Integration of the EU broiler meat markets – Application of Regular Vine Copulas

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Abstract

This article examines the degree and structure of price dependence in the major broiler meat markets within the European Union. The state of play for the EU broiler meat sector has changed especially in terms of political strand and trade environment. The increasing market orientation and international competition faced by the producers in the EU provide a reason to increase our knowledge of the market dynamics and thus, help the policy makers to evaluate how the gains from trade will be distributed. In addition, results will provide insights whether the long-run EU policy objective of market integration has been reached for the EU broiler meat markets.

The empirical investigation applied mixed regular vine copulas which provide a flexible set of tools for multivariate analysis. The data used consists of monthly prices of broiler meat from eight EU member states from 2004:05 until 2017:10. The countries under examination were the Netherlands, Belgium, Poland, Germany, the United Kingdom, France, Spain and Italy. The results suggest asymmetric but weak price dependencies within the EU broiler meat markets. The empirical model revealed that only negative price changes tend to transmit between the pairs of countries. Based on the overall results, it seems that the EU policy objective considering the single market has not been reached when it comes to the markets for broiler meat.

Introduction

The competitiveness of the European Union in global markets is directly tied to the performance of its member states which further depends on national policies and structural factors. Disparities in the performance may inhibit market integration and thus, lead to market inefficiencies and distorted gains from trade (European Commission 2016.) It is no wonder, that market integration has been one of the fundamental and long-standing objectives for the European Union. The Common Agricultural Policy (CAP) which initially consisted of twenty-one common market organizations (CMOs) was among the first EU policies to reach this objective for agricultural markets. (Moussis 2016; EEC No 2777/75.)

Policy interventions have caused imbalances in the functioning of the EU agricultural markets which may have impeded market integration. (Götz et al. 2013, Zanias 1993). The EU Single Market Programme launched in 1993 intended to strengthen market integration by harmonizing all tariff and non-tariff measures within the EU trade. Harmonization of trade rules included a long-term objective to enhance the capability of the EU to negotiate international agreements behalf of all the member states. (European Commission 2017.) The CAP reforms, and particularly the transition from twenty-one separate CMOs into a single one in 2007, further aimed at increasing market orientation and integrity within the EU agricultural markets. (European Parliament 2017a & 2017b; EC No 1234/2007.)

Due to the policy reforms in Common Agricultural Policy and the EU enlargements, the state of play for the EU agricultural markets have changed. For instance, after the enlargements a relatively new member state Poland has become the largest producer of broiler meat in the EU and thus a source of trade (AVEC 2016). Furthermore, the EU is facing an increasing pressure from international level to free its agricultural trade. Lately, competitive agricultural producers such as the United States and MERCOSUR-countries have opened discussions with the EU to increase trade including meat products. (European Commission 2017.) It is necessary for policy makers to know the price transmission mechanisms within the EU markets, and to understand the causal effects that international commitments may have throughout the EU markets.

The degree of policy intervention has varied among the agricultural sectors. (European Commission 2017). Particularly, broiler meat sector has been relatively more market oriented than many other agricultural sectors within the EU. First, the sector has received no public intervention at the EU level after 2013 since export subsidies have no longer been granted. Second, a short production cycle and vertical integration within the supply chain facilitate the adjustment to market developments. (AVEC 2016.) However, certain impeding characteristics exists such as high degree of concentration within the sector. For example, Sexton et al. (1991) pointed out that non-competitive market behaviour may impede market integration between spatially distinct markets. In addition, production costs have been found to vary between the member states which sets a challenge for the pricewise comparability of the sector across the EU. (van Horne 2017; AVEC 2016; Fousekis 2007.)

Serra, Gil and Goodwin (2006) along their study of EU pork meat markets noted that also the EU broiler meat markets are economically relevant to analyze spatial price relationships. In addition to the previously described characteristics, broiler meat is relatively homogenous product among the EU consumers. The sector has also undergone Highly Pathogenic Avian Influenza (HPAI) outbreaks which have caused trade bans and disruptions in production, further leading to variation in broiler meat prices. (AVEC 2016; USDA 2017; Serra et al. 2006.)

The number of studies examining market integration within the EU broiler meat markets is limited. Fousekis (2007) examined pork and poultry meat prices within the EU by using a clustering algorithm in order to evaluate the market integration of the two sectors. The results indicated large disparities in prices and thus rejected the existence of market integration. Tremma and Semos (2017) investigated price transmission of broiler meat markets between four EU member states. The results suggested slight degree of market integration between the observed four countries. However, the number of countries included in the analysis was not sufficient to draw definite conclusions about market integration within the principal broiler meat markets in the EU.

Market integration and price transmission studies have conventionally utilized methodologies such as co-integration, vector error correction models and threshold autoregressive models (Assefa et al. 2013; Listorti & Esposti 2012; Fackler & Goodwin 2001). Recently, the statistical tool of copulas have attracted attention in applied economics and market integration studies because of their suitability for modelling joint behaviour in multivariate random processes. Copulas provide sophisticated tools to model dependence behaviour enabling numerous symmetric and asymmetric (extreme) dependence structures to be detected (e.g. Joe 2015; Kurowicka & Joe 2011; Patton 2012; Nelsen 2006.)

Recent applications utilizing copulas to examine market integration within the EU agricultural markets have been done by Emmanouilides, Fousekis and Grigoriadis (2014) who investigated price dependence in the principal EU olive oil markets, and Grigoriadis, Emmanouilides and Fousekis (2016) who examined the integration of pig meat markets in the EU. Other applications within agricultural economics and price dynamics include e.g. Fousekis and Grigoriadis (2017, 2016), Qiu & Rude (2016), Fousekis, Emmanouilides, Grigoriadis (2016), Panagiotou and Stavrakoudis (2015), Zimmer (2015), Emmanouilides and Fousekis (2015, 2014) and Emmanouilides, Fousekis and Grigoriadis (2014). Market integration within other sectors has been studied e.g. by Roberedo (2011) and Serra (2012).

Against the provided background, the purpose of this article is to examine the degree and structure of price dependence within the EU broiler meat markets by applying the statistical tool of vine copulas to time series data. The results can be utilized to argue whether the policy objective of market integration has been reached for the considered EU broiler markets. Furthermore, the results will provide information about the existing linkages between the markets. In this article, we define spatial market integration as the degree of price co-movement between different regions (Fackler & Goodwin 2001).

Analytical Framework

A copula is a multivariate distribution with uniform margins on [0,1]. Copulas allow multivariate dependence structure and marginal distributions to be investigated separately as any distribution of a continuous random variable can be converted to follow a uniform distribution by using probability integral transform (Joe 2015). Let $\boldsymbol{X} = (X_1, \ldots, X_d)$ be a vector of random variables and $F = (F_1, \ldots. F_d)$ the d-dimensional distribution function of $\boldsymbol{X}$. According to Sklar's theorem (Sklar 1959) for every multivariate distribution of $F = (F_1, \ldots. F_d)$, there exists a copula C linking multivariate distribution function and their respective univariate margins

$$F(x_1, \ldots x_n) = C\big(F_n(x_1), \ldots., F_n(x_n)\big). \tag{1}$$

Furthermore, if strictly holds $F(x_1, \ldots x_d) \in [-\infty, \infty]$ then the copula function (1) can be expressed in terms of inverse distribution functions of the marginals

$$C(u_1, \ldots u_d) = F\Big(F_1^{-1}(u_1), \ldots., F_d^{-1}(u_d)\Big). \tag{2}$$

Applying the chain rule, the density of F is given by f

$$f(x_1, \ldots. x_d) = \left[\prod_{k=1}^{c} f_k(x_k)\right] \cdot c\big(F_1(x_1), \ldots., F_d(x_d)\big) \tag{3}$$

, where $c\big(F_1(x_1), \dots, F_d(x_d)\big)$ is the copula density. (See e.g. Joe 2015; Aas et al. 2009.)

The copula based dependence structures among random variables are examined with bivariate concordance measures and tail dependence measures. Functional dependence i.e. concordance is measured using a rank based correlation measure Kendall's tau which provides information of co-movement across the entire joint distribution function. In addition, other copula-based correlation measures exists such as Spearman's rho or Blomqvist's beta. However, Kendall's tau is commonly applied in empirical literature and is easily compatible with copula parameters (Embrechts et al. 2003). Consider that U_1 and U_2 are uniformly distributed random variables on [0, 1] and C is a copula function. Then, Kendall's tau is defined as

$$\tau = 4 \iint C(u1, u2) dC(u1, u2) - 1. \tag{4}$$

Tail dependence measure provides information about extreme co-movement between random variables. In other words, the measure indicates how extreme large or small values of a random variable appear simultaneously with large or small values of another random variable. The upper tail dependence λ_U and the lower tail dependence λ_L coefficients for a bivariate copula C are defined as

$$\lambda_U = \lim_{u \to 1} \frac{1 - 2u + C(u, u)}{1 - u} \in [0,1] \tag{5}$$

$$\lambda_L = \lim_{u \to 0} \frac{C(u, u)}{u} \in [0,1]. \tag{6}$$

Thus, bivariate tail dependence is measured from the upper-quadrant tail (positive shocks) or from the lower-quadrant tail (negative shocks) of a bivariate distribution. (Joe 2015; Nelsen 2006.)

The representation of (1) – (3) is for multivariate copulas in dimensions $d > 2$. As such, applications of standard multivariate copulas suffer from certain limitations as they do not allow for different dependence structures between pairs of variables. To overcome the inflexibility problem, initially Joe (2015, originally in 1996) and later Bedford and Cooke (2001, 2002) showed that a multivariate density can be constructed with $d(d - 1)/2$ bivariate (conditional) copulas. These are called pair-copula constructions (PCCs) or vine copulas. Vines are graphical representations of PCCs which decompose multivariate distributions into pairs allowing each dependence structure between pairs of variables to be modelled independently. (Brechmann & Schepsmeier 2013; Bedford & Cooke 2002.)

The additional flexibility that vines offer for higher dimensions stems from the existence of wide range of well investigated copula families for bivariate dependence structures. Vines utilize both the class of Elliptical copulas and Archimedean copulas. The class of Elliptical copulas include one or two parameter copulas such as Gaussian or Student's t-copula. The other class, Archimedean copulas, includes a wide range of one or two parameter copulas such as the Clayton, Gumbel or Frank, reflecting various patterns of extreme tail behavior. Details of different copula parameters, Kendall's taus and tail dependence measures for copula families see e.g. Schepsmeier et al. (2017) and Joe (2015).

Regular vines (R-vines) present the most flexible class of vine modeling. The two boundary cases of R-vines, namely C- and D-vines, are common in empirical application as they provide slightly less complexity in the procedures (see e.g. Aas et al. 2009; Kurowicka & Joe 2011). This research applies R-vines because they allow examination of flexible dependence structures which may be present in the observed data of the broiler meat prices across the European Union.

The general structure for vine copulas is determined by a set of bivariate copulas. The structure is presented graphically with a *vine tree.* For vines, the density $f(x_1, \dots x_n)$ can be presented as a product of pair copula densities and marginal densities. Consider a vector of three random variables $\boldsymbol{X}$ = $(x_1, x_{2,} x_3)$ with strictly increasing and continuous marginal densities $\boldsymbol{F}$ = $(f_1, f_{2,} f_3)$ and their respective margins. The *joint density* can be written by using recursive conditioning as follows:

$$f(x_1, x_{2,} x_3) = f_1(x_1) \cdot f(x_2|x_1) \cdot f(x_3|x_1, x_2). \tag{7}$$

Applying Sklar's theorem to (4), the three-dimensional *conditional density* function becomes

$$f(x_2|x_1) = \frac{f(x_1, x_2)}{f_1(x_1)} = \frac{c_{12}(F_1(x_1), F_2(x_2))\, f_1(x_1) f_2(x_2)}{f_1(x_1)} = c_{12}(F_1(x_1), F_2(x_2))\, f_2(x_2) \tag{8}$$

and

$$f(x_3|x_{1\,,} x_2) = \frac{f(x_2, x_3|x_1)}{f(x_2|x_1)} = \frac{c_{23|1}\{F(x_2|x_1), F(x_3|x_1)\}\, f(x_2|x_1) f(x_3|x_1)}{f(x_2|x_1)} \tag{9}$$

$$= c_{23|1}(F(x_2|x_1), F(x_3|x_1))\, f(x_3|x_1) \tag{10}$$

$$= c_{23|1}(F(x_2|x_1), F(x_3|x_1)) c_{13}(F_1(x_1), F_3(x_3))\, f_3(x_3). \tag{11}$$

Eventually, the joint density can be expressed as a product of pair-copulas and marginal densities

$$f(x_1, x_{2,} x_3) = f_1(x_1) \cdot f_2(x_2) \cdot f_3(x_3) \\ \cdot c_{12}\{F_1(x_1), F_2(x_2)\} \\ \cdot c_{13}\{F_1(x_1), F_3(x_3)\} \\ \cdot c_{23|1}\{F(x_2|x_1), (x_3|x_1)\} \qquad (12)$$

, where c_{12} and c_{13} are the unconditional copula densities and $c_{23|1}$ is the conditional copula density. However, this construction is not unique as reordering of the variables would result in a different conditioning outcome (Aas et al. 2009). Furthermore, Joe (2015) showed that the conditional distribution functions for vines can be computed recursively when the arguments of the conditional pair copula in (12) can be written in form F(x|**v**), where **v** = ($\mathbf{v}_j$, $\mathbf{v}_{-j}$),

$$F(x|\boldsymbol{v}) = \frac{\partial C_{xv_j;v_{-j}}(F(x|\boldsymbol{v}_{-j}), F(v_j|\boldsymbol{v}_{-j}))}{\partial F(v_j|\boldsymbol{v}_{-j})}. \qquad (13)$$

According to Bedford and Cooke (2001, 2002) a set of nested trees $V = (T_1, T_2, \ldots, T_{n-1})$ is a regular vine on *n* elements if and only if

1. Tree T_j has d+1–j nodes and d–j edges
2. Edges in tree Tj become nodes in tree T_{j+1}
3. Proximity condition holds: if two nodes are joined by an edge in T_{j+1}, the corresponding edge in tree T_j must share a common node.

The distribution of a regular vine has three components. The first component is the tree structure $\boldsymbol{V}$ of linked trees which identifies the pairs of variables and conditioning variables. The second component is the set of parametric bivariate copulas $B = B(\boldsymbol{V})$ for each edge in the tree structure. The third component is the set of corresponding parameter values $\boldsymbol{\theta}\{B(\boldsymbol{V})\}$. As a result, regular vine is fully specified by R($\boldsymbol{V}, \boldsymbol{B}, \boldsymbol{\theta}$). Furthermore, the density of a R-vine distribution is defined by the product of pair copula densities over the *n(n-1)/2* edges which are identified by the tree structure and the product of marginal densities. Thus, the general density for regular vines is given as

$$f(x_1, \ldots, x_d) = \left[\prod_{k-1}^{d} f_k(x_k)\right] \times \left[\prod_{j=d-1}^{1} \prod_{i=d}^{j+1} c_{m_{j,j}, m_{i,j}; m_{i+1,j}, \ldots, m_{n,j}}\right] \qquad (14)$$

, where $m_{i,j}$ refers to element (*i*,*j*) in the matrix representation of the R-vine. (Dissmann et al. 2013; Bedford & Cooke 2001 & 2002.)

The number of R-vine structures for n nodes is defined by $(\frac{n!}{2} x\; 2(n - 2^{\binom{n-2}{2}})$ meaning that the number of possible structures escalates as n increases and the manual interpretation becomes infeasible (Joe & Kurowicka 2015; Morales-Nápoles 2010). Computational selection of a regular vine tree can be done by using a sequential algorithm developed by Dissmann et al. (2013). The sequential approach makes use of the empirical Kendall’s tau as starting values to select the strongest pairwise dependencies and to build the maximal spanning tree accordingly. The process begins with estimating the first tree T_1 and proceeds to the lower trees as a top-down method. The selection of the estimated parameters and the tree structure is based on the Akaike Information Criterion (Akaike 1973) as it has been found to be reliable under similar processes. (Schepsmeier et al. 2017; Dissmann et al. 2013; Brechmann et al. 2012.)

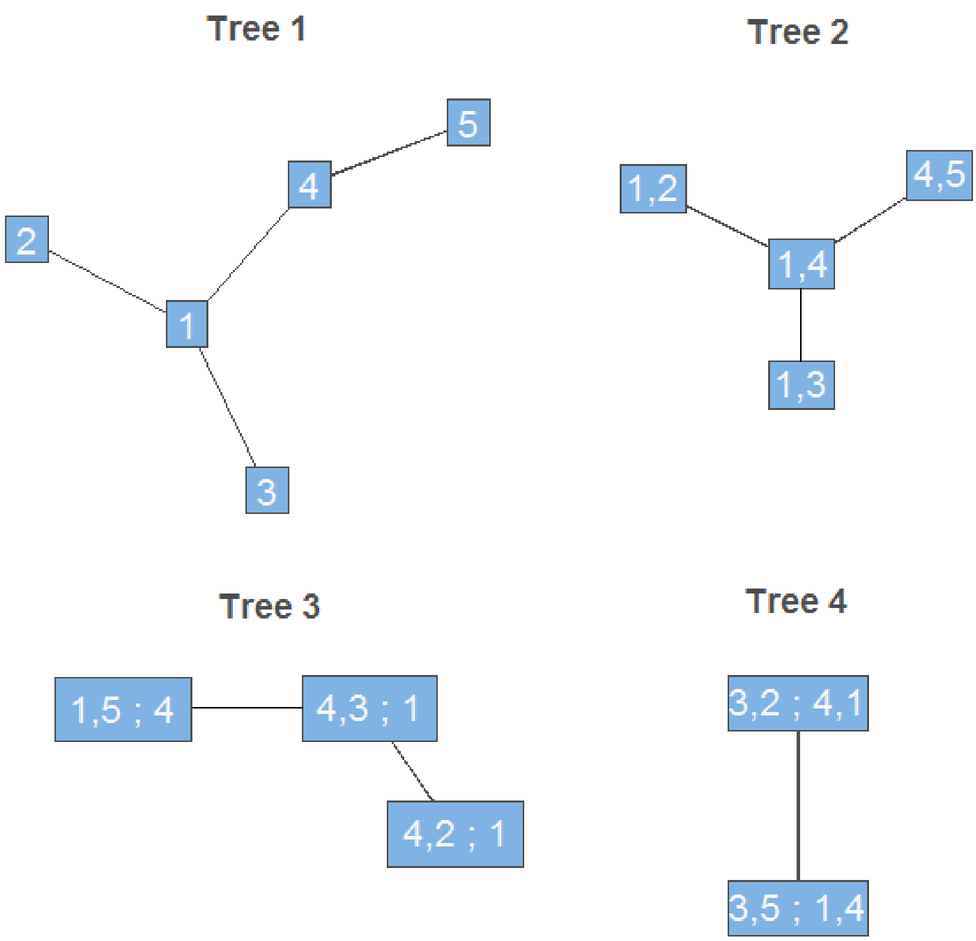

Figure 1 Hypothetical tree structure constructed with four random variables.

Figure 1 shows a hypothetical construction of a four-dimensional R-vine tree where Tree 1 shows the unconditional bivariate copulas between the variables. The second tree shows the conditioned bivariate copulas between variables in Tree 1. The latter trees are built accordingly. In figure 1 the conditioned sets are indicated as (*i*,*j*) and the conditioning set as (; *k*). Notice that each R-vine tree contains unique but necessary information to distinguish it from other possible R-vine tree structures. For more properties and details of R-vines are found for instance in Bedford and Cooke (2001, 2002) and Kurowicka and Joe (2011).

Empirical model and results

The European Union is a significant producer of poultry meat globally and a net exporter into the world markets. In 2016, the total production of poultry meat reached 14.693 million tons of which broiler meat accounted for 82%. The major producing member states are Poland (16%), France (12%), the United Kingdom (12%), Germany (11%), Spain (10%) and Italy (9%). In total, the six member states produce 72% of broiler meat in the EU. (European Commission 2017b.)

In terms of trade, the EU is the third largest exporter of poultry meat into the world markets after Brazil and the US. In 2016, the exports to the world markets totalled 1.397 million tons while the imports from the world markets totalled 0.828 million tons. However, the majority of the EU broiler meat trade occurs within the EU borders. The main intra-importers are Germany, France, the UK, the Netherlands, Belgium and Spain whereas the main exporters are the Netherlands, Poland, Germany, France, Belgium and the UK. (USDA 2017; FAO 2016, AVEC 2016.)

Spatially distinct markets are linked via trade meaning that trade is a necessary albeit not sufficient condition for market integration (Fackler & Goodwin 2001). For this reason, the countries were selected based on to their role as a trading country rather than a producing country. However, one can notice that same member states seem to be listed as large producers and traders. The analysis included eight countries: the Netherlands (NL), Germany (DE), Poland (PL), France (FR), the United Kingdom (UK), Belgium (BE), Spain (ES) and Italy (IT).

The data consists of monthly prices of broiler meat in the eight countries from 2004:05 until 2017:10 and has been obtained from the European Commission (2017b). The prices are expressed in €/100kg carcass weight. The usage of broiler meat data sets a challenge for our analysis because the prices are not fully comparable between the member states due to differences in market structures and production costs. For example, van Horne (2016) studied the competitiveness of the EU broiler meat sector and noted that the production and processing costs vary largely among the member states. In addition, some degree of market concentration has been detected within the sector. (AVEC 2016; Fousekis 2007).

Our analysis employs the semi-parametric approach (Chen & Fan 2006). In the first stage, each univariate price series is filtered with an ARMA(p,q)-GARCH(1,1) model with Skewed-t or standard normal distributions in order to take into account the possible dynamics in the conditional mean and conditional variance (Ghalanos 2017; Joe 2015; Tsay 2010). This procedure is widely applied into financial time series data and can be found in applications among agricultural economics (See e.g. Nikoloulopoulos et al. 2012; Patton 2012; Aas et al. 2009; Fousekis et al. 2017 & 2016). In the second stage, the obtained standardised residuals are converted into *copula data* with uniform margins on [0,1]. Eventually, the estimates of copula parameters are obtained by using the maximum likelihood estimation.

In the first stage, we used the raw price shocks calculated as rates of price change, $d \ln p_{st}$, where d is the first difference in price p, and p_{st} is the price of broiler meat in a member state (NL, DE, PL, FR, UK, BE, ES, IT) s at time t. The appropriate ARMA(p,q) models were tested with various lag lengths ($p,q \leq 4$). The constant mean model was rejected for the series NL (1,0), FR (4,0) and DE (1,0). For the rest of the series the appropriate models were found to be PL (2,1), ES (2,1), IT (2,1), UK (2,1) and BE (1,2). Three series (PL, UK and ES) were modelled with Skewed-t distributions and the other series with standard normal distribution. Ljung-Box tests and ARCH LM tests (Fisher & Gallagher 2012) proved that the filtered series (standardized residuals) are free from autocorrelation and ARCH-effects.

In the next step, the standardized residuals were transformed into copula data by using the empirical distribution functions and their probability integral transforms (Brechmann et al 2013; Patton 2012; Genest et al. 1995.) Unlike for the raw time series data, for copula estimators the asymptotic properties under the assumption of i.i.d. have been established (Haff 2013; Genest et al. 1995). The estimation procedures were performed using R-Software and the package VineCopula by Schepsmeier et al. (2017).

The values for empirical Kendall's tau and the corresponding sums for each market pairs were calculated to examine the underlying dependence structures. The results are presented in table 1. One can observe that the correlation measures are rather low for all market pairs suggesting weak integration between the considered markets. However, the sums of absolute empirical Kendall's tau indicate that Belgium shows the highest degree of overall co-movement with other countries. The Netherlands, Italy and Poland follow. Belgium, the Netherlands and Poland are among the major traders in broiler meat which may explain the highest values of Kendall's tau with other markets. Notice, that the values are not evenly high between all countries but certain country pairs show stronger connections. Italy seems to have highest values of Kendall's tau with Germany, Poland and France. Germany and France have lower values of Kendall's tau with other markets than with Italy which could be an indication of some degree of clustering. The lowest values for overall Kendall's tau were indicated by Spain, France and the UK. The low degree of interdependence may be explained by market concentration.

Table 1 Values for empirical Kendall's tau and the corresponding sums of Kendall's tau.

Country	NL	DE	PL	UK	FR	BE	ES	IT	$\sum_{j,j\neq i} \|\hat{\tau}_{i.j}\|$
NL	1.000								0.830
DE	0.087	1.000							0.590
PL	0.148	0.035	1.000						0.710
UK	0.082	0.056	0.069	1.000					0.510
FR	0.031	0.112	0.059	0.073	1.000				0.450
BE	0.263	0.129	0.243	0.140	0.004	1.000			1.000
ES	0.143	-0.019	0.007	-0.040	0.067	0.132	1.000		0.510
IT	0.076	0.150	0.152	0.052	0.195	-0.037	0.099	1.000	0.760

The estimation of the copula parameters and the corresponding empirical R-vine tree structure for our dataset was obtained using the sequential approach (Dissmann et al. 2013). As an initial data analysis, the independence test for bivariate copula data is proposed in the cases when the strength of dependence appears to be small. The test statistic for independence is calculated with the following formula where n is the number of observation and $\hat{\tau}$ is the empirical value of Kendall's tau

$$T = \sqrt{\frac{9n(n-1)}{2(2n+5)}} \times |\hat{\tau}|. \tag{15}$$

In the selection of the appropriate bivariate copula families the mixed R-vine approach was applied meaning that the number of copula families to be considered was not restricted in order to ensure maximal flexibility. Thus, all elliptical and Archimedean copulas including rotated versions and independence copula were allowed. We utilized the Shiny App provided by the VineCopula R-package which enables graphical and analytical comparisons of different copula models. The final selection of the models was based on the Akaike Information Criterion (AIC) (Akaike 1973). The copula parameters were obtained via maximum likelihood estimation.

Tree 1 in figure 2 shows the selected R-vine tree structure and the corresponding parameter estimates and copula families. The empirical estimation suggest that Belgium (BE) is the market which have linkages with the other considered EU markets. Belgium have straight connection with markets in Poland (PL) and the United Kingdom (UK). The results suggest that these two countries (PL, UK) have no straight link with the rest of the countries. Furthermore, Belgium have connection with Italy (IT) which further have connection with Germany (DE). Lastly, Belgium is linked with the Netherlands (NL) which shares a node with Spain (ES) and eventually Spain with France (FR).

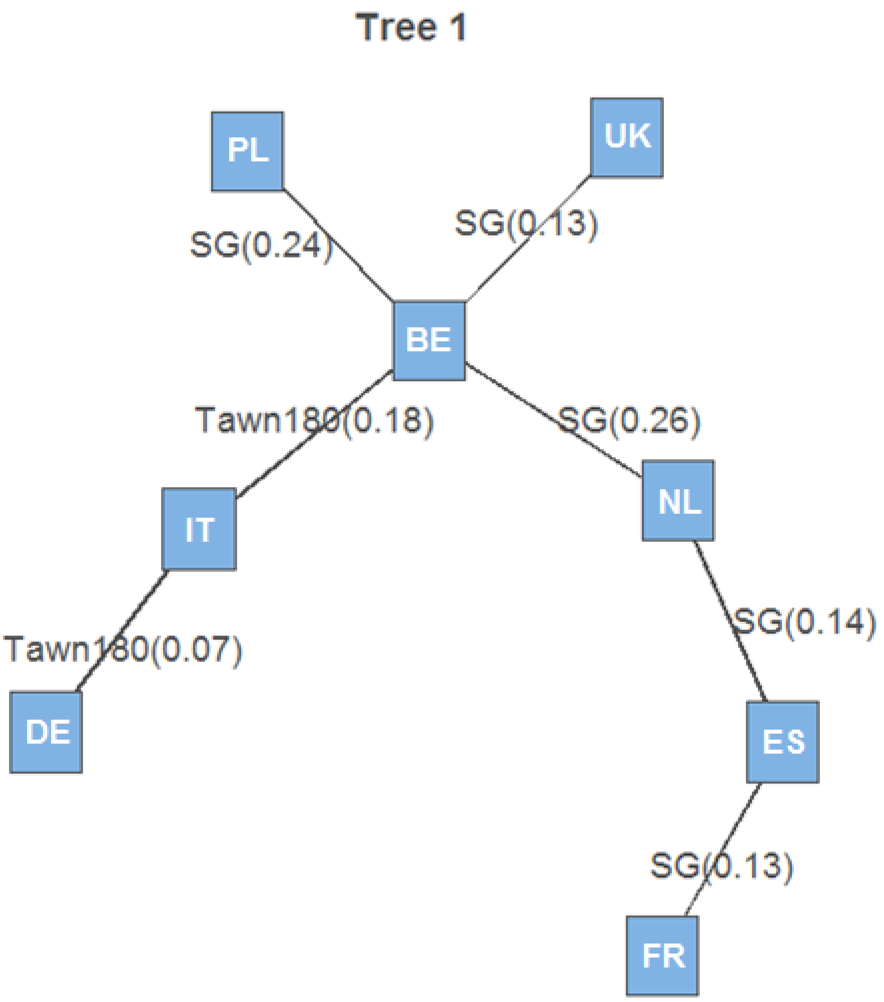

Figure 2 The empirical R-vine tree for the broiler meat prices in the EU (SG = Survival Gumbel; Tawn180 = Rotated Tawn type 1, 180 degrees)

The estimation produced trees in seven levels but dependence was found only Tree 1. In the lower trees, the dependence structures were characterised by independence copula meaning that after conditioning the unconditional variables in the Tree 1, the variables became independent from each other. However, Nikoloulopoulos et al. (2012) noted that the necessary condition for tail dependence to exist in all bivariate margins of a vine copula, tail dependence is needed only for bivariate copulas in level 1 (tree 1) and not necessarily in lower trees based on conditional bivariate copulas (Joe et al. 2011, Nikoloulopoulos et al. 2012).

The MLE estimation results for the copula parameters are shown in table 2. The obtained values for the overall co-movement parameter Kendall's tau and for the copula parameter estimates are statistically significant. The values of Kendall's tau are also in line with the empirical values shown in table 1. Notice, that the values are quite low for each estimated market pair (lowest 0.07 and highest 0.26), indicating weak dependencies over the entire joint distributions.

Table 2 Estimation results of the selected copula models

Market pair	Copula model	Parameters $\hat{\theta}$ (Standard Error)	Kendall's tau (p-value)	Tail dependence
BE - PL	Survival Gumbel	$\hat{\theta}$ 1.32 (0.11)	0.24 (< 0.01)	$\lambda_L = 0.31$
BE - UK	Survival Gumbel	$\hat{\theta}$ 1.15 (0.09)	0.13 (0.02)	$\lambda_L = 0.17$
BE - NL	Survival Gumbel	$\hat{\theta}$ 1.36 (0.11)	0.26 (< 0.01)	$\lambda_L = 0.34$
NL- ES	Survival Gumbel	$\hat{\theta}$ 1.16 (0.09)	0.14 (< 0.01)	$\lambda_L = 0.18$
ES - FR	Survival Gumbel	$\hat{\theta}$ 1.15 (0.09)	0.13 (0.01)	$\lambda_L = 0.17$
BE - IT	Rotated Tawn type 1 180 degrees	$\hat{\theta}_1$ 1.79 (0.34) $\hat{\theta}_2$ 0.28 (0.11)	0.18 (< 0.01)	$\lambda_L = 0.22$
IT - DE	Rotated Tawn type 1 180 degrees	$\hat{\theta}_1$ 3.07 (1.11) $\hat{\theta}_2$ 0.07 (0.02)	0.07 (< 0.01)	$\lambda_L = 0.07$

Two types of copula families were found to best characterise the price co-movement patterns. The majority of the market pairs (BE–PL, BE–UK, BE–NL, NL–ES and ES–FR) were characterised by Survival Gumbel copula which is a one-parameter copula capturing asymmetric tail dependence and giving more weight to the lower tail. Two market pairs (BE–IT and IT–DE) were characterised by rotated Tawn type 1 copula (180 degrees) which is a two-parameter copula capturing asymmetric negative tail dependence. Thus, the results suggest that only negative price co-movements occur in the broiler meat markets across the EU. Reboredo (2011) notes that asymmetric price co-movement is an indication of a low degree market integration.

Belgium shows the highest level of overall co-movement with Poland and the Netherlands. This makes sense as Belgium and the Netherlands are significant trading countries both in intra- and extra-EU trade. Poland is the main producing country of broiler meat in the EU and thus, it is likely that the two countries import broiler meat from Poland. Furthermore, the geographical proximity may increase the integration of the broiler meat markets between Belgium and the Netherlands.

The United Kingdom shows the weakest straight linkage with the markets in Belgium. In addition, the linkage between the Netherlands and Spain, and Spain and France is rather low. This may be explained by market conditions in which vertical coordination (e.g. marketing ad production contracts, a few companies in the markets) takes place within the broiler meat supply chain. In addition, the United Kingdom does not share the same currency with the rest of the considered markets which may partly explain the weak overall linkages for the country. Somewhat surprising are the results for Germany which according to the empirical model has only a very weak connection with Italy and the remaining countries. Germany is, however, among both the main producing and trading countries.

Tail coefficients were estimated only for the lower quantiles as both selected copula families captured asymmetric, negative tail dependence. The coefficients for tail dependence are well in line with the overall dependence measures (Kendall's tau). The negative tail coefficients imply that only extreme negative downturns in broiler meat prices transmit from one market to another but positive shocks not. One has to note that values of all estimated coefficients turned out to be low indicating rather weak extreme tail dependence between the considered markets.

Discussion and conclusions

This article investigated the degree and structure of price dependence within the principal EU broiler meat markets from 2004 until 2017. During this time period, new member states have entered the EU, the Common Agricultural Policy has been reformed and the international trade environment has been changing. As these conditions continue to be changing in future and market uncertainties are on the rise, all agents from farmers to policy makers benefit from novel information of the existing market structures. Information is needed to develop better strategies at farm level, and to be able to make sustainable policy decisions and reforms at national and international level.

The statistical tool of mixed regular vine copulas was applied to monthly data of broiler meat prices from eight European Union member states. The selection of the member states was based on their significance in intra- and extra-EU broiler meat trade but also as a producer of broiler meat. Our findings indicate that the overall price dependence structures are relatively weak between all the considered EU markets. Belgium and also the Netherlands turned out to have the strongest overall price dependence with the other markets explained by their role as a central trading country and geographical proximity. Surprisingly, results suggested that Germany has weakest linkages with other considered countries.

The estimation results revealed that the markets in Belgium have straight (but weak) connections with Poland, the United Kingdom, and the Netherlands. Furthermore, the markets in the Netherlands were linked to the markets in Spain and the markets in Spain with markets in France. All these dependence structures were characterised by Survival Gumbel copula which captures negative tail dependence and thus, asymmetry. In addition, the markets in Belgium turned out to have a straight but weak linkage with the markets in Italy. Lastly, markets in Italy were connected with the markets in Germany. These dependence structures were identified by Tawn type1 (rotated 180) copula which also captures asymmetric, negative tail dependence.

Based on the empirical evidence presented, we conclude that the overall market integration within the EU broiler meat sector is weak and thus, the EU objective for establishing single market has not been successful for the broiler meat markets. The structure of price dependence across the considered EU markets is asymmetric so that only negative price developments are transmitted between the markets. This suggests the presence of inefficiency in the EU broiler meat markets. When markets function efficiently prices tend to co-move fully and symmetrically. (Fackler & Goodwin 2001). The underlying reasons to the weak linkages might be due to differences in market structures (i.e. market power conditions) as broiler meat production is mainly based on marketing and production contracts. Also the production costs vary largely across the member states due to climatic conditions and regulatory practices (van Horne 2016).

The future research would benefit from applying dynamic R-vine copula models especially when the considered time period is as long as in the present study. At the time of conducting this research, time varying R-vine models for our purpose were not available.

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