Integration and Hierarchy of Pork Markets in the EU: An Analysis from the Vantage of Graph Theory

Panos Fousekis and Vasilis Grigoriadis
Aristotle University, Thessaloniki, Greece

Abstract

The work investigates empirically the degree of integration and the hierarchical structure of the EU pork meat markets using tools and concepts from Graph Theory. The empirical results suggest: First, the strength of price co-movement has been closely related to the physical distance between national markets. This, has given rise to market clustering that largely corresponds to different geographical EU regions. Second, major players in the production and in the intra-EU trade tend to be more important in the process of price formation. The power structure (hierarchy), however, has not been rigid but it has been changing over time. Third, although the price linkages have becoming stronger the complexity of the system of markets has been rising.

Key Words

market hierarchy; pork meat; EU

1 Introduction

The integration versus segmentation of spatial (geographically separated) markets has long been a focal point of theoretical and empirical economic research as well as an important issue in the public domain. The keen interest in the topic stems from the recognition that integration is a prerequisite for economic efficiency, that is, for maximization of benefits accruing to the society from the existence and the operation of markets (e.g. GOODWIN and PIGGOTT, 2001; ASCHE et al., 1999). Key indications of market integration across space are the strength and the pattern of price linkages (REBOREDO, 2011; SERRA et al., 2006).

With regard to policy formulation, the European Union (EU) is an example where the integration of member state (geographically separated) markets has been vigorously pursued for more than thirty years. The Single Market Program, formally adopted in 1985, led to the elimination of all tariff and non-tariff barriers to intra-Community trade by 1993. The Single Market Review, launched in 2006, placed its emphasis on understanding the price adjustment mechanisms and the obstacles preventing markets from functioning well. Cornerstones of the new strategy have been the monitoring and the benchmarking of price differences among member states (EC, 2013). This has not been accidental; survey-based evidence from super markets around the EU indicates that persistent and sizable price differentials still exist for virtually identical commodities even between neighboring and/or comparable member-states (EC, 2013).

Much of the formal economic research on the integration of the EU markets has been directed to the farm and the food sector; the bulkiness and perishability of the sector's commodities, the importance of transportation costs, the potential for existence of local market power, as well as the quality differentiation have rendered the spatial EU markets for food an interesting case study (e.g. GRIGORIADIS et al., 2016; EMMANOULIDES and FOUSEKIS, 2015; EMMANOULIDES et al., 2014; SERRA et al., 2006). A market that has received considerable attention is the one for pork meat. The pork sector is among the most important in the EU agriculture; it accounts for 9% of the annual value of the total agricultural output and for 51% of the annual value of the production of all meats (MARQUER et al., 2016).

SANJUAN and GIL (2001) assessed the integration of seven major EU pork meat markets using multivariate co-integration analysis. They found that a number of common stochastic trends existed among the respective prices. SERRA et al. (2006) analyzed price transmission between the German, the Spanish, the French, and the Danish markets using both parametric and non-parametric techniques. According to their results, the four markets were well integrated in the long-run, but short-run price transmission was predominantly asymmetric. EMMANOUILIDES and FOUSEKIS (2012) tested for the validity of the Law-of-One Price (LOP) in the same four markets using nonlinear integration techniques. They found that the LOP hypothesis was consistent with the real world data. GRIGORIADIS et al. (2016) investigated price interdependence among seven major EU pork meat markets using the statistical tool of vine copulas. They detected strong price linkages between the German, the

French, the Dutch, and the Belgian markets but relatively weak and asymmetric ones between these and the Spanish, the Danish, and the Italian markets.

The present study revisits the question of integration of the EU pork markets using tools and notions from Graph Theory that has been long utilized in Mathematics and Physics but only recently it found its way into Economics and Finance (MANTEGNA, 1999). With regard to the research question at hand, the analysis from the vantage point of Graph Theory has certain advantages relative to other approaches such as multivariate cointegration, copulas, and non-parametric regression. First, it is not subject to the so called “curse of dimensionality”; provided that a sufficient number of observations are available a researcher may employ it to investigate the linkages among prices in a very large number of markets. Second, it is intuitively appealing and suitable for characterizing both the taxonomy (hierarchical structure) of a set of markets as well as its temporal state (i.e. the dynamics of the taxonomy). One, therefore, may identify central (hub) and spoke (peripheral) markets, potential market clusters, and detect changes in the importance (power) of the different markets in the hierarchical arrangement over time. This is achieved using information contained in price time series only and appropriately defined measures of synchronous association between them. Third, earlier empirical applications showed that the taxonomies (and their respective dynamics) obtained through Graph Theory are generally meaningful from an economic standpoint.

There have been a number of works on the integration and on the hierarchical structure of financial markets. For example, ONNELA et al. (2003), SINGHAL and SIHNA (2014), and COLETTI (2016) investigated the interdependence among stocks traded in the US, the Indian, and the Italian markets, respectively; LAUTIER and RAYNAUD (2013) and SCIECZKA and HOLYST (2009) focused on commodity futures contracts traded in the US, in the UK, and in China, RESOVSKY et al. (2013) on global currency markets, and DIEBOLD et al. (2017) on Blumberg commodities. It appears, however, that there has been just one work that dealt with physical commodity markets across space. That has been the recent study by JI and FAN (2016) on regional crude oil markets. To the best of our knowledge, there have been no earlier Graph Theory-based studies on the integration of geographically separated agricultural and food commodity markets. Nevertheless, there have been a few past works in agricultural and food economics that applied Directed Acyclic Graphs to identify contemporaneous causal linkages between prices as well as between exchange rates, agricultural exports, and foreign receipts (e.g. XU, 2014; SHANE et al., 2008). Also, BENEDEK et al. (2017) utilized information on trade flows (but not on prices) and network analysis to investigate whether the EU milk markets have become more inter-connected since the early 2000s.

Against this background, the objective of this work is to investigate empirically the degree of integration and the power structure in a panel of national (geographically separated) EU pork markets. The analysis is dynamic in the sense that it allows both the degree of integration and the taxonomy of the markets to change over time.

In what follows section 2 presents the analytical framework (ultrametric spaces, hierarchical arrangements, market importance, assessment of the evolution and the stability of linkages) and section 3 the data, the empirical models, and the empirical results. Section 4 offers conclusions and suggestions for future research.

2 Analytical Framework

2.1 Distance, Minimal Spanning Tree, Hierarchical Structure and Vertex Importance

A key notion in the study of the taxonomy for a set of spatial markets is that of the *distance* between synchronously evolving price pairs. Let r_{it} and r_{jt} $(t=1,2,...,T)$ be two time series of price log-returns (rates of change) for a given commodity in the geographically separated markets i and j, respectively. Let also A_{ij}, where $-1 \le A_{ij} \le 1$, be an appropriate measure of association between r_{it} and r_{jt}. As known, association measures capture the intensity and the type of the relationship between two variables (here, price log-returns). The metric

$$d_{ij} = \sqrt{2(1-A_{ij})}, \tag{1}$$

where $0 \le d_{ij} \le 2$ and A_{ij} is such as:

(a) $d_{ij}=0 \Leftrightarrow i=j$; (b) $d_{ij}=d_{ji}$; and (c) $d_{ij} \le d_{ik}+d_{kj}$ defines a Euclidean distance (MANTEGNA, 1999).

Small (large) values of d_{ij} imply strong positive (negative) association between price changes in markets i and j.

A set of N market-specific price log-returns equipped with the notion of the Euclidean distance d_{ij} between any pair (r_{it}, r_{jt}) constitutes a *metric space*. To obtain, however, a taxonomy of price relationships that corresponds to an exclusive hierarchical structure one needs not simply a metric space but an *ultrametric* one. Ultrametric spaces are generated from (1) by replacing property/axiom (c) with the so called *strong triangle* or *ultrametric inequality*, (d) $d_{ij} \le \max\{d_{ik}, d_{kj}\}$ (JI and FAN, 2016; MANTEGNA and STANLEY, 2004).

With N spatial markets and time series of price log-returns there are several possible ultrametric structures (taxonomies). However, a single one stands out because of its simplicity and its remarkable properties. This is the *subdominant ultrametric structure* obtained by using the symmetric NxN matrix of the ultrametric distances to determine the *minimal spanning tree* (MST). A minimal spanning tree, in turn, is a simply weighted graph that connects all N markets (nodes/vertices) with N-1 edges (links) in such as way that the sum of all edges weights (distances), $\sum_{d_{ij} \in MST} d_{ij}$, is minimum. MSTs do not show all possible interactions but only the strongest ones; they are, therefore, very useful tools for visualizing price linkages between the pairs of the N spatial markets. More importantly, as shown by WEST (1996) any MST provides a well defined topological sequence corresponding to a unique hierarchical structure.

Several measures can be employed to determine the importance (power) of vertex $i \in N$ in a minimal spanning tree. The first is the *degree*, defined as the number of the edges attached to that node. It is calculated as

$$K(i) = \sum_{j=1}^{N} a_{ij}, \quad j \ne i, \tag{2}$$

where $\alpha_{ij} = 1$ if nodes i and j have an edge in the MST and $\alpha_{ij} = 0$, otherwise (e.g. SIECZKA and HOLYST, 2009). The higher the degree, the higher the number of spatial markets that are connected to market i. The second is the *strength*, defined as the sum of the absolute values of the association measures of a given market with the other spatial markets. It is calculated as

$$S(i) = \sum_{j=1}^{N} \left|A_{ij}\right|, \quad j \ne i. \tag{3}$$

The higher the strength, the higher the intensity of interdependence between market i and the rest N-1 (e.g. CZADO et al., 2012). The third is the *normalized betweenness centrality*, defined by the number of shortest paths going through node i. It is calculated as

$$B(i) = \frac{2}{n^2 - 3n + 2} \sum_{(j,v)} \frac{\sigma_{jv(i)}}{\sigma_{jv}}, \quad j \ne i \ne v, \tag{4}$$

where $\sigma_{jv(i)}$ is the number of the shortest paths from j to v passing through i, while σ_{jv} is the number of the shortest paths from j to v (e.g. O'KELLY, 2016; FREEMAN, 1978). The MST has the unique shortest path for any pair of nodes. Therefore, $\frac{\sigma_{jv(i)}}{\sigma_{jv}}$ is 0 (if the path from vertex j to vertex v does not pass through vertex i) or 1 (if the path from j to v passes through vertex i). The measure $B(i)$ reflects the degree to which the other markets rely on market i; higher values of $B(i)$ indicate higher reliance. The fourth is the *closeness centrality* calculated as the inverse mean distance of the shortest paths from node i to the remaining nodes

$$C(i) = \frac{N-1}{\sum_{j}^{N} d_{ij}^{s}}, \quad i \ne j, \tag{5}$$

where the superscript s denotes shortest (e.g. SABIDUSSI, 1966). Higher values of $C(i)$ indicate closer distance of the given spatial market to the rest N-1.

2.2 Distribution Dynamics, Evolution and Stability of Linkages

MSTs can be constructed for different windows of the data span. As noted by ONNELA et al. (2003), however, they are not independent of each other but they form a series through time and they may well be interpreted as a sequence of evolutionary steps of a single dynamic tree. The evolution and stability of the relationships for a set of spatial markets can be investigated through a number of measures. Four of them are actually basic statistics of the distribution of the association measure, A_{ij}; these are the mean, the variance, the skewness, and the kurtosis. The relevant formulas are:

$$M_1(t) = \frac{2}{N(N-1)} \sum_{(i,j)} A_{ij}(t), \tag{6}$$

$$M_2(t) = \frac{2}{N(\mathrm{N}-1)} \sum_{(i,j)} \left(A_{ij}(t) - M_1(t) \right)^2, \tag{7}$$

$$M_3(t) = \frac{2}{N(N-1)} \sum_{(i,j)} \left(A_{ij}(t) - M_1(t) \right)^3 / M_2^{3/2}(t), \tag{8}$$

and

$$M_4(t) = \frac{2}{N(N-1)} \sum_{(i,j)} \left(A_{ij}(t) - M_1(t) \right)^4 / M_2^2(t), \tag{9}$$

respectively (JI and FAN, 2016).

The other two measures are the *normalized tree length* and the *multi-step survival ratio of edges*. The former is defined as

$$L(t) = \frac{1}{N-1} \sum_{d_{ij}(t) \in MST(t)} d_{ij}(t) \tag{10}$$

(JI and FAN, 2016). A reduction in the value of $L(t)$ with the time implies that the spatial markets become more concentrated (the price linkages/co-movement become stronger). The latter is defined as

$$\sigma(t,k) = \frac{1}{N-1} \left| E'(t) \cap E'(t-1) \cdots E'(t-k+1) \cap E'(t-k) \right| \tag{11}$$

(COELHO et al., 2007; ONELLA et al., 2003) and it measures the number of common edges in k consecutive trees at times t, $t-1$, ... , $t-k-1$ and $t-k$. In (11), E' denotes the set of edges, $\cap$ the intersection operator, and $|\cdots|$ denotes the number of elements in the set. When an edge between two nodes breaks even once in k steps and then reappears, it is not counted as a survived connection. The measure $\sigma(t,k)$ indicates the robustness of the MST (and of the linkages between the spatial markets) over time; for a given k, the higher the value of $\sigma(t,k)$, the higher the level of robustness. Note that in all (6) to (11) the lower case t (in parenthesis) denotes the time interval for which these measures are calculated.

3 The Data, the Model and the Empirical Results

3.1 The Data and the Model

The data for the empirical analysis are monthly wholesale carcass prices (expressed in Euros per 100kg) for the period 1995: 1 to 2017: 12. They have been obtained from the EC (2018) and they come from the 15 oldest member-states; namely, Belgium (BE), Germany (DE), Denmark (DK), Spain (ES), France (FR), Greece (GR), Ireland (IE), Italy (IT), Luxemburg (LU), the Netherlands (NE), Austria (AU), Portugal (PT), Finland (FI), Sweden (SE), and the United Kingdom (UK). For Italy, the price time series refer to R-grade carcass while for the remaining 14 countries they refer to E-grade carcass[1].

The 13 newest member-states have been left out due to the lack of sufficient number of observations; monthly price data for them are available only after 2006. Nevertheless, the 15 national (spatial) markets of pork meat considered here are quite representative of the aggregate EU pork meat market. Taken together, they accounted for about 86% of the total production, 92 % of the total intra-imports, and 71% of the total intra-exports in the EU-28 during 2015 (Table A.1, Appendix A). Also, except for DK, SE, and the UK the member-states considered belong to the Euro area; this means, the potential impact of nominal exchange rate variability on spatial price co-movement (and on the empirical findings of the present work) is not an issue for the large majority of markets under study.

Table A.2 in Appendix A (panels (a) and (b)) presents descriptive statistics of the logarithmic prices and the returns for the period 1995-2017. There are considerable differences in the mean price levels (for example between GR and the NE). The mean price

[1] Under EU rules, pig meat carcass is classified into S, E, U, R, O, and P based on lean meat percentage (http://hccmpw.org.uk/market_prices/industryinformation/carcaseclassification-pork/). Grades U, O, and P are not important. The overwhelming majority of countries contribute to grades S and E. The European Commission reports prices for grades S, E, and R. Italy is the only country in the panel where R (mean lean percentage 45 to 49) is the dominant grade. Traditionally, price comparisons have been based on E-grade carcass (mean lean percentage 55 to 59) because publication of S-grade (mean lean percentage above 60) prices only begun in 2014 (http://pork.ahdb.org.uk/prices-stats/news/2016/october/how-big-is-your-premium-comparing-uk-and-eu-pig-prices/).

log-returns are similar (all very close to zero). The price risk (captured by the standard deviation of the returns), however, appears to be quite high in certain markets (e.g. ES and PT) relative to others (e.g. FI and IE). The application of the KWIATKOWSKI et al. (KPSS) (1992) test suggests that the price levels in five spatial markets (FI, IE, IT, SE, and the UK) contain unit roots, while those of the remaining do not. All time series of price log-returns, however, are weakly stationary. The results from the individual KPSS unit root tests are further reinforced by the findings from the application of HARDI'S (2000) panel unit root test (Table B.1, Appendix B). To avoid mixing of time series with different degrees of integration, and in line with earlier empirical studies, the analysis here is carried out using rates of price change.

The various metrics, the MST, and the hierarchical structures discussed in Section 2 are expressed in terms of a generic coefficient of association, A_{ij}. They are nevertheless valid only when A_{ij} is such that the resulting metric space is an ultrametric one. All earlier relevant empirical works (e.g. JI and FAN, 2016; SIECZKA and HOLYST, 2009; MANTEGNA and STANLEY, 2004; ONNELA et al., 2003; MANTEGNA, 1999) employed Pearson's correlation coefficient which is known to satisfy properties (a) and (b) as well as the strong triangle inequality (property (d)).

Pearson's *rho*, however, has two serious limitations. First, it measures linear association only; second, it is not invariant to strictly monotonic (increasing) transformations of the data. Several researchers in the field of the analysis of co-movement among stochastic processes (such as returns of financial assets or of prices in the physical and in the product quality space) have strongly recommended the use of rank-based association measures (e.g. LI, 2014; PATTON 2013; REBOREDO, 2011). A number of such measures are available in the literature (e.g. Kendall's *tau*, Spearman's *rho*, Bloomqvist's *beta*, Hoeffding's *phi*, and Gini's *gamma*).

The present work considers Kendall's *tau* that is very commonly used in empirical investigations of co-movement. It is defined as

$$\tau_{ij} = \frac{P_{ij} - Q_{ij}}{\binom{T}{2}} = \frac{4P_{ij}}{T(T-1)} - 1, \qquad (12)$$

(e.g. PANAGIOTOU and STAVRAKOUDIS, 2015; PATTON, 2013), where P_{ij} (Q_{ij}) are the number of concordant (discordant) pairs of observations for the stochastic processes i and j. It measures the difference between the probability of concordance and the probability of discordance.[2] As a rank-based coefficient of association it is not affected by strictly increasing transformations of the data and, moreover, it captures both linear and non-linear co-movement; it ranges from +1 (perfect concordance) to -1 (perfect discordance).

The metric $d_{ij} = \sqrt{2(1-\tau_{ij})}$ satisfies the property $d_{ij} = 0$ for $i = j$ (because in such case there is perfect concordance, that is, $\tau_{ij} = \tau_{ii} = \tau_{jj} = 1$) and the property $d_{ij} = d_{ji}$ (because $\tau_{ij} = \tau_{ji}$, by definition); as shown in Appendix C, it also satisfies the strong triangle inequality. Consequently, a metric space with Kendall's *tau*-based distance is an ultrametric one.[3] The empirical investigation in this work has been carried out employing Kendall's *tau* because of its superior properties relative to Pearson's coefficient.

3.2 The Empirical Results

3.2.1 Clusters and Power of Individual Markets

Table 1 presents the full-sample Kendall correlation matrix. There is strong positive price co-movement between certain market pairs but also weak and (in a few cases) negative co-movement between others. Given that the full sample spans more than two decades, the finding of weak co-movements is an indication that the spatial EU pork markets have not been very well integrated. Using relation (1) the correlation matrix has been converted into a matrix of subdominant ultrametric distances. From the latter the full-sample MST (Figure 1) has been obtained by employing PRIM'S (1957) algorithm and the *igraph* package in *R* (CSARDI and NEPUSZ, 2006). Observe that, in Figure 1, a node's radius is proportional to its strength

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2 Here, the observations are price log-returns. A pair of log-returns (r_{it}, r_{jt}) is concordant when $(r_{it})(r_{jt}) > 0$ and discordant, otherwise. The higher the values of Kendall's *tau*, the more likely is the concordance of observations (i.e. the more likely is that the EU pork market resembles a "great pool" in which national prices move in sync) (e.g. REBOREDO, 2011).

3 Whether other association measures (e.g. Spearman's *rho*, Gini's *gamma*, etc) satisfy the strong triangle inequality is beyond the scope of this work. Nevertheless, it could be an interesting topic for future research. The larger the number of appropriate association measures, the greater the scope for selection and comparison.

Table 1. Full-sample Kendall correlation matrix *

	BE	DE	DK	ES	FR	GR	IR	IT	LU	NE	AU	PT	FI	SE	UK
BE	1.000	0.806 (0)	0.449 (0)	0.467 (0)	0.536 (0)	0.207 (0.023)	0.309 (0)	0.281 (0)	0.699 (0)	0.773 (0)	0.753 (0)	0.437 (0)	-0.019 (1)	0.173 (0.12)	0.168 (0.145)
DE		1.000	0.46 (0)	0.497 (0)	0.546 (0)	0.242 (0.062)	0.336 (0)	0.275 (0)	0.731 (0)	0.797 (0)	0.799 (0)	0.472 (0)	-0.009 (1)	0.19 (0.055)	0.187 (0.062)
DK			1.000	0.329 (0)	0.415 (0)	0.188 (0.119)	0.523 (0)	0.239 (0.003)	0.483 (0)	0.431 (0)	0.451 (0)	0.307 (0)	0.103 (1)	0.398 (0)	0.301 (0)
ES				1.000	0.576 (0)	0.17 (0.129)	0.346 (0)	0.13 (0.6)	0.441 (0)	0.469 (0)	0.529 (0)	0.802 (0)	0.029 (1)	0.031 (1)	0.214 (0.015)
FR					1.000	0.233 (0.004)	0.367 (0)	0.281 (0)	0.52 (0)	0.538 (0)	0.575 (0)	0.553 (0)	0.001 (1)	0.144 (0.367)	0.187 (0.062)
GR						1.000	0.151 (0.28)	0.336 (0)	0.245 (0.002)	0.217 (0.012)	0.276 (0)	0.204 (0.025)	0.05 (1)	0.114 (1)	0.039 (1)
IE							1.000	0.133 (0.543)	0.371 (0)	0.333 (0)	0.349 (0)	0.344 (0)	0.129 (0.6)	0.3 (0)	0.359 (0)
IT								1.000	0.299 (0)	0.259 (0.001)	0.307 (0)	0.141 (0.406)	0.043 (1)	0.224 (0.008)	-0.01 (1)
LU									1.000	0.651 (0)	0.705 (0)	0.426 (0)	-0.012 (1)	0.205 (0.025)	0.191 (0.053)
NE										1.000	0.726 (0)	0.459 (0)	-0.026 (1)	0.162 (0.181)	0.195 (0.043)
AU											1.000	0.516 (0)	0.013 (1)	0.184 (0.07)	0.167 (0.145)
PT												1.000	0.031 (1)	-0.01 (1)	0.183 (0.07)
FI													1.000	0.158 (0.205)	0.041 (1)
SE														1.000	0.187 (0.062)
UK															1.000

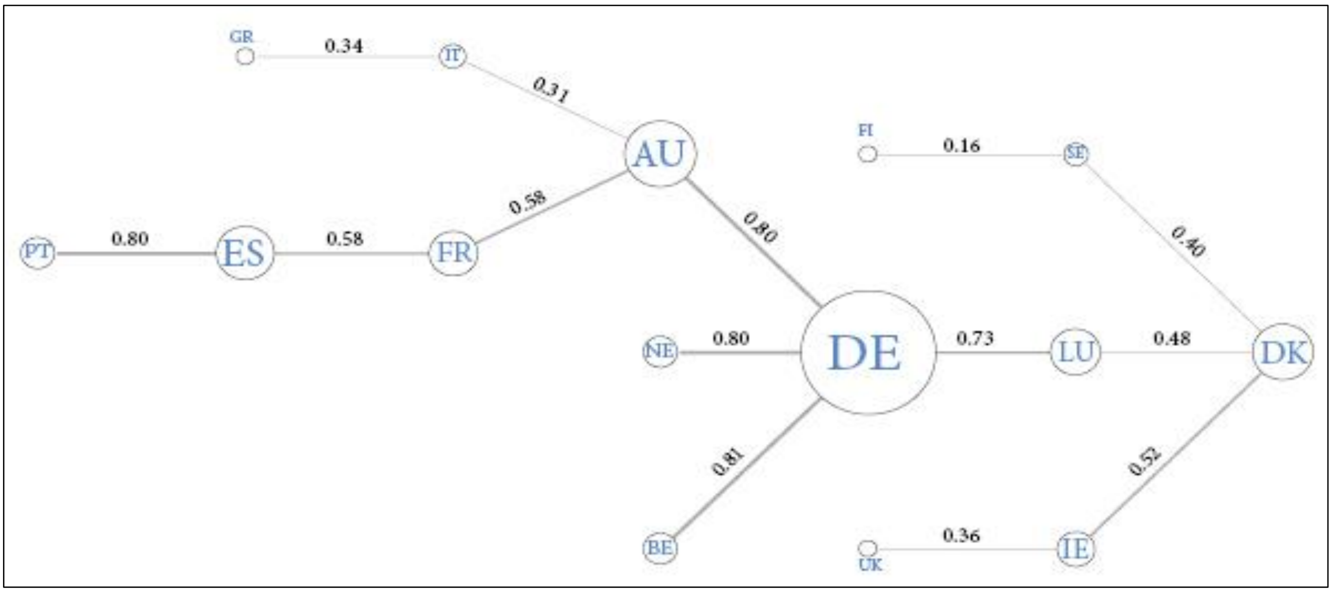
* *p*-values in parentheses

and an edge's width is proportional to its corresponding Kendall's *tau.*[4]

Two notable and, at the same time, very intuitive features of the EU pork market may be deduced from the full-sample MST. First, it is the central position of DE; second, it is that the linkages between the 15 spatial markets exhibit clear geographical attributes. Germany's status is hardly a surprise. DE is the largest producer and its people consume more pork meat relative to those in other member-states. Furthermore, it is one of the world's leading exporters and a major importer. As such, it is expected to have a strong influence on pork meat markets throughout the EU. Second, the markets of BE, NE, AU, and LU are linked directly to the German one. BE and NE, despite of their small size, are leading pork meat producers directing their surpluses primarily within the EU. To sustain their competitive position they track price changes in each other as well as in Germany which is, by far, the major outlet for their exports. DE is also a very important market for AU's pork meat exports. A potential cluster emerging from the examination of the full-sample MST is the one involving DE, BE, NE, AU, and LU; we may call it cluster of the Central EU markets. The UK, IE, DK, SE, and FI are linked as a straight line. DK (like BE and NE), despite its small size, is also a leading exporter of pork meat in the EU. Among the main destinations of Danish pork meat exports are the UK, SE, and FI. The UK is an important market for the Irish exports. We may call the potential cluster of the UK, DK, IE, SE, and FI as the one of the Northern EU markets. FR, ES, and PT are also linked in a straight line. ES shares borders with FR and PT and, at the same time, it is by far the biggest exporter of pork meat to France. These three markets appear to form a cluster (we may call it the South-Western EU one). Finally, Italy (the biggest

[4] As noted by an anonymous reviewer, regional variation can be lost when using national averages for large countries such as France and Germany. This, in turn, may render the idea of a single node connecting two such markets fuzzy. Regional price time series, however, are not available. For an alternative interpretation of the values in Table 1 note that, from the definition of *tau* and the fact that the sum of the probability of concordance and the probability of discordance equals 1, follows that the probability of concordance can be written as $(1+\tau)/2$ and that of discordance as $1-(1+\tau)/2$. Therefore, the value 0.546 for the pair FR and DE (for example) implies a probability of concordance 0.773 and of discordance 0.227.

Figure 1. The minimal spanning tree (MST) for the full sample



importer of pork meat in the EU) and Greece (another country that relies heavily on imports) may also be members of the same cluster (the South-Eastern EU one).[5] Judging from the positions of the various nodes in the MST one may infer that France, Denmark, and Austria play some role in connecting the South-Western, the Northern and the South-Eastern clusters, respectively, with the Central one.

To further visualize the taxonomy of the EU pork market, Figure 2 displays the hierarchical structure (constructed using the *stats* package in *R*) of the sub-dominant ultrametric space associated with the full-sample MST. The results of the hierarchical arrangement are slightly different from the MST ones. This happens because although certain links exist in the MST, the ultrametric distance between those links is large (e.g. JIN and FAN, 2016). The hierarchical structure confirms the clustering of the central EU markets and of the South-Western (ES and PT) ones. France, however, may be a member of either of those two clusters provided that one sets the threshold ultrametric distance close the 0.9. If France joins the other five central EU markets (BE, DE, LU, NE, and AU) one ends up with a cluster covering almost the whole main pork meat production basin of the EU. For even higher thresholds, the UK, SE, DK, and IE on the one hand and IT and GR on the other form their own clusters. Finland, however, appears to be a somehow isolated (disconnected from the others) spatial market.

Observe that in the hierarchical arrangement there are clusters formed of markets that depart early (i.e. at high values of distance) from the MST and clusters formed of markets that depart later on (i.e. at low values of distance). For the first category, price developments are mainly affected by factors that are cluster-specific while for the second one price developments are affected both by factors that are market-specific as well as by factors that are common to all markets. The relative importance of the two types of factors is reflected in the length of the segments observed for each group from a branching to the successive one (MANTEGNA, 1999).

Table 2 presents measures of power of the individual markets in the hierarchical structure. The strength measure receives its highest values for DE, AU, and DK, in this order, and its lowest values for FI, GR, and the UK, again in this order. The degree measure receives it highest value for DE followed by those for DK and AU and it lowest value for BE, GR, NE, PT, FI, and for the UK. The betweenness centrality measure receives its highest value for DE followed by those for AU and LU and its lowest value for BE, GR, NE, PT, FI, and the UK. Finally, the closeness centrality measure receives its highest values for DE followed by those for LU and AU and its lowest values for the PT, UK and ES.

The values of the four measures corroborate the evidence from the MST about the influence of Germany in the first place (and to a lesser extend of DK

[5] Information about the trade relationships between the countries in the sample has been obtained from various reports available at the Pig Site, http://www.thepigsite.com/.

and of AU) on the price formation of pork in the EU and the marginal role of the Finish, the Portuguese, the Greek, and the UK markets. Leading producers and traders such as Spain and France appear to have certain influence with respect to some metrics of power (strength and degree) but a rather limited influence with respect to other ones (betweenness and closeness).

3.2.2 Dynamics and Statistical Tests

For completeness and also as a prelude to the analysis of distribution dynamics, MSTs and measures of power have been obtained for three sub-periods, 1995-2002, 2003-2009, and 2010-2017 (Appendix D). There are changes in the positions of the spatial markets in the hierarchy. Nevertheless, markets like DE and DK generally tend to occupy the highest positions

Figure 2. The hierarchical structure associated with the full-sample MST

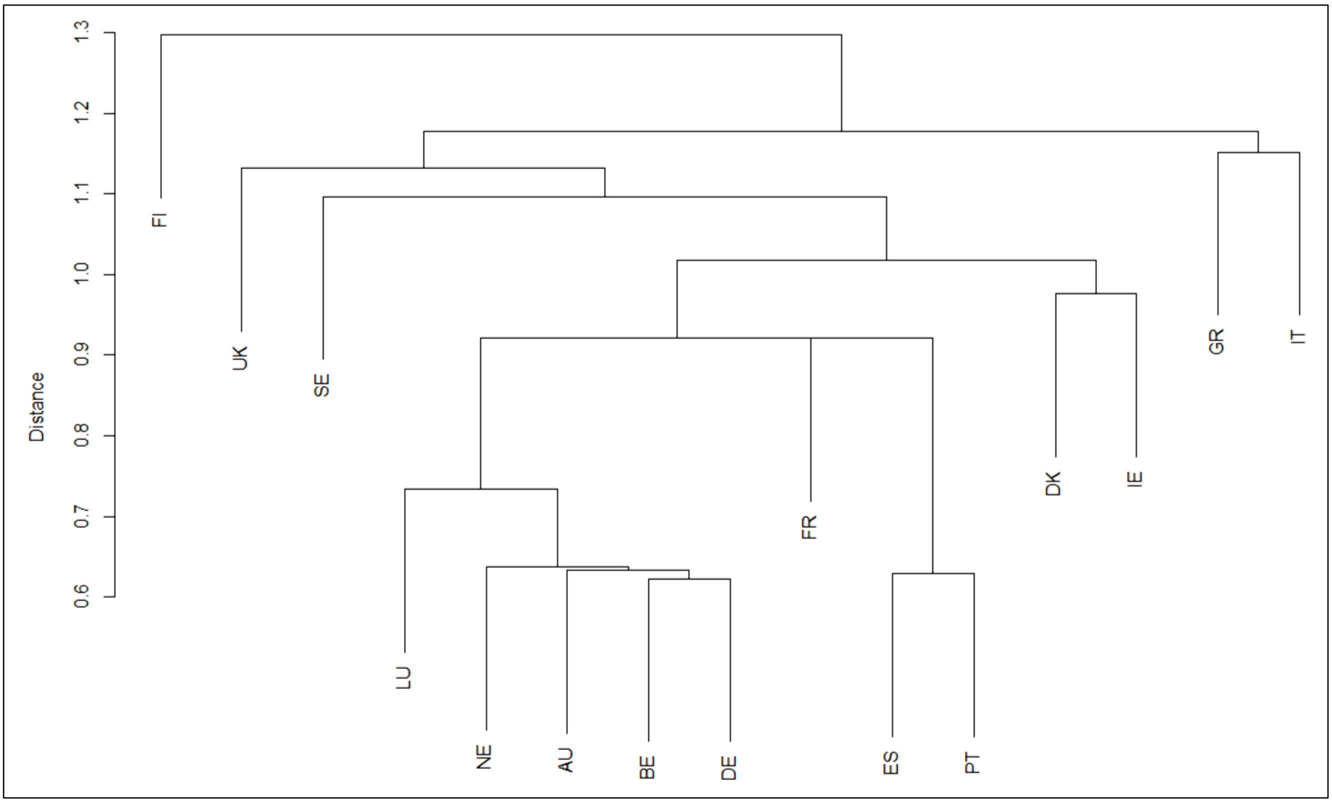


Table 2. Full-sample measures of importance

Spatial Market	Strength	Degree	Betweenness Centrality	Closeness Centrality
BE	0.81	1	0	0.46
DE	3.13	4	0.67	0.69
DK	1.4	3	0.48	0.56
ES	1.38	2	0.14	0.41
FR	1.15	2	0.26	0.5
GR	0.34	1	0	0.46
IE	0.88	2	0.14	0.46
IT	0.64	2	0.14	0.53
LU	1.21	2	0.49	0.63
NE	0.8	1	0	0.46
AU	1.68	3	0.56	0.62
PT	0.8	1	0	0.31
FI	0.16	1	0	0.45
SE	0.56	2	0.14	0.48
UK	0.36	1	0	0.4

while markets like the UK, FI, and GR tend to occupy the lowest ones. An interesting development is that the status of BE has been improved; this is especially evident during the last sub-period. The status of FR, ES, the NE, and DK remained fairly stable while that of AU has deteriorated.

For the study of the evolution and the stability of the complex system of spatial markets a "rolling" time window of length 48 months has been employed.[6] The length choice always involves a tradeoff between the level of noise on the one hand and the reliable estimation of the temporal correlation coefficient on the other. The dynamic measures (the moments of the distribution of Kendall's *tau*, the normalized length tree, and the multi-step survival ratio of edges) have been calculated recursively moving along the time scale with one step length. Given this specification, the overall number of windows for the full sample is 227.

Figure 3 presents the evolution of the four moments for Kendall's *tau*. The mean had a decline early in the sample and a recovery from 2005 to 2010. Since then, it fluctuates around 0.35. The variance was relatively stable from 1995 to 2002 and it rose sharply over 2003 to 2006. During the last 10 years the variance has stabilized at about 0.07. The skewness has showed considerable variability but remained positive (pointing to a distribution with an elongated upper tail, that means, one with a large number of moderate and small Kendall's *tau* values and a small number of high values). The kurtosis remained below 3 for the overwhelming majority of the windows considered (pointing to a platykurtic distribution, that means, one with peak shallower than that of the normal).

Figure 4 presents the dynamics of the normalized tree length. The measure is also quite volatile with a peak of 0.95 around 2004 and a trough of 0.85 around 2010. Figure 5 displays the evolution of the survival ratio under different steps $(k = 1, 6, 12, \text{and } 24)$ where k stands for the number of months. As expected, the average value of the survival ratio decreases as the number of steps considered goes up; it is 0.76 for six months, 0.65 for 12 months and 0.5 for 24 months. There is an indication, therefore, that the status of different spatial markets in the hierarchy changes, provided that one allows for a sufficient amount of time to elapse. This is consistent with what has been already transpired from Table D.1 (Appendix D). All four series exhibit a drop around 2010 and they show a recovery in the most recent years.

A number of figures above (e.g. those for variance, skewness, and normalized tree) offer certain visual evidence with regard to the presence of monotonic patterns. It is legitimate, therefore, to test formally whether that evidence reflects real market trends or just noise fluctuation. To this end, this work employs BRILLINGER'S (1989) approach that involves weighting the data by a linear combination in order to induce a strong temporal contrast between the initial and the final levels of the series under consideration (Appendix E).

Table 3 presents the results. The empirical values of the tests statistics for the mean and three out of four survival ratios are not statistically significant at the conventional levels. The empirical values of the tests statistics for the remaining measures considered, however, are. The value for the normalized length tree is negative suggesting that the 15 spatial markets become more concentrated over time (or equivalently, that, on average, price co-movement has become stronger with the time). The value for the variance is positive suggesting that the dispersion of the Kendall's *taus* in the panel of markets has been getting larger with time. This result when viewed in the light of the increasing value of (positive) skewness may point to the existence of a group of markets with very high degrees of interdependence among each other that somehow distance themselves for the rest[7]. The value for the

Table 3. The results from Brillinger's test +

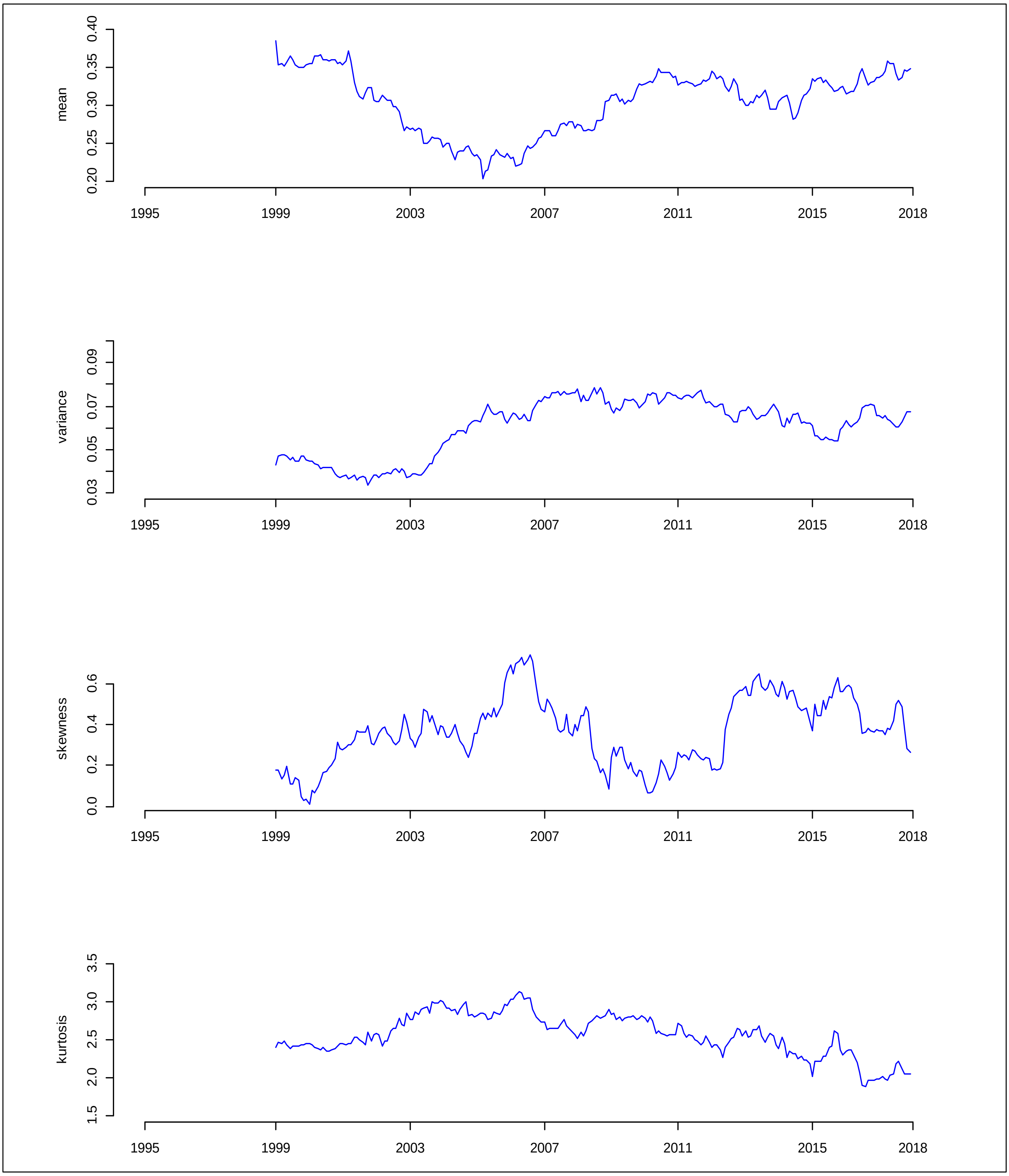
Series	Empirical value of the test statistic
Mean	0.03
Variance	4.41***
Skewness	2.58***
Kurtosis	-3.04***
Normalized Tree Length	-2.03**
Survival Ratio (*k*=1)	0.05
Survival Ratio (*k*=6)	-0.62
Survival Ratio (*k*=12)	-1.09
Survival Ratio (*k*=24)	-1.60*

+ The tests are one-sided; ***, ** (*) statistically significant at the 1, the 5(10) level or less.

[6] Windows of smaller (36) and of larger (60) months length have been tried as well without a qualitative change in the results. Patton (2013) notes that an advantage of the "rolling" window relative to the alternatives (i.e. "expanding" and "fixed") is that it provides robustness against structural breaks in the data generation process.

[7] As noted by QUAH (1996) one moment cannot capture the evolution of a distribution of a cross-section over time. Convergence, on average, may be consistent with an increase in the variance or even development of multi-modality.

Figure 3. The evolution of the four moments for Kendall's *tau*



kurtosis is negative indicating the distribution of the pair-wise co-movement measures has becoming more platykurtic. Finally, the value for the survival ratio (at *k*=24) is negative implying that the robustness in the hierarchy for the longer time horizons has been decreasing (the structure of the MSTs has becoming more liquid or the mobility of the spatial markets in it has been increasing).

Figure 4. The evolution of the normalized tree length

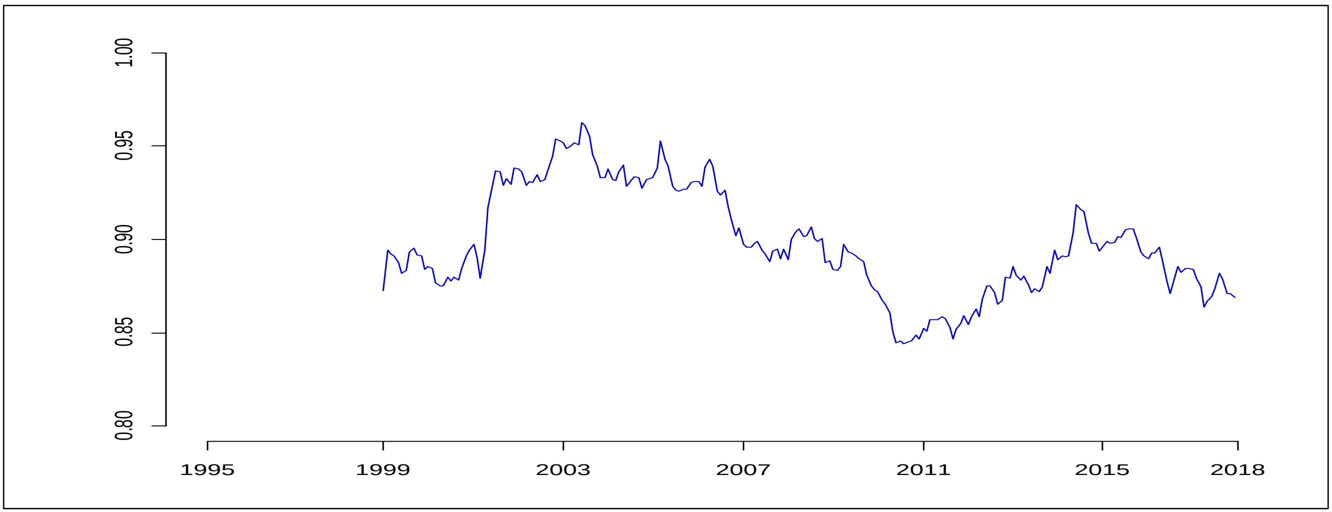
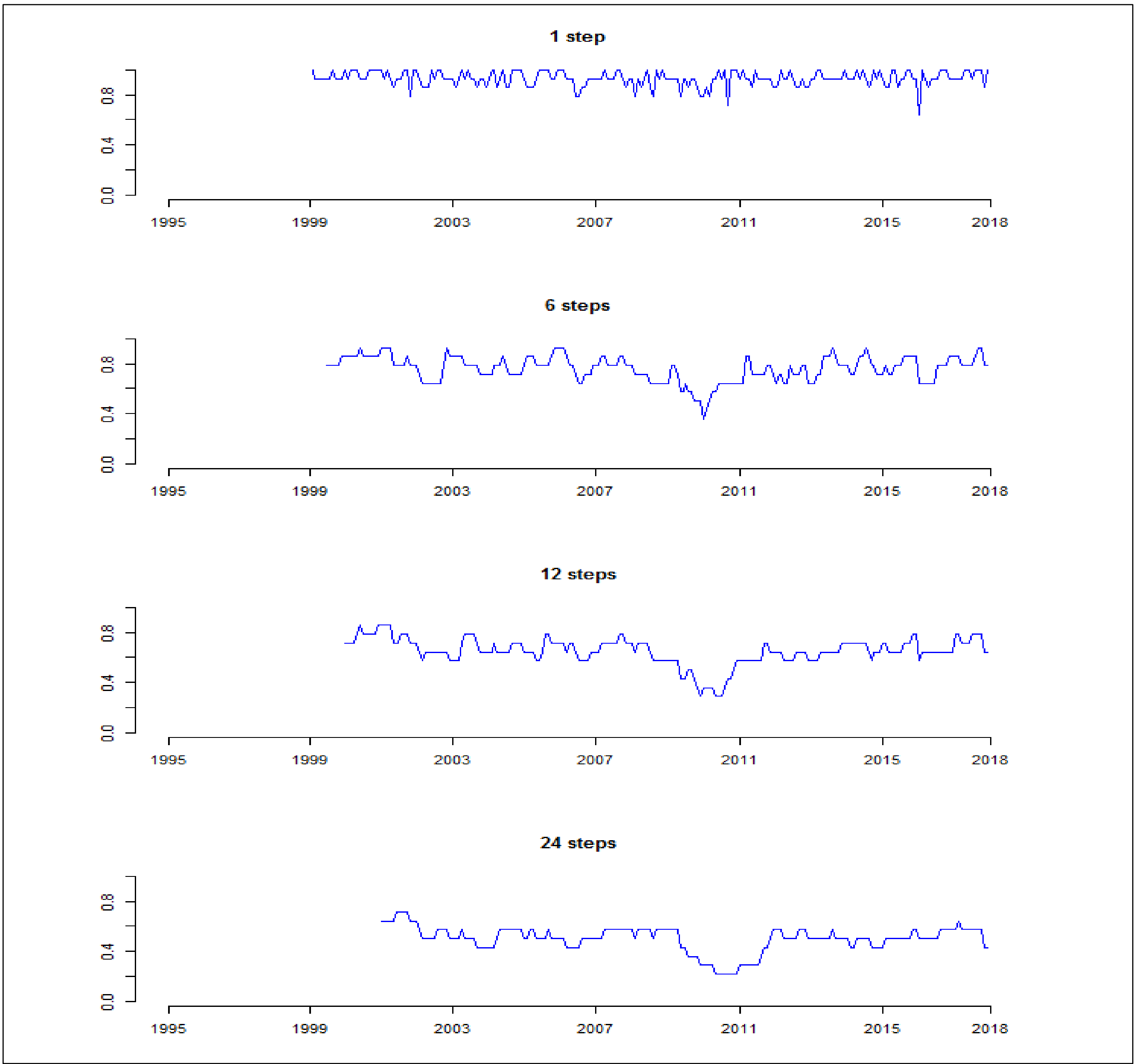


Figure 5. The evolution of survival ratio under different steps



4 Discussion and Conclusions

The strength, the structure, and the evolution of spatial price linkages are important indicators of market efficiency (well-functioning) and they may provide valuable information for policy formulation. The present study aims at characterizing the EU pork market from the viewpoint of Graph Theory. In particular, it employs a flexible measure of association (the Kendall's *tau*) to capture both linear and non-linear co-movement between price shocks in 15 national pork markets; it constructs the minimal spanning tree and the associated with it taxonomy (hierarchical arrangement). The analysis is dynamic, allowing both the degree of integration and the taxonomy of the markets to change with time.

The empirical results suggest:

a) The EU pork market is far from a "great pool" in which prices in all national markets tend to move together. There is a large number of very weak linkages even over the full-sample period that extends from 1995 to 2017.

b) The intensity of price co-movement is closely related with the geography (location).Indeed, the findings point to the presence of four market clusters; the Central containing Germany, Belgium, the Netherlands, Austria, Luxemburg, and (possibly) France, the Northern consisting of Denmark, the UK, Ireland, Finland, and Sweden, the South-Western and the South-Eastern comprising Spain and Portugal, and Italy and Greece, respectively. The members of the Central cluster are the most exposed to systemic (whole EU) market risk while for those of the South-Eastern and, to a great extent, of the Northern cluster the region-(location-) specific risk appears to be particularly relevant. Bakucks et al. (2015) also found evidence that the LOP (i.e. perfect price co-movement) is more likely to hold among neighboring than distant national milk markets in the EU.

c) The power of an individual market in the hierarchical structure is generally related to the member-state's share in the EU's pork meat production and intra-trade. Italy, the biggest importer, is a notable exception (possibly because it produces predominantly R-grade pork meat).

d) The taxonomy is not stable, in the sense that the importance of individual markets in the hierarchical structure may change over time.

e) The moments and other relevant features of the distribution of correlations exhibit interesting dynamics. Although the length of the minimal spanning tree has been decreasing indicating higher concentration, the variance and the skewness have been increasing. The liquid hierarchy together with a rising variance implies that the complexity of the system has been rising. Specifically, when the taxonomy changes there is uncertainty about the importance of a market at a given point of time and with a larger variance of correlations it is difficult for one to speculate on the potential response of prices in the other markets to a shock in an important market.

The results here corroborate, to a certain extent, the evidence obtained by the earlier study of GRIGORIADIS *et al*. (2016) suggesting that there are strong linkages between price changes in Germany, Belgium, the Netherlands, and in France and weaker between that group of markets and the Spanish, the Danish, and the Italian ones. The work of SANJUAN and GIL (2001) is also relevant since the number of cointegrating relationships those authors found turned out to be half of that required for perfect market integration.

The evidence in favor of clusters along with certain aspects of the distribution dynamics indicate that the national pork markets in the EU are not very well integrated (at least in the short-run that is the focus of the present analysis). This is surprising given that: first, pork meat is a rather homogenous commodity; second, the internal EU pork meat market has been essentially a free one; and third, the overwhelming majority of the member-states considered here have adopted Euro as their currency long ago. All three are *a priori* expected to facilitate transmission of price shocks across space[1].

The segmentation (clustering) of the national EU markets may be attributed to several reasons:

a) The use of non-tradable inputs in the production and processing of pork meat (e.g. EMMANOUILIDES and FOUSEKIS, 2015; DREGER et al., 2008; CRUCINI et al., 2005). Indeed, considerable differences in labor relations (e.g. working schedules, payments, social security contributions and benefits) still exist even among the oldest EU member states. We note that in 2013 Belgium

[1] The European Commission has recently established the EU Meat Market Observatory to foster transparency by taking stock of the market developments and highlighting and assessing the current market situation for the sake of economic operators and the Commission services (https://ec.europa.eu/agriculture/market-observatory/meat_en).

filed a complaint against German firms involved in meat processing for paying too low wages (BBC news http://www.bbc.com/news/world-europe-22080862).

b) The inactivity bands created by the presence of transaction costs (e.g. MEYER and VON CRAMON-TAUBADEL, 2004). Within such bands (typically located around the median of the joint distribution of price shocks, that is, where the absolute value of shocks is small) the linkages between spatial markets become weak or even break down. There are thresholds that price shocks in one spatial market have to overcome in order to trigger a response to another spatial market. The size of the thresholds is expected to be positively related with the distance between two spatial markets. Our empirical findings that physical proximity is strongly related with the intensity of price co-movement and that the clusters correspond to geographical regions within the EU appears to be in line with the relevant literature.

c) The possession of local market power. Pork meat processing in the EU is a highly concentrated industry; just 5 abattoirs (the Danish Crown, the VION, the Tonnies Fleisch, the Westfleisch/Barfu, and the Cooperel Arcatlantique) account for 65% of total slaughtering (BROSSARD and MONTAGE, 2012).

d) The national preferences; North and Central Europe tends to prefer heavy carcasses while Southern Europe opts for lighter animals.

It appears that there are two avenues for future research. The first, may include in the analysis the 13 newest member states (this is likely to be feasible in the next few years). The accession of new members has led to certain shifts in the production patterns and the trade flows within the EU and it may have had an effect on price interrelationships among the oldest ones. The second, may explore the use of alternative metrics of price co-movement. Potential candidates can be other rank-based measures such as the quantile coefficients of co-movement which have already produced interesting results in the context of the copula models of price linkages (e.g. EMMANOUILIDES et al., 2014; REBOREDO, 2011).

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Contact author:
PROF. DR. PANOS FOUSEKIS
Dept. of Economics
Aristotle University
Thessaloniki 541 24, Greece
e-mail: fousekis@econ.auth.gr

Appendix

A. Importance of Markets and Price Statistics

Table A.1 Shares of the 15 member-states in the production, intra-imports, and intra-exports of pork (EU-28, 2015), %*

Member	Production	Intra-Imports	Intra-Exports
BE	4.92	1.44	10.32
DE	24.32	14.01	27.13
DK	6.99	1.33	12.08
ES	17.03	2.03	17.91
FR	8.60	8.19	4.87
GR	0.39	4.00	0.06
IE	1.21	1.11	2.35
IT	6.50	18.40	0.95
LU	0.05	0.15	0.07
NE	6.37	3.29	10.73
AU	2.31	2.94	2.38
PT	1.65	2.72	0.49
FI	0.84	0.57	0.24
SE	1.02	2.70	0.32
UK	3.93	7.80	1.75
Total	86.13	91.64	70.78

* Calculated from Eurostat's database. Production refers to total carcass weight of pigs slaughtered in slaughterhouses. Imports and exports refer to fresh, chilled or frozen pork meat value.

Table A.2 Descriptive Statistics for the logarithmic prices and the price returns (1995: 1 to 2017: 12)

(a) Logarithmic prices

Spatial Market	Mean	0.25 Quantile	Median	0.75 Quantile	Max	Min	SD
BE	4.925	4.837	4.931	5.017	5.367	4.437	0.148
DE	5.006	4.924	5.014	5.097	5.39	4.452	0.144
DK	4.879	4.788	4.885	4.984	5.24	4.48	0.142
ES	4.993	4.901	4.986	5.107	5.366	4.321	0.164
FR	4.935	4.844	4.929	5.029	5.282	4.555	0.133
GR	5.144	5.055	5.142	5.247	5.477	4.713	0.14
IE	4.925	4.863	4.922	5.01	5.169	4.49	0.126
IT	5.086	4.989	5.081	5.193	5.404	4.62	0.146
LU	5.043	4.953	5.03	5.122	5.526	4.711	0.131
NE	4.874	4.796	4.882	4.972	5.288	4.224	0.16
AU	4.995	4.909	5.001	5.088	5.371	4.491	0.143
PT	5.034	4.946	5.042	5.134	5.379	4.451	0.15
FI	4.966	4.907	4.973	5.022	5.217	4.685	0.102
SE	4.998	4.901	4.976	5.096	5.278	4.593	0.146
UK	5.052	4.993	5.051	5.141	5.297	4.519	0.136

(b) Price log returns

Spatial Market	Mean	0.25 Quantile	Median	0.75 Quantile	Max	Min	SD
BE	0	-0.037	-0.001	0.037	0.226	-0.198	0.059
DE	0.001	-0.039	0.001	0.037	0.257	-0.16	0.059
DK	0.001	-0.03	0	0.027	0.24	-0.117	0.046
ES	0	-0.04	0.001	0.042	0.213	-0.184	0.071
FR	0.001	-0.036	0.001	0.038	0.245	-0.17	0.061
GR	0.002	-0.023	-0.005	0.024	0.456	-0.261	0.06
IE	0.001	-0.021	0.001	0.021	0.208	-0.114	0.036
IT	0.002	-0.04	-0.002	0.044	0.19	-0.14	0.061
LU	0.001	-0.032	-0.002	0.032	0.221	-0.129	0.055
NE	0.001	-0.043	0.001	0.04	0.263	-0.195	0.067
A U	0.001	-0.037	-0.001	0.032	0.21	-0.157	0.058
PT	0.001	-0.032	0.004	0.037	0.234	-0.183	0.069
FI	0.001	-0.008	0.001	0.01	0.2	-0.089	0.023
SE	0.002	-0.018	0.002	0.022	0.224	-0.122	0.041
UK	0.002	-0.015	0.002	0.024	0.217	-0.184	0.043

Source: authors´s calculations based on the price data (https://ec.europa.eu/agriculture/market-observatory/meat/pigmeat/historical-series_en)

B. Unit Root Tests on the Logarithmic Prices and on the Price Log-Returns

Table B.1 Results from the KPSS and the Hardi tests*

(a) Individual (KPSS)

Market	Level	Return
BE	0.057	0.056
DE	0.275	0.068
DK	0.33	0.055
ES	0.334	0.082
FR	0.175	0.075
GR	0.278	0.043
IE	0.749	0.063
IT	0.892	0.059
LU	0.155	0.068
NE	0.35	0.054
AU	0.237	0.056
PT	0.346	0.075
FI	0.775	0.067
SE	1.26	0.071
UK	1.037	0.069

(b) Panel (Hardi)

	Level	Return
	8.614 (0)	-2.693 (0.997)

* The critical values for the individual tests are 0.739, 0.463, and 0.347 at the 1, the 5, and the 10 percent level, respectively; *p*-values for the group test in parentheses.

C. Kendall's *tau* and the Strong Triangle Inequality

Let three time series (1, 2, and 3) of length *T*. Let also that $\lambda \geq 0$ pairs of observations are concordant for both the time series pairs (1,3) and (2,3), $\mu \geq 0$ pairs of observations are discordant for both the time series pairs (1,3) and (2,3), and the remaining $\nu \geq 0$ pairs of observations are discordant for time series pair (1,3) and concordant for the time series pair (2,3): Then, the very definition of concordance implies that there would be $\lambda + \mu$ concordant and ν discordant pairs of observations for the time series pair (1, 2): But $\nu \leq \mu + \nu = \max\{\mu + \nu, \nu\}$, where $\mu + \nu$ is the number of discordant pairs of observations for the time series pair (1,3) and ν the number of discordant pairs of observations for the time series pair (2,3): Given the positive relationship between discordance and distance, one obtains $d_{12}(\nu) \leq \max\{d_{13}, d_{23}\}(\mu + \nu)$. The last suggests that Kendall's *tau* satisfies the strong triangle inequality.

D. Hierarchical Analysis for 1995-2002, 2003-2009 and 2010-2017

Table D.1 Measures of importance by sub-period*

Spatial Market	1995-2002				2003-2009				2010-2017			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
BE	0.752	1	0	0.429	1.685	2	0.143	0.442	2.242	3	0.67	0.606
DE	2.26	3	0.275	0.612	2.529	3	0.56	0.628	2.561	3	0.275	0.457
DK	1.42	3	0.484	0.7	1.544	3	0.484	0.626	1.587	4	0.396	0.513
ES	1.335	2	0.143	0.632	1.4	2	0.143	0.45	1.485	2	0.363	0.447
FR	1.038	2	0.495	0.787	1.136	2	0.264	0.561	1.065	2	0.264	0.375
GR	0.776	2	0.143	0.687	0.604	2	0.143	0.423	0.32	1	0	0.305
IE	0.932	2	0.143	0.551	0.876	2	0.143	0.491	0.521	1	0	0.411
IT	0.376	1	0	0.554	0.303	1	0	0.378	0.72	2	0.143	0.336
LU	0.609	1	0	0.586	1.938	3	0.692	0.708	0.869	1	0	0.334
NE	0.74	1	0	0.431	0.836	1	0	0.329	0.858	1	0	0.335
AU	2.937	5	0.78	0.876	1.136	2	0.264	0.47	1.367	2	0.527	0.585
PT	0.774	1	0	0.435	0.833	1	0	0.334	1.469	3	0.538	0.547
FI	0.312	1	0	0.476	0.113	1	0	0.483	0.091	1	0	0.523
SE	0.8	2	0.143	0.553	0.579	2	0.143	0.51	0.163	1	0	0.476
UK	0.439	1	0	0.45	0.318	1	0	0.429	0.307	1	0	0.448

* (a) strength, (b) degree, (c) betweenness, (d) closeness

E. Brillinger's test for the Presence of a Monotonic Trend

For the testing procedure a series (call it Y_t) is expressed as

$$(E.1) \quad Y_t = n_t + \varepsilon_t \,,$$

where n_t is a monotonic trend component (i.e. the level of Y_t) and ε_t is a stationary and zero-mean process. Under the null, $n_t = n$ for all *t* while under the alternative $n_{t+1} \le n_t$ with a strict inequality for some *t* (if one wishes to test for a downwards trend) or $n_{t+1} \ge n_t$ with a strict inequality for some *t* (if one wishes to test for an upward strend): The relevant test statistic is

$$(E.2) \quad BR = \frac{\sum w_t Y_t}{(V_L \sum w_t^2)^{0.5}}$$

that under the null follows the standard normal.

In $(E.2)$ $w_t = [(t-1)(1-\frac{t-1}{T})]^{0.5} - [t(1-\frac{t}{T})]^{0.5}$ and V_L is an estimate of the long-run variance of the residuals from the OLS regression of Y_t on a linear trend. Note that, by construction, the weights in the first half of the sample are negative and in the second half are positive and that $w_{T-j} = -w_{j+1}$ implying $\sum w_t = 0$. A positive (negative) and statistically significant value of *BR* is consistent with an increasing (decreasing) trend. The long-run variance can be estimated from the autocovariances of the regression residuals as suggested by NEWEY and WEST (1987).