purposes. (JEL Classifications: C19, G13, L66)

Keywords: Bordeaux futures, copula functions, wine ratings.

I. Introduction

Every spring, young wines made from the most recent harvest in Bordeaux are sold during *élevage* (initial maturation stage) in the Bordeaux wine futures market, the *en primeur*, ahead of bottling, which may occur up to two years later. Traditionally, buyers were limited to *négociants*, or merchants, but since the 1970s, buyers have included wine merchants, importers, and private consumers, among others. There are obvious benefits to such a futures market. In particular, wines sold during *en primeur* provide early cash flow to their producers, while buyers reap the opportunity to secure allocations for particular vintages, typically at much lower prices than are

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charged when the bottled wines are released. Nevertheless, the realized price premium, defined by the spread between the bottle price and the *en primeur* price, largely depends on the quality of the bottled wine upon release. Consequently, wine critics play a significant and vital role in the fluidity of exchange in the *en primeur* market.

Prior to the opening of the *en primeur* market each year, wine critics and potential buyers gather to sample and rate the young wines still aging in barrel. Because significant discrepancies in quality between the aging wine and the final product may arise due to *élevage*, blending, and the bottling process itself, the influence of experts' opinions on potential buyers is significant. Numerous studies, such as Noparumpa, Kazaz, and Webster (2015), Ali, Lecocq, and Visser (2010), Ashenfelter (2010), and Jones and Storchmann (2001), have found that *en primeur* initial price offerings by the *châteaux* are heavily dependent on expert ratings during this period. Furthermore, the wine critic Robert Parker Jr., generally regarded as the foremost authority on Bordeaux wines, is the most influential in the setting of *en primeur* prices. Due to upward pressure on Bordeaux wine prices, Parker has declined in some years to release his reviews for *en primeur* wines prior to the initial price offerings by the *châteaux*.

The impact of Parker's reviews on *en primeur* prices is well documented and shown to be statistically significant, but the actual distributional relationship has not been clearly identified or examined at length. For example, using data from the 2010 vintage, Noparumpa et al. (2015) provide graphical evidence of a nonlinear relationship between Parker's ratings and *en primeur* prices. Given these documented nonlinearities, questions regarding the uniformity of Parker's ratings across the price distribution arise. For example, is the impact on price more prevalent at the upper echelon of ratings scores than elsewhere? To address this question, we use a copula-function approach to model the bivariate distribution between Parker's ratings and *en primeur* prices.

Copula functions are a practical method to characterize joint multivariate distributions independent of the specification of the underlying univariate marginal distributions. Furthermore, they are also relatively tractable when used to examine nonlinearities over the range of a distribution, such as tail dependence within a bivariate distribution. Identifying and characterizing the nonlinearities between expert ratings and prices are important. The exhaustive review of hedonic wine-pricing models by Oczkowski and Doucouliagos (2015) notes more than 60 studies examining more than 180 models over the past 20 years. Additionally, they carry out a meta-regression analysis of more than 30 suitable hedonic pricing models after correcting for outliers. Their results confirm a moderate, but significant, impact of quality ratings on wine prices, after controlling for various attributes, including a wine's reputation. However, inherent in their study as well as in most other hedonic pricing models is the implicit assumption of a linear correlation between ratings and prices. Some nonlinear techniques, such as the semiparametric approach used in Kwong, Cyr, Kushner, and Ogowang (2011) and Kwong, Ogowang, and Sun (2017), have been applied, yet model misspecification can still be an issue.

Our results, which employ Parker’s ratings and *en primeur* prices for the period of 2004 through 2010, demonstrate the presence of a significant upper-tail dependence in the data. That is, a strong correlation exists between high ratings and high *en primeur* prices. However, the correlation between Parker’s ratings and *en primeur* prices is not as prevalent elsewhere in the distribution of ratings. This observation holds true for the entire data set (2004–2010) as well as for each vintage examined in isolation. Furthermore, our results are somewhat consistent with the findings of Ali et al. (2010).

The remainder of this paper is organized as follows: Section II provides a brief overview of copula-function modeling, followed by a description of the data and analysis in Section III; Section IV summarizes the results and offers suggestions for future research.

II. Copula-Function Modeling

Copula functions originate from the work of Sklar (1959), who developed a theorem stating that if F is a joint distribution function of m random variables (y_1, \dots, y_m) with marginal distributions F_1, \dots, F_m , then there exists an m -dimensional copula $C: [0,1]^m \rightarrow [0,1]$ (from the unit m -cube to the unit interval) that satisfies the following three conditions:

1. If the realizations of $m-1$ variables are known, each with a probability of 1, then the joint probability of the m outcomes is the same as the probability of the remaining uncertain outcomes a_n :

$$C(1, \dots, 1, a_n, 1, \dots, 1) = a_n \text{ for every } n \leq m \text{ and for all } a_n \text{ in } [0, 1]. \tag{1}$$

2. The joint probability of all outcomes is zero if the marginal probability of any outcome is zero:

$$C(a_1, \dots, a_m) = 0 \text{ if } a_n = 0 \text{ for any } n \leq m. \tag{2}$$

3. C is m -increasing, and the C -volume of any m -dimensional interval is non-negative.

Given $F(y_1, \dots, y_m)$ with univariate marginal distributions $F_1(y_1), \dots, F_m(y_m)$ and inverse functions $F_1^{-1}, \dots, F_m^{-1}$, then

$$y_1 = F_1^{-1}(u_1) \sim F_1, \dots, y_m = F_m^{-1}(u_m) \sim F_m, \tag{3}$$

where $U = u_1, \dots, u_m$ are uniformly distributed variates and

$$\begin{aligned} F(y_1, \dots, y_m) &= F(F_1^{-1}(u_1), \dots, F_m^{-1}(u_m)) = \Pr[U_1 \leq u_1, \dots, U_m \leq u_m] \\ &= C(u_1, \dots, u_m). \end{aligned} \tag{4}$$

C is the unique copula function associated with the distribution function and

$$(F_1(y_1), \dots, F_m(y_m)) \sim C. \quad (5)$$

If $U \sim C$, then

$$(F_1^{-1}(u_1), \dots, F_m^{-1}(u_m)) \sim F. \quad (6)$$

Sklar's theorem demonstrates that any multivariate distribution can be written in terms of its univariate marginal distribution functions, along with a copula function that describes the dependence structure between the variables. The copula is a multivariate probability distribution for which the marginal probability distribution of each variable is uniform. A key element of Sklar's theorem is that in modeling a multivariate distribution, it allows for the separation in the modeling of the individual univariate marginal distributions from the dependence structure, captured by the copula function C . In particular, for an m -variate function F , the copula associated with F is a distribution function:

$$C : [0, 1]^m \rightarrow [0, 1] \text{ that satisfies } F(y_1, \dots, y_m) = C(F_1(y_1), \dots, F_m(y_m); \theta), \quad (7)$$

where θ is a vector of parameters referred to as the *dependence parameter*, measuring the dependence between the marginal distributions. In bivariate applications, θ is typically a scalar.

Goodness-of-fit testing for copula functions remains a complex and relatively unresolved area. Issues arise primarily due to the high dimensionality of the problem, particularly for copula modeling where $m \geq 3$. Summaries of the problems and approaches attempted in terms of copula goodness-of-fit testing are provided by Fermanian (2013), Okhrin (2012), Genest, Remillard, and Beaudoin (2009), and Berg (2009), among others. In general, the power of the tests proposed to date differs depending on the sample size, the dimensionality, and the copula function being tested (Berg, 2009). Although there is no universally agreed-upon methodology, a practical and frequently employed approach to bivariate copula selection is to use maximum-likelihood goodness-of-fit tests, such as the Akaike information criterion (AIC), to choose between copulas (Hasebe, 2013).

Although the number of copula functions is theoretically infinite, parametric copulas can capture typical dependence structures between covariates, with known parameters that can be estimated. These parametric forms then allow the classification of copula functions into families. A description of copula families is provided in Nelsen (2006); two important examples worth noting are the elliptical and the Archimedean families. Copulas from the elliptical family include the Gaussian (normal) copula and the Student T copula. Although they do not have simple closed-form solutions, they are easily extendable to multivariate applications where $m \geq 3$. However, they are limited to radial symmetry, restricting their ability to fully capture nonlinear, and particularly asymmetric, tail-dependence structures.

Figure 1 provides simulation plots with 10,000 observations of typical Gaussian and T copulas.

Where different upper- and lower-tail behavior is called for, copulas from the Archimedean family may be employed. They include some relatively simple closed forms with dependence parameters that allow for asymmetric tail-dependence structures between covariates in a tractable way. In particular, upper- (λ_U) and lower- (λ_L) tail-dependence measures can frequently be derived from the copula parameters as well as, in limited cases, the relationship to standard dependence measures, such as Kendall's *tau* (τ_K) and Spearman's *rho* (ρ_S) (Cherubini, Luciano, and Vecchiato, 2004).

Common forms of the Archimedean family employed are the Clayton, Gumbel, and Frank copulas. The Clayton copula allows for greater correlation, or tail dependence, in the lower values of the covariates, while the Gumbel copula captures tail dependency primarily in the higher values. The Frank copula captures greater correlation in the middle of the marginal distribution values as opposed to the tails. **Figure 2** provides simulation plots of typical bivariate Clayton, Gumbel, and Frank copula functions generated with 10,000 observations. As can be observed in **Figure 2**, the Gumbel copula does capture some lower-tail dependence as well. The greater dependence in the middle of the marginal distributions, exhibited by the Frank copula, can be readily seen when compared to the plot of the Gaussian copula.

It should be noted that through linear inversion ($1 - a$) of either, or both, of the two uniform distributions (a_n), other forms of asymmetric tail dependence may be captured. **Figure 3**, for example, provides plots of the Clayton copula where a negative transformation of the x (a_1) (Clayton (2)) or the y (a_2) (Clayton (3)) covariate, or both (Clayton (4)), has been applied. Hence, asymmetric positive tail dependence can also be modeled employing the Clayton copula on the linearly inverted uniform variates.

The relationship of the above-noted Archimedean copulas to their respective copula parameter θ , upper ($\lambda_U \in [0,1]$) and lower ($\lambda_L \in [0,1]$) asymptotic tail-dependence measures, and rank correlation measures, such as Kendall's *tau* and Spearman's *rho*, where tractable, is provided in **Table 1**, below.

The parameter of asymptotic upper-tail dependence, λ_U , is the conditional probability in the limit that one variable takes a very high value, given a high value in the other variable. Similarly, the asymptotic lower-tail dependence, λ_L , is the conditional probability in the limit that one variable takes a very low value, given a very low value in the other (Nelsen, 2006).

In the case of the Clayton copula, an upper-tail-dependence measure results in a value of zero, as it is implicitly not measured. Similarly, the Gumbel copula parameter results in a lower-tail-dependence measure of zero. However, in both cases, as noted, linear inversions of the x and y covariates can result in implicit measures of

Figure 1

Bivariate Plots of Gaussian and Student *T* Copulas

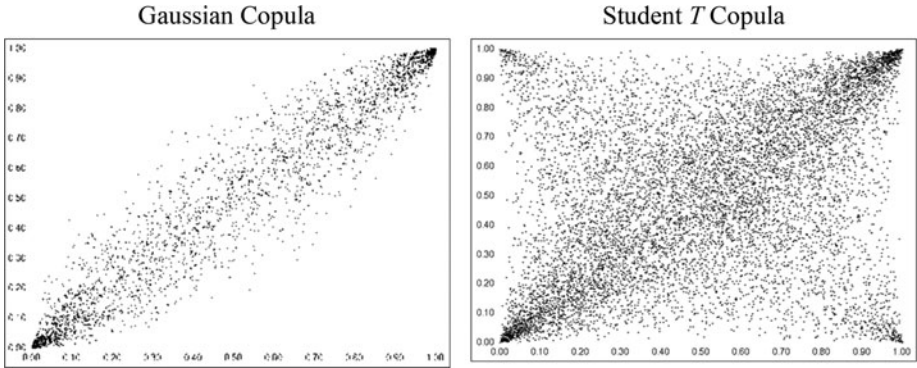
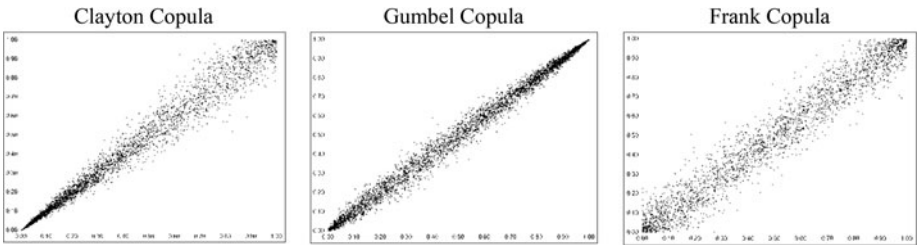


Figure 2

Bivariate Plots for Clayton, Gumbel, and Frank Copulas



upper- or lower-tail dependency, respectively. The Frank copula, which explicitly models dependency in the middle of the marginal distributions, results in upper- and lower-tail dependency values of zero.

A. Use of Copula Functions

The first application of copula functions within financial economics came from Embrechts, McNeil, and Straumann (1999). However, its usage is most infamous in terms of its wide application to the modeling of collateralized debt obligations (CDOs), and the implications for their pricing, prior to the 2008 financial crisis. Based primarily upon the seminal work of Li (2000), investment firms frequently employed a Gaussian copula function, given its simplicity in high-dimensional problems, to model the multivariate distribution of the probability of default associated with the payoffs dependent upon numerous mortgage contracts. The implied

Figure 3

Plots of Clayton Copula with Negative Transformation of Covariates

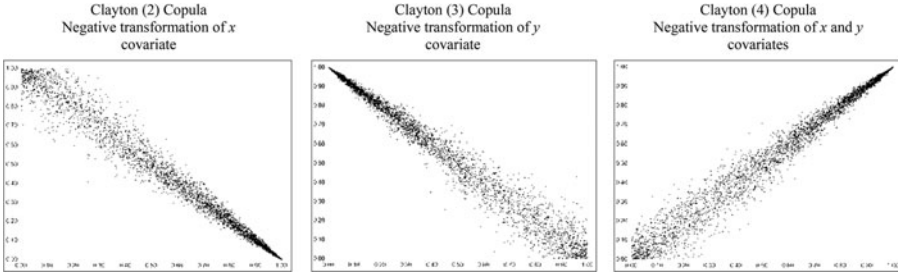


Table 1
Archimedean Copulas and Dependence Parameters

Copula	Kendall's tau (τ)	Spearman's rho (ρ_S)	Upper Tail (λ_U)	Lower Tail (λ_L)
Clayton	$\frac{\theta}{\theta + 2}$	complicated	0	$2^{-1/\theta}$
Gumbel	$1 - \theta^{-1}$	no closed form	$2 - 2^{1/\theta}$	0
Frank	$1 + 4[D_1(\theta) - 1]/\theta$	$\rho = 1 - 12[D_2(-\theta) - D_1(-\theta)]/\theta$	0	0

In the case of the Frank copula, Kendall's tau and Spearman's rho require the calculation of the Debye function, where

$$D_k(\alpha) = \frac{k}{\alpha^k} \int_0^\alpha \frac{t^k}{\exp(t) - 1} dt, \quad k = 1, 2.$$

diversification effect from combining the payoffs from multiple mortgage contracts in this manner contributed to CDOs' receiving high-quality debt ratings from bond-rating agencies. Unfortunately, the application of this particular copula tended to underestimate the tail dependence associated with the probability of default across multiple mortgage contracts. In particular, when the housing market in the United States slowed, the probability of default increased. In turn, the implicit correlation between the default probability of multiple mortgage contracts also increased. Salmon (2009) provides a succinct description of the role that incorrect copula-function modeling played in the 2008 financial crisis.

The use of copula-function modeling has since expanded quickly in several areas of research, but particularly in civil and mechanical engineering as well as climatology (e.g., Xu, Filler, Odening, and Okhrin, 2010; Schölzel and Friederichs, 2008). In the area of agricultural economics, given the tail dependence frequently observed and the implications for crop insurance, copulas have seen increasing attention and use in modeling the bivariate relationships between weather variables, prices, and crop yields (e.g., Zimmer, 2016; Bozic, Newton, Thraen, and Gould, 2014;

Okhrin, Odening, and Xu, 2013; Bokusheva, 2011; Woodard, Paulson, Vedenov, and Power, 2011; Vedenov, 2008). The only known application related to viticulture or wine is that of Cyr, Eyler, and Visser (2013).

III. Data and Analysis

We estimate and test the bivariate influence of Parker's scores on *en primeur* prices using a novel dataset obtained from <http://www.bordoverview.com>, created and maintained by the Dutch wine sellers Bolomey Wijnimport. The dataset comprises annual initial-release *en primeur* prices along with a number of wine critics' barrel ratings, including those of Parker. It has been suggested that Parker's barrel ratings have had a significant impact on rising *en primeur* prices; therefore, we examine the period of 2004 through 2010, because this span includes the renowned 2005 harvest and a stable, sustained bull run in futures prices through 2010. Primarily due to the global economic recession, between 2010 and 2014, lower sales plagued the market and exerted downward pressure on prices. In addition, in 2003, Parker's barrel ratings were released after the *en primeur* prices were set by châteaux (Ali et al., 2010).

A. Copula-Function Identification

Vose's ModelRisk software was employed to estimate various standard copula functions in defining the bivariate relationship between prices and Parker's ratings. In particular, the nonlinear relationship was examined for each year in the sample to determine the stationarity of the bivariate relationship, as well as for each Left and Right Bank vintage. As noted above, the issues surrounding goodness-of-fit tests arise primarily due to the high dimensionality of the problem (Fermanian, 2013; Panchenco, 2005). However, a standard approach to copula-function modeling is to fit several copula functions to the data and apply maximum-likelihood goodness-of-fit tests to identify which functional form models the dependency structure relatively better. This approach does not provide for a power of the test, and complexities still exist with respect to the identification of optimal goodness-of-fit tests for copulas. Choosing the copula with the largest log-likelihood can be done by choosing the copula with the smallest information criterion if the marginal distributions are fixed and the numbers of parameters to estimate are the same (Hasebe, 2013).

Table 2 provides a summary of the results for each of the years from 2004 to 2010 and for the Left and Right Banks, the number of observations of combined price and rating, and the results combining the data across both banks as well as across all years. The table reports, in each case, the best-fitting copula from the set of Gumbel, Clayton, Gaussian, Frank, and T copulas, employing the AIC maximum-likelihood test. In each case, the linear transformation of covariates was included when estimating Gumbel and Clayton copulas. Along with the best-fitting copula, Table 2 reports the dependence measures of Kendall's τ (τ),

Table 2
Maximum-Likelihood Test Results for Best-Fitting Copula

	<i>Left Bank</i>							<i>Right Bank</i>						
	<i>Copula</i>	<i>obs</i>	τ	ρ_P	θ	λ_U	λ_L	<i>Copula</i>	<i>obs</i>	τ	ρ_P	θ	λ_U	λ_L
2004	Gumbel	80	0.52	0.63	2.14	0.62	0.00	Gumbel	81	0.47	0.48	1.88	0.55	0.00
2005	Gumbel	150	0.57	0.58	2.33	0.65	0.00	Frank	149	0.55	0.35	6.77	0.00	0.00
2006	Clayton (4)	98	0.52	0.51	2.16	0.00	0.73	Clayton (4)	85	0.51	0.59	2.07	0.00	0.71
2007	Clayton (4)	91	0.45	0.42	1.63	0.00	0.65	Clayton (4)	98	0.37	0.37	1.19	0.00	0.56
2008	Gumbel	105	0.63	0.68	2.67	0.70	0.00	Clayton (4)	109	0.58	0.57	2.75	0.00	0.78
2009	Clayton (4)	114	0.63	0.63	3.38	0.00	0.81	Gumbel	130	0.59	0.51	2.43	0.67	0.00
2010	Gumbel	110	0.61	0.63	2.57	0.69	0.00	Gumbel	115	0.63	0.55	2.71	0.71	0.00
2004–2010	Gumbel	748	0.55	0.52	2.24	0.64	0.00	Gumbel	767	0.51	0.42	2.03	0.59	0.00

<i>Combined Left and Right Bank</i>							
	<i>Copula</i>	<i>obs</i>	τ	ρ_P	θ	λ_U	λ_L
2004	Gumbel	161	0.49	0.49	1.97	0.58	0.00
2005	Gumbel	299	0.57	0.39	2.32	0.65	0.00
2006	Clayton (4)	183	0.51	0.54	2.05	0.00	0.71
2007	Clayton (4)	189	0.40	0.39	1.35	0.00	0.60
2008	Gumbel	214	0.60	0.53	2.49	0.68	0.00
2009	Clayton (4)	244	0.60	0.58	3.04	0.00	0.80
2010	Gumbel	225	0.61	0.57	2.58	0.69	0.00
2004–2010	Gumbel	1515	0.53	0.45	2.14	0.62	0.00

Pearson's ρ_P , (the copula coefficient for the Gaussian and T copulas) and upper- or lower-tail-dependence parameters in the case of the Gumbel and Clayton copulas. It is important to note again that in the case of a linear transformation of both covariates, the lower-tail-dependence measure for the Clayton (4) copula actually reflects upper-tail dependence in terms of the untransformed data.

Our results easily conclude that *en primeur* prices and Parker's ratings exhibit fairly consistent upper-tail dependence in terms of the identified best-fitting copula as being the Gumbel or the transformed-data (Clayton (4)) copula. Only in the case of Right Bank wines in 2005 is the identified best-fitting copula not the Gumbel or the Clayton (4). In that particular case, the Frank copula is best fitting, indicating greater dependence in the middle of the bivariate distribution as opposed to at the tails. When the Left and Right Bank data are combined, all seven years exhibit a high value of tail dependence; when the data are employed across all years, the Gumbel copula is identified for the Left and Right Bank data, jointly and separately.

As previously noted, the upper-tail-dependence parameter represents the conditional probability in the limit that one variable (wine price) exhibits a high value, given a high value in the other variable (critic's rating). In terms of the Left Bank, when the data across all seven years are combined, this conditional probability is 0.64; for the Right Bank, it is 0.59. When the Left and Right Bank data are combined, the conditional probability of a high wine price given a high wine rating is 0.62.

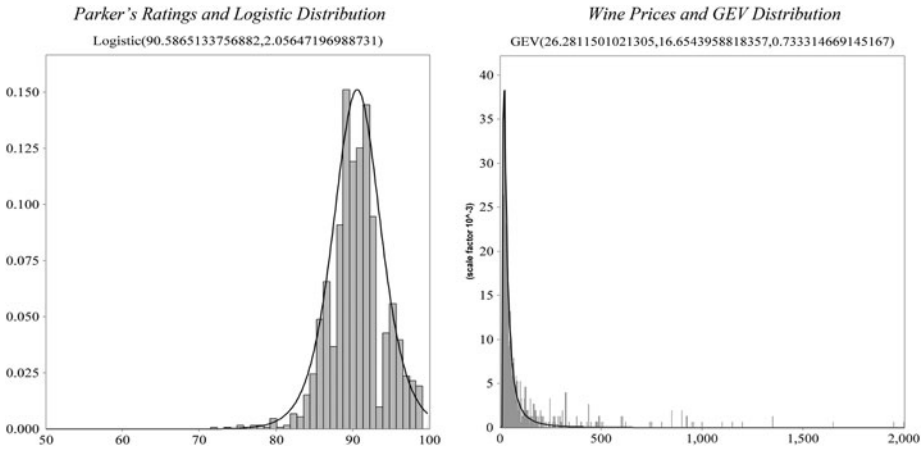
The importance of the upper-tail dependence is also exhibited in terms of the linear-dependence parameters. Kendall's τ and Pearson's correlation coefficient indicate positive correlation ranging, in the case of Pearson's ρ_P from $\rho_P = 0.35$ for the 2005 Right Bank data to $\rho_P = 0.68$ for the 2008 Left Bank data. However, in all cases (except for the 2005 Right Bank data), the linear-correlation results are driven by nonlinear upper-tail dependence.

B. Marginal-Distribution Identification

As noted previously, the benefit of copula-function modeling is the ability to identify marginal distributions independently from the identification of the copula function. For Parker's ratings and for wine prices, the AIC maximum-likelihood test statistic is employed to identify the most representative probability-distribution function. In the case of Parker's ratings, truncation of the lower tail at a value of 50 and an upper-tail limit of 100 is controlled for, while in the case of wine prices, the distributions are constrained with a truncated lower tail of zero, given non-negative prices. Ninety different possible continuous and discrete probability distributions are considered and ranked in each case using the AIC statistic for Parker's ratings and for wine prices. The results (available from the authors) for the Left and Right Banks and for 2004 through 2010 are consistent. In particular, Parker's ratings exhibit significant

Figure 4

Histogram and Plot of Best-Fitting Distribution for Parker’s Ratings and Wine Prices: 2004–2010 Left and Right Banks



negative skewness for each of the years and for the Left and Right Banks, while wine prices exhibit significant positive skewness.

Given the relative stationarity in terms of results for the Right and Left Bank data as well as across years, the combined data of 1,515 observations are employed to identify suitable marginal distributions. The best-fitting distribution functions and their parameters are found to be the Logistic distribution ($\alpha = 90.59$, $\beta = 2.06$) in the case of Parker’s ratings and the Generalized Extreme Value (GEV) distribution ($a = 26.28$, $b = 16.65$, $c = 0.73$) in the case of wine prices. The marginal distributions are illustrated in Figure 4, plotted along with the histograms of the 1,515 observations of rating and price data.

C. Monte Carlo Simulation

Employing the Logistic distribution for Parker’s ratings, the GEV distribution for prices, and the identified Gumbel copula ($\theta = 2.13676$) based on the combined 2004–2010 Left and Right Bank data, Monte Carlo simulation is used to generate 5,000 observations of Parker’s ratings and wine prices. Figure 5 provides a bivariate uniform-distribution plot of the data from the simulation, which indicates primarily upper-tail dependence and slight lower-tail dependence consistent with the Gumbel copula.

Figure 6 shows the plot of the 5,000 simulated Parker’s ratings and wine prices, which indicates a strong nonlinear relationship between ratings and prices, consistent with the findings of Noparumpa et al. (2015).

Figure 5

Bivariate Uniform-Distribution Plot of Simulated Parker's Ratings and Wine Price Data

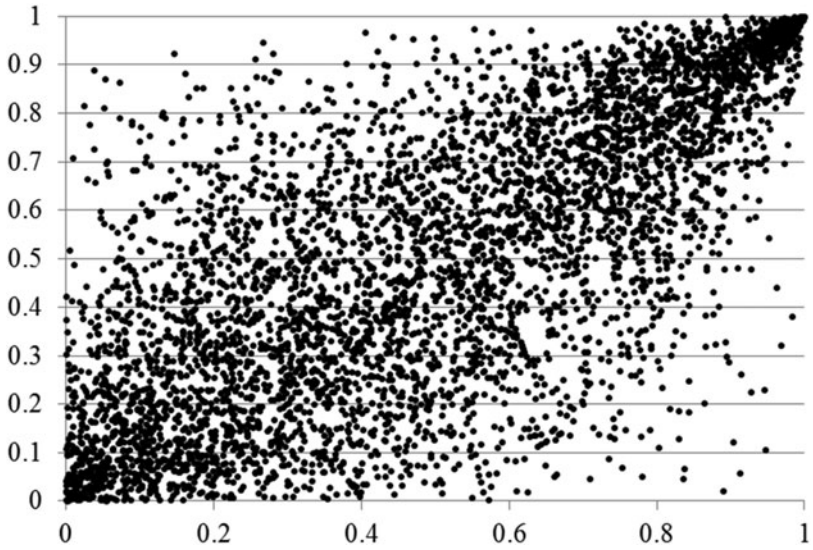


Figure 6

Graph of Simulated Parker's Ratings and Wine Prices

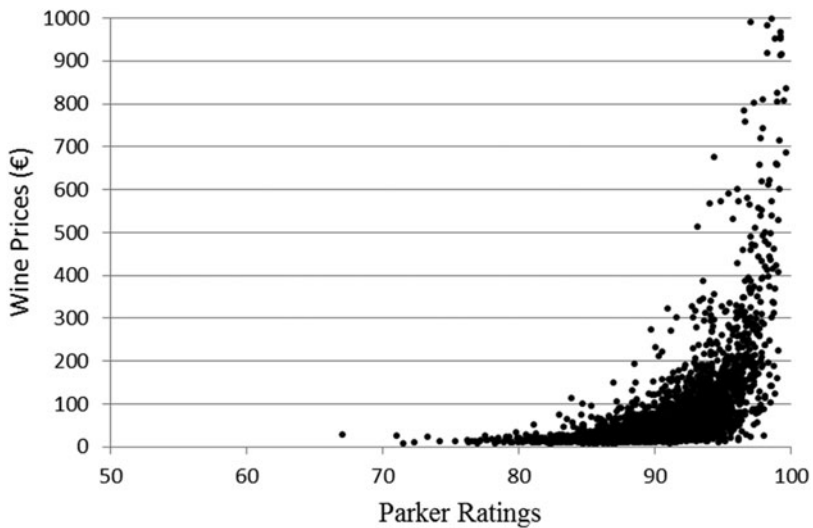


Table 3
Price Average, Standard Deviation, and Price/Rating Correlation for Different Ranges of Parker's Ratings

<i>Rating</i>	<i>Average Price</i>	<i>Standard Deviation</i>	<i>Pearson Correlation</i>
75–80	15.83 €	5.81 €	0.27
80–85	19.42 €	12.05 €	0.15
85–90	27.55 €	16.93 €	0.21
90–95	59.27 €	63.68 €	0.36
95–100	391.96 €	779.63 €	0.52

The value of the simulation is in ascertaining the relationship between Parker's ratings and *en primeur* prices. We categorize the 5,000 simulated data points by ratings, and calculate the Pearson correlation coefficient between ratings and prices in each respective category to provide a more intuitive sense of the relationship. The results, shown in Table 3, provide a practical indication of the nonlinear relationship between the two variables. In particular, some lower-tail dependence is exhibited with a Pearson correlation coefficient of 0.27 in the 75–80 rating range, while the highest correlation is in the 95–100 rating range, with a correlation coefficient of 0.52.

The review of the impact of expert ratings on wine prices by Oczkowski and Doucouliagos (2015) affirms a moderate but significant impact of quality ratings on wine prices; however, our results indicate a significant nonlinearity in the relationship, with the greatest correlation occurring at the positive tail of the bivariate distribution. This result has significant ramifications for producers in determining the potential impact of experts' ratings on prices.

IV. Conclusions and Future Research

Although Parker is the leading wine critic, he has recently discontinued his provision of barrel ratings (Lyons, 2015). Therefore, further study could include an examination of the nonlinear relationship of wine futures prices to other wine critics' ratings. The database includes, for example, the wine ratings of 11 other critics, including the renowned Jancis Robinson and *Decanter* magazine. One approach in terms of further research could include an examination of *en primeur* prices with respect to an index of ratings. Standardization of wine critics' ratings is therefore a related issue (Cardebat and Paroissien, 2015). In addition, a copula-function approach to the relationship between various wine critics' ratings would be insightful.

Other factors affecting wine prices, such as reputation, could also be explored through more complex multivariate copula-function modeling. Limitations exist, as of yet, in terms of computational complexity. In addition, more complex copula functions, such as the Joe–Clayton copula, could also be employed. This particular copula function could provide a more refined estimate of lower-tail

dependence along with the strong upper-tail dependence observed. Clearly, however, upper-tail dependence between Parker's ratings and *en primeur* prices is the dominant relationship.

Additional opportunities exist for the use of copula-function modeling within the endeavor of viticulture and wine, particularly in terms of weather variables, harvests, and wine quality. These possibilities are evidenced by recent applications in agricultural economics with respect to many other agricultural commodities and the implications for risk management. Other opportunities may also exist in terms of consumer-preference research.

References

- Ali, H. H., Lecocq, S., and Visser, M. (2010). The impact of gurus: Parker grades and *en primeur* wine prices. *Journal of Wine Economics*, 5(1), 22–39.
- Ashenfelter, O. (2010). Predicting the quality and prices of Bordeaux wine. *Journal of Wine Economics*, 5(1), 40–52.
- Berg, D. (2009). Copula goodness-of-fit testing: An overview and power comparison. *European Journal of Finance*, 15(7–8), 675–701.
- Bokusheva, R. (2011). Measuring dependence in joint distributions of yield and weather variables. *Agricultural Finance Review*, 71(1), 120–141.
- Bozic, M., Newton, J., Thraen, C. S., and Gould, B. W. (2014). Tails curtailed: Accounting for nonlinear dependence in pricing margin insurance for dairy farmers. *American Journal of Agricultural Economics*, 96(4), 1117–1135.
- Cardebat, J. M., and Parioissien, E. (2015). Standardizing expert wine scores: An application for Bordeaux *en primeur*. *Journal of Wine Economics*, 10(3), 329–348.
- Cherubini, U., Luciano, E., and Vecchiato, W. (2004). *Copula Methods in Finance*. West Sussex, U.K.: Wiley.
- Cyr, D., Eyler, R., and Visser, M. (2013). The use of copula functions in pricing weather contracts for the California wine industry. Working Paper. Brock University.
- Embrechts, P., McNeil, A., and Straumann, D. (1999). Correlation and dependence in risk management: Properties and pitfalls. *RISK*, May 1999, 69–71.
- Fermanian, J. D. (2013). An overview of the goodness-of-fit test problem for copulas. In Jaworski, P., Durante, F., and Härdle, W. K. (eds.), *Copulae in Mathematical and Quantitative Finance: Proceedings of the Workshop Held in Cracow, 10-11 July* (pp. 61–89). Berlin: Springer.
- Genest, C., Remillard, B., and Beaudoin, D. (2009). Goodness-of-fit tests for copulas: A review and a power study. *Insurance: Mathematics and Economics*, 44(2), 199–213.
- Hasebe, T. (2013). Copula-based maximum-likelihood estimation of sample-selection models. *Stata Journal*, 13(3), 547–573.
- Jones, G. V., and Storchmann, K. (2001). Wine market prices and investment under uncertainty: An econometric model for Bordeaux crus classes. *Agricultural Economics*, 26(2), 115–133.
- Kwong, L. M. K., Cyr, D., Kushner, J., and Ogowang, T. (2011). A semiparametric hedonic pricing model of Ontario wines. *Canadian Journal of Agricultural Economics*, 59(3), 361–381.

- Kwong, L. M. K., Ogowang, T., and Sun, L. (2017). Semiparametric versus parametric hedonic wine price models: An empirical investigation. *Applied Economics Letters*, 24(13), 897–901.
- Li, D. X. (2000). On default correlation: A copula function approach. *Journal of Fixed Income*, 9(4), 43–54.
- Lyons, W. (2015). Robert Parker steps down from Bordeaux futures. *Wall Street Journal*, February 26, 2015. Accessed at <http://www.wsj.com/articles/robert-parker-steps-down-from-bordeaux-futures-1424966697>.
- Nelsen, R. B. (2006). *An Introduction to Copulas*, 2nd ed. New York: Springer.
- Noparumpa, T., Kazaz, B., and Webster, S. (2015). Wine futures and advanced selling under quality uncertainty. *Manufacturing and Service Operations Management*, 17(3), 1–16.
- Okhrin, O. (2012). Fitting high-dimensional copulae to data. In *Handbook of Computational Finance* (pp. 469–501). Berlin: Springer.
- Okhrin, O., Odening, M., and Xu, W. (2013). Systemic weather risk and crop insurance: The case of China. *Journal of Risk and Insurance*, 80(2), 351–372.
- Oczkowski, E., and Doucouliagos, H. (2015). Wine prices and quality ratings: A meta-regression analysis. *American Journal of Agricultural Economics*, 97(1), 103–121.
- Panchenko, V. (2005). Goodness-of-fit test for copulas. *Physica A: Statistical Mechanics and Its Applications*, 355(1), 176–182.
- Salmon, F. (2009). Recipe for disaster: The formula that killed Wall Street. *Wired Magazine*, February 23, 2009. Accessed at http://archive.wired.com/techbiz/it/magazine/17-03/wp_quant?currentPage=all.
- Schölzel, C., and Friederichs, P. (2008). Multivariate non-normally distributed random variables in climate research – Introduction to the copula approach. *Nonlinear Processes in Geophysics*, 15(5), 761–772.
- Sklar, A. (1959). Fonctions de répartition à n dimensions et leurs marges. *Publications de l'Institut de Statistique de l'Université de Paris*, 8, 299–321.
- Vedenov, D. V. (2008). Application of copulas to estimation of joint crop yield distributions. Contributed paper at the Agricultural and Applied Economics Association 2008 Annual Meeting, Orlando, Florida, USA, July. Accessed at <http://ageconsearch.tind.io/bitstream/6264/2/464004.pdf>.
- Woodard, J. D., Paulson, N. D., Vedenov, D., and Power, G. J. (2011). Impact of copula choice on the modeling of crop yield basis risk. *Agricultural Economics*, 42(s1), 101–112.
- Xu, W., Filler, G., Odening, M., and Okhrin, O. (2010). On the systemic nature of weather risk. *Agricultural Finance Review*, 70(2), 267–284.
- Zimmer, D. M. (2016). Crop price comovements during extreme market downturns. *Australian Journal of Agricultural and Resource Economics*, 60(2), 265–283.