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PRICE LINKS AMONG QUALITATIVELY DIFFERENTIATED MEATS: EVIDENCE FROM THE UK WHOLESALE BEEF MARKET

Panos Fousekis
Aristotle University, Department of Economics, Greece, Email: fousekis@econ.auth.gr ORCID: 0000-0002-7386-362X

Abstract

This work investigates the price links among four quality differentiated beef meats in the UK using the recently developed QVAR connectedness approach. The empirical results suggest: (a) Prices are more tightly linked to each other under extreme shocks (regardless of sign) than under small shocks. (b) Higher quality meats tend, in most cases, to be net transmitters of price shocks to lower quality ones. (c) The strength and the internal structure of the four-market network are time-varying; in periods of economic turmoil, the level of total connectedness rises and the position of individual markets in the network as net transmitters or receivers of price shocks may change.
Keywords: *Quality, Price Transmission, Beef, UK, Asymmetry*
JEL Codes: *Q11, C12*

1. Introduction

The total value of agricultural production in the UK in 2022 was 32.6 billion GBP; 59 per cent of it came from the livestock sector. Within the livestock sector, meat production, with a total value of 12.5 billion GBP, was by far the most important economic activity. Beef farming, with a contribution of 3.8 billion GBP was the leading section within meat production (Department for Environmental, Food, and Rural Affairs (DEFRA), 2024). Home-fed beef meat in the UK comes from steers and heifers (about 68 per cent), cows and adult bulls (about 27 per cent), and the rest from young bulls and calves[i]. Steers, heifers, and young bulls constitute the so-called prime beef whereas cows and adult bulls are sold at a discount. Thus, beef meat that arrives at the wholesale market level is not a homogenous commodity. Higher- and lower- priced beef meats satisfy essentially the same nutrition needs. Depending on the price differentials consumers may substitute one meat for another. Premiums and discounts, in turn, are determined by the individual and the joint price dynamics (i.e., by the strength and the pattern of price links).

Price interrelationships in the physical and/or in product quality space are of keen interest to traders, policymakers, and research economists because they provide information about market efficiency. Well-connected markets constitute a great pool. Prices in such markets tend to move in tandem and the full exploitation of arbitrage opportunities results in welfare maximization; in contrast, incomplete and/or asymmetric price spillovers point to potential efficiency losses (e.g., Meyer & von Cramon Taubadel, 2005; Serra *et al*., 2006; Panagiotou & Stavrakoudis, 2023); In recent years, there have been several empirical works on the joint price dynamics of qualitatively differentiated food commodities. Wurriehausen *et al*. (2015), Dolgopolova & Roosen (2018), and Kim & Seok (2022) considered conventional and organic foods; Fousekis & Grigoriadis (2017) and Otero *et al*. (2018) coffee beans; and Fousekis (2022) olive oil. The overwhelming majority of earlier works relied on bivariate modelling. For example, Wurriehausen *et al*. (2015), Dolgopolova & Roosen (2018), and Otero *et al*.

(2018) relied on bivariate cointegration whereas Fousekis & Grigoriadis (2017) and Panagiotou & Starvrakoudis (2023) on bivariate copulas. This is quite problematic; in systems involving more than two inter-related markets, an estimate of the link between any two prices in isolation of the remaining is likely to be biased due to the omission of relevant variables (Gujarati & Porter, 2009).

In this context, the objective of the present work is to assess the price links among qualitatively differentiated beef meats in the UK. This is pursued using the recently proposed Quantile Vector Autoregression (QVAR) connectedness approach (Ando *et al*., 2022). Relative to earlier utilized methodologies, the QVAR has three distinct advantages. First, it is a system-wide approach closely related to the modern theory of directed and weighted graphs. The QVAR model here treats the individual markets of qualitatively differentiated beef meats as components of a network; the strength and the pattern (e.g., symmetric *vs* asymmetric) of price links capture the network's internal structure. Knowledge of the latter makes it possible to illuminate important questions such as the role of each individual market in the network (e.g., net transmitter vs net receiver of price shocks) and the relative influence of own- and cross-shocks in beef price volatility. Second, the QVAR allows price relationships to depend on the size and the sign of shocks. Market state-dependence (or equivalently quantile-dependence) is a well-known source of non-linear and asymmetric price links in food commodities markets (e.g., Meyer & von Cramon Taubadel, 2005; Fousekis & Grigoriadis, 2017; Panagiotou & Stavrakoudis, 2023). Third, precisely because the QVAR is a system-wide approach, it is far less susceptible to biases due to the omission of relevant variables.

A few recent studies have utilized variants of the connectedness approach (but not the QVAR model) to study spillovers in agricultural and food markets. Szabo *et al*. (2023) focused on spatial price volatility (price risk) spillovers; in particular, they employed the standard (Diebold & Yilmaz, 2014) methodology to investigate price risk connectedness among a number of major pork -producing EU member states. They found that about 50 per cent of the forecast error variance for the system of the relevant markets was explained by spatial price volatility spillovers. Uçak *et al*. (2022), examined price volatility connectedness among fertilizers and selected agricultural products markets using the Time-Varying Parameters (TVP) vector autoregression (VAR) approach (Antonakakis *et al*., 2019). According to their results, fertilizers (i.e., the production inputs) were more likely to transmit price risk to agricultural products than the other way round. Uçak *et al*. (2024a) considered price risk connectedness among chicken meat, soybeans, maize, and wheat markets using, again, the TVP-VAR approach. They found that about one-third of the forecast error variance for the system of the relevant markets was attributed to risk spillovers and that the intensity of interconnectedness varied under the influence of global shocks. Uçak, *et al*. (2024b), employing the TVP-VAR methodology, examined price volatility connectedness among fertilizers and rice in a number of major rice-producing countries. They reported values of total connectedness in the range of 40 to 55 per cent and a decline in the intensity of spillovers after 2010; they also concluded that the outbreak of the COVID-19 pandemic in 2020 had a negligible influence on connectedness (probably because the production cost in 2019 had already been incorporated into rice prices). Fousekis (2023), also using the TVP-VAR approach, investigated price (in contrast to price volatility) connectedness among dairy futures markets in the US. His results suggested that connectedness was not strong (two-thirds of the forecast error variance was due to idiosyncratic price shocks); Class III milk futures prices were tightly connected to cheese prices but weakly connected to those of butter and dry whey; the transmission of price shocks tended to be from the raw farm product (Class III milk) to the processed products (i.e., cheese, butter, and dry whey). In addition, in the early phases of the COVID-19 pandemic and of the war in Ukraine, the intensity of price spillovers increased probably due to disruption of supply chains and the concerns about the energy costs and the availability of cow feed and fertilizers, respectively.

To the best of my knowledge, this is the first work that employs the QVAR approach to investigate price connectedness in agricultural and food markets. At the same time, it is the first attempt to assess price relationships among qualitatively differentiated meats in the UK.

2. Methodology

The QVAR (Ando *et al.*, 2022) is an extension of the standard connectedness model by Diebold & Yilmaz (2014). The difference between the two is that the former relies on quantile VAR while the latter on linear VAR regression analysis. Consider a *N*-variate stationary stochastic process in *T* time periods, $X_t = (X_{1t}, X_{2t}, \dots, X_{Nt})$ (with *t*=1, … , *T*), a forecast horizon (denoted as *H*), and a quantile of the joint distribution of X_t (denoted as *Q*). The building block for developing connectedness measures is the representative element, $\theta_{ij}(H,Q)$ (*i, j = 1,2, …, N)* of the Generalized Forecast Error Variance (GFEV) decomposition matrix of the QVAR[ii]. $\theta_{ij}(H,Q)$ gives the proportion of the GFEV of the stochastic process *i* that can be explained by shocks (innovations) to process *j*; that is, the *spillover* from *j* to *i* at forecast horizon *H* and at quantile *Q*.

The difference

$$NPCD_{ij} = \theta_{ij}(H,Q) \text{-} \theta_{ji}(H,Q) \tag{1}$$

with $i \neq j$,, is the *net pair directional spillover*; when positive (negative) , process *i* is a net receiver (transmitter) of shocks from (to) *j* at *H* and *Q*. The sum

$$TO_i(H,Q) = \sum_{j=1}^{N} \theta_{ji}(H,Q) \tag{2}$$

is *the total directional spillover* from *i* to all other *N*-1 processes taken together whereas the sum

$$FROM_i(H,Q) = \sum_{j=1}^{N} \theta_{ij}(H,Q) \tag{3}$$

is the *total directional spillover* from all other *N*-1 processes taken together to *i*. The difference

$$NET_i(H,Q) = TO_i(H,Q) - FROM_i(H,Q) \tag{4}$$

is the *net total directional spillover*; when positive (negative) process *i* is a net transmitter (receiver) of shocks to (from) the remaining *N*-1 processes. Finally, the sum

$$TCI(H,Q) = \frac{N}{N-1}\sum_{i=1}^{N} TO_i\,(H,Q) = \frac{N}{N-1}\sum_{i=1}^{N} FROM_i\,(H,Q) \tag{5}$$

(that lies in (0,1)) is the *total connectedness index*; it captures the average shock spillover from one stochastic process to another (Stenfors *et al.*, 2022). Higher (lower) values of it imply that the *N* stochastic processes are more (less) tightly connected to each other.

3. The Data and the Empirical Models

The data for the empirical analysis is weekly deadweight cattle prices for steers, heifers, young bulls, and cows. They have been obtained from the Agriculture and Horticulture Development Board (AHDB) in the UK, are expressed in GBP per 100 kilos, and refer to the period 1/5/2019 (the earliest observation is available) to 2/24/2024[iii]. Figure 1 shows the evolution of the four prices. Steers and heifers with an average value of 4.02 and 4.01, respectively, have had the highest prices followed by young bulls (3.87) and cows (2.84). The prices of prime beef meats exhibited a strong tendency to move in tandem; the price of cows often deviated from the rest.

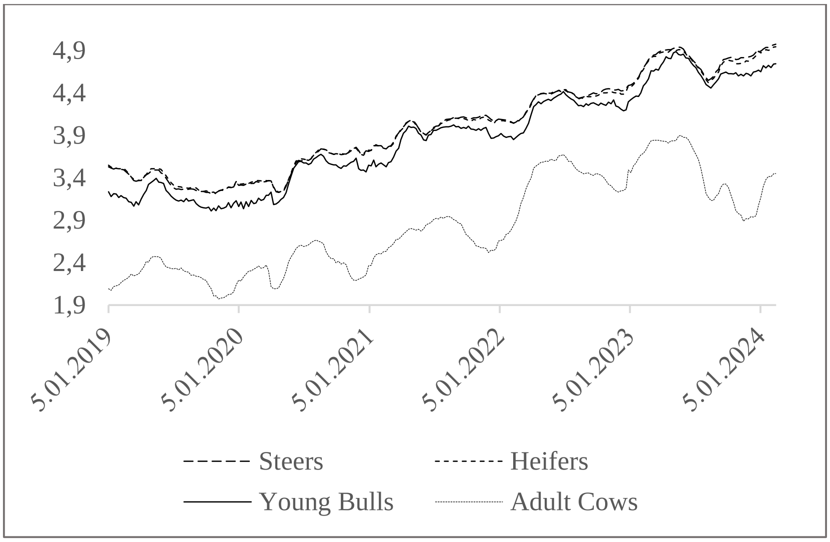

Figure 1. The Evolution of Prices

The natural logarithms of prices are in all cases non-stationary; their log-price returns, however, are not (Table A.1, Appendix). Therefore, the empirical analysis here relies on returns. Table A.2 (Appendix) provides descriptive statistics and tests on their distributions. The price of cows has had a higher growth rate and a higher volatility relative to the remaining. The distributions of returns for steers and young bulls have been symmetric; that for heifers has exhibited positive skewness pointed to the presence of few extremely positive returns whereas the opposite has been the case for cows. All four distributions of returns have been leptokurtic and departed strongly from normality.

For the estimation of the QVAR model, the forecast horizon (*H*) has been set equal to 12 months. It has been already established that the results of connectedness models are quite robust to the choice of the forecast horizon (e.g., Diebold & Yilmaz, 2014; Ando *et al*., 2022; Fousekis, 2023). The quantile (*Q*), has been set equal to 0.05, 0.50, and 0.95. This a rather typical choice in the relevant empirical literature on price links of food commodities (e.g., Qui & Goodwin, 2013; Fousekis & Grigoriadis, 2017; Fousekis, 2022) as it allows one to compare the strength and the mode of connectedness at the lower extremes (0.05), the median (0.5), and the upper extremes (0.95) of a joint returns distribution. Finally, following Ando *et al*. (2022), the lag length for the QVAR has been selected using the Bayesian Information Criterion.

4. The Empirical Results

4.1 Static (Full-Sample) Analysis

Table 1 presents the connectedness estimates at Q=0.05 (i.e., at a market state involving extreme negative shocks). The own-spillovers are the diagonal elements and the cross-spillovers are the off-diagonal ones. The own-spillovers range from 28.64 for heifers to 33.34 for cows suggesting that: (a) the idiosyncratic (own-) shocks, in all cases, explain less than 1/3 of the volatility of individual series; the rest must be attributed cross-spillovers and (b) the market for heifers (cows) is the most (least) tightly connected to the remaining. The off-diagonal row sums are the total directional FROM spillovers; the market of Heifers is the top receiver of innovations. The off-diagonal column sums are the total directional TO spillovers; the market of steers is the top transmitter of innovations. The bottom row shows the net total directional spillovers. From the vantage point of the network at Q=0.05 , there is very limited evidence of asymmetric connectedness; the market of steers, at the 10 per cent level of significance, appears to be a net transmitter of shocks to the other three. All cross-spillovers are statistically significant at the conventional levels suggesting that there is a two-way connectedness for all pairs. The order of magnitude of cross-spillovers follows closely that of the average prices (or, equivalently, the quality of beef meat) in the sample. For instance, the highest TO spillover from steers corresponds to heifers and the lowest to cows while the highest TO spillover from cows corresponds to young bulls followed by that to heifers. The TCI (bottom-right element) is almost 70 per cent implying that the four markets are well-connected to each other under extreme negative shocks. Table 2 shows the net pair spillovers. None is statistically significant at the conventional levels; thus, there is no evidence of asymmetric pair connectedness at Q =0.05.

Table 1. Connectedness estimates (Quantile 0.05)

Markets	Steers	Heifers	Young Bulls	Cows	Total directional FROM others
Steers	29.52 (<0.01)	27.18 (<0.01)	24.05 (<0.01)	19.25 (<0.01)	70.48 (<0.01)
Heifers	28.61 (<0.01)	28.64 (<0.01)	23.29 (<0.01)	19.47 (<0.01)	71.36 (<0.01)
Young Bulls	25,82 (<0.01)	23.79 (<0.01)	30.86 (<0.01)	19.53 (<0.01)	69.14 (<0.01)
Cows	22.95 (<0.01)	22.8 (<0.01)	20.91 (<0.01)	33.34 (<0.01)	66.66 (<0.01)
Total directional TO others	77.38 (<0.01)	73.71 (<0.01)	68.25 (<0.01)	58.25 (<0.01)	
Total connectedness					
Net total directional	6.98 (0.08)	2.47 (0.58)	-0.89 (0.84)	-8.41 (0.28)	69.41 (<0.01)

Note*:* *p*-values in parentheses; obtained using the Wald statistic (Patton, 2013) and block bootstrap (Politis & Romano, 1994) with 2500 replications.

Table 2. Net Pair Spillovers (Quantile 0.05)

Market pairs	**Test statistic**
Steers, Heifers	1.43 (0.43)
Steers, Young Bulls	1.77 (0.21)
Steers, Cows	3.7 (0.21)
Heifers, Young Bulls	0.5 (0.75)
Heifers, Cows	3.33 (0.23)
Young Bulls, Cows	1.38 (0.63)

Note: The test statistic is spillover from the first to the second market in a pair;*:* *p*-values in parentheses; obtained using the Wald statistic (Patton, 2013) and block bootstrap (Politis & Romano, 1994) with 2500 replications

Table 3. Connectedness Estimates (Quantile 0.5)

Markets	Steers	Heifers	Young Bulls	Cows	Total directional FROM others
Steers	41.64 (<0.01)	33.74 (<0.01)	19.05 (<0.01)	5.57 (0.07)	58.35 (<0.01)
Heifers	35.86 (<0.01)	39.37 (0.01)	17.79 (<0.01)	6.98 (0.01)	60.63 (<0.01)
Young Bulls	25.3 (<0.01)	23.16 (<0.01)	46.46 (<0.01)	5.08 (0.05)	53.54 (<0.01)
Cows	6.43 (0.07)	9.55 (0.008)	4.03 (0.15)	79.99 (<0.01)	20.01 (0.03)
Total directional TO others	67.58 (<0.01)	66.45 (<0.01)	40.86 (<0.01)	17.63 (0.03)	
Total connectedness					
Net total directional	9.12 (0.09)	5.82 (0.21)	-12.68 (0.01)	-2.38 (0.81)	48.13 (<0.01)

Note*:* *p*-values in parentheses; obtained using the Wald statistic (Patton, 2013) and block bootstrap (Politis & Romano, 1994) with 2500 replications.

Table 3 shows the connectedness estimates at the median (i.e., at a market-state involving positive or negative shocks of small size). Steers have the highest total directional FROM and, at the same time, the highest total directional TO spillover. From the network perspective, the market for steers is, therefore, a *price risk connector* at this quantile (e.g., Nguyen *et al.*, 2020). There is weak evidence that the market of steers is a net transmitter of shocks to the remaining and strong evidence that the market of young bulls is a net receiver one. The vast majority of cross-spillovers are statistically significant at the conventional levels. The order of magnitude of cross-spillovers follows, generally, that of average prices. The TCI is only 48.13; less than 50 per cent of the GFEV can be attributed to cross-spillovers. This is an indication that, under shocks of small size, the four markets are not as well connected as at the low extremes of the joint returns distribution. Table 4 presents the net pair spillovers. Three out of six differences are statistically significant at the conventional levels. In all three cases, the asymmetry points to higher-quality beef meats as net transmitters of shocks to lower-quality ones.

Table 4. Net Pair Spillovers (Quantile 0.5)

Market pairs	**Test statistic**
Steers, Heifers	2.12 (0.08)
Steers, Young Bulls	6.25 (0.03)
Steers, Cows	0.86 (0.83)
Heifers, Young Bulls	5.37 (<0.01)
Heifers, Cows	2.57 (0.48)
Young Bulls, Cows	-1.05 (0.74)

Note: The test statistic is spillover from the first to the second market in a pair;*:* *p*-values in parentheses; obtained using the Walde statistic (Patton, 2013) and block bootstrap (Politis & Romano, 1994) with 2500 replications

Table 5. Connectedness Estimates (Quantile 0.95)

Mrkets	Steers	Heifers	Young Bulls	Cows	Total directional FROM others
Steers	28.61 (<0.01)	27.12 (<0.01)	24.07 (<0.01)	20.2 (<0.01)	71.39 (<0.01)
Heifers	27.38 (<0.01)	27.99 (<0.01)	23.86 (<0.01)	20.77 (<0.01)	72.01 (<0.01)
Young Bulls	25.56 (<0.01)	25.55 (<0.01)	29.05 (<0.01)	19.84 (<0.01)	70.95 (<0.01)
Cows	21.96 (<0.01)	32.04 (<0.01)	21.18 (<0.01)	33.81 (<0.01)	66.19 (0.03)
Total directional TO others	74.9 (<0.01)	75.72 (<0.01)	69.11 (<0.01)	60.81 (<0.01)	
					Total connectedness
Net total directional	3.51 (0.03)	3.71 (0.02)	-1.84 (0.36)	-5.38 (0.06)	70.14 (<0.01)

Note: *p*-values in parentheses; obtained using the Wald-type statistic (Patton, 2013) and block bootstrap (Politis & Romano, 1994) with 2500 replications.

Table 6. Net Pair Spillovers (Quantile 0.95)

Market pairs	**Test statistic**
Steers, Heifers	0.26 (0.55)
Steers, Young Bulls	1.49 (0.04)
Steers, Cows	1.76 (0.15)
Heifers, Young Bulls	1.69 (0.01)
Heifers, Cows	2.27 (0.03)
Young Bulls, Cows	1.34 (0.2)

Note: The test statistic is spillover from the first to the second market in a pair;*:* *p*-values in parentheses; obtained using the Wald statistic (Patton, 2013) and block bootstrap (Politis & Romano, 1994) with 2500 replications

Table 5 presents the connectedness estimates at Q=0.95 (i.e., at a market state involving extreme positive shocks). Given the magnitudes of the total directional FROM and TO spillovers the market for heifers is the price risk connector. Three out of four net directional spillovers are statistically significant at the conventional levels. From the vantage point of the network, the markets of steers and heifers are net transmitters and that of cows is a net receiver of innovations. All cross-spillovers are statistically significant and their order of magnitude follows closely that of average prices. The TCI is 70.14, slightly higher than that at Q=0.05. Table 6 presents the net pair spillovers. Three out of six differences are statistically significant at the conventional levels. Again, the higher-quality beef meats are net transmitters of shocks to lower-quality ones. From the comparison of Tables 3, 4, and 5 follows that the strength of total connectedness and the internal structure of the four-market network are quantile-dependent.

4.2 Dynamic Analysis

The full-sample (static) analysis may mask the impact of time-specific events on the intensity and the mode of connectedness. The dynamic (rolling-windows) analysis may address this potential limitation. The application of the QVAR to each individual quantile yields 29 connectedness measures. Presenting the evolution of all of them will require a very large number of figures. Because of this, the present work focuses on the evolution of the TCI and the net total directional spillovers. The TCI is a summary measure of connectedness while the net total directional spillovers provide information about the position (net receiver or net transmitter of shocks) of each individual market relative to the others in the network. For the rolling-windows analysis, the forecast horizon (*H*) and the quantile (*Q*) are the same as for the full-sample analysis and the window length has been set equal to 48 (to ensure that each sub-period includes a sufficient number of observations for estimating the QVAR model)[iv].

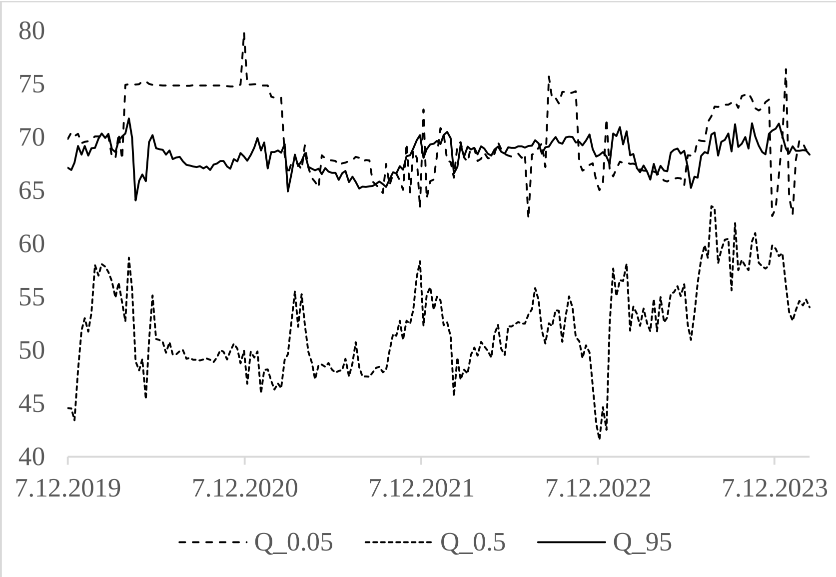

Figure 2. The Evolution of the Total Connectedness Index

Figure 2, presents the evolution of total connectedness. The TCI value at the 0.95 quality remained relatively stable. However, its values at the 0.5 and 0.05 quantiles fluctuated widely. For windows ending in the first half of 2020, the TCI value at the 0.05 quantile jumped by almost 10 percentage points and it remained high through the first half of 2021; in contrast, the TCI at the 0.5 quantile experienced a notable reduction over the same sub-periods. It appears, therefore, the impact of COVID-19 pandemic on connectedness was not the same at all parts of the joint distribution of price returns. For windows ending in 2022 (thus, covering the outbreak of the War in Ukraine and subsequent rally in food prices) the TCI at 0.5 quantile increased. During most of 2023 (a year also marked by very high food inflation rates in the UK) the TCIs at both the 0.05 and the 0.5 quantiles showed strong upward trends. In the last quarter of 2023 and in the first two months of 2024, the TCIs at the 0.05 and 0.5 quantiles were decreasing.

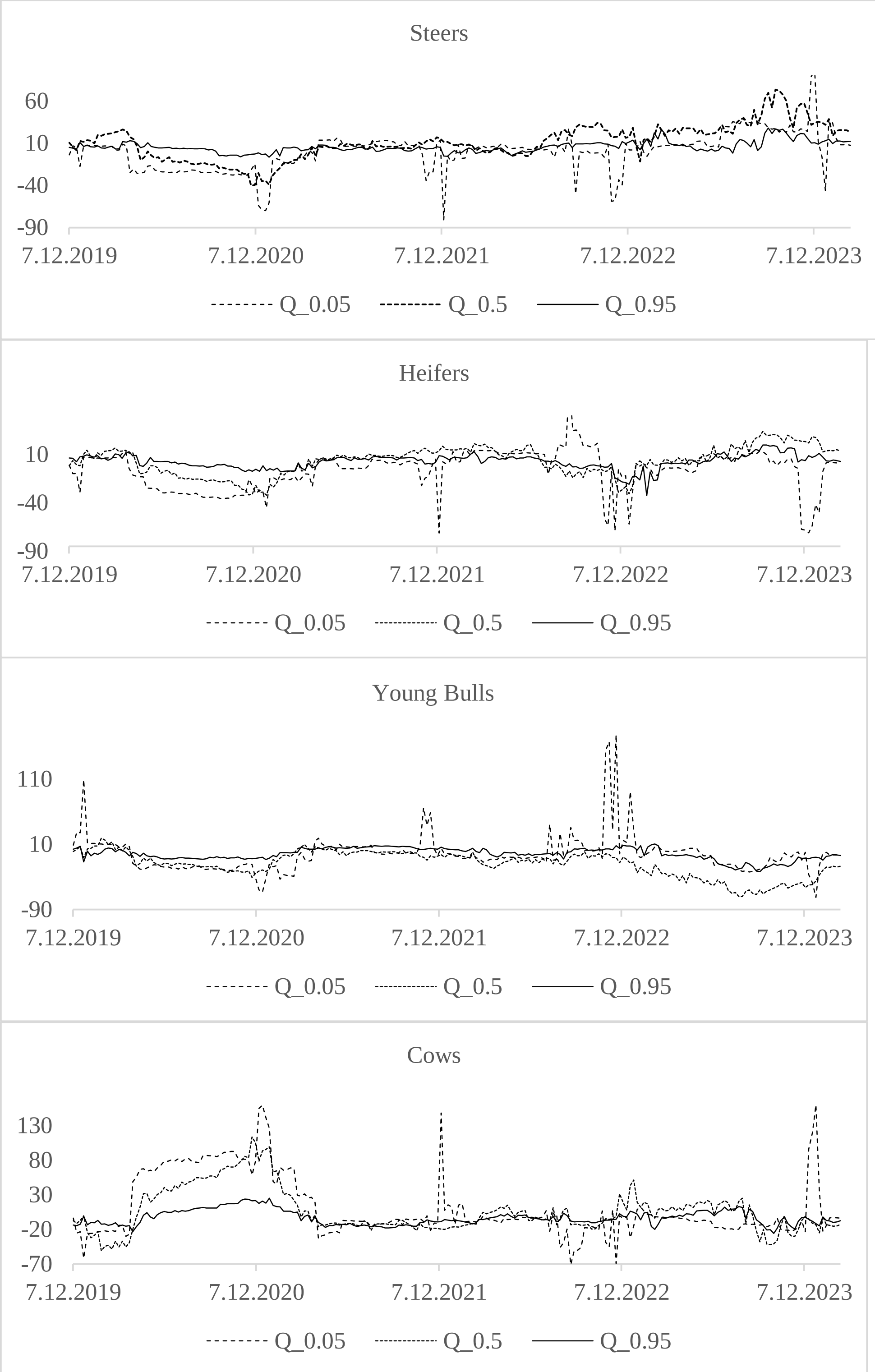

Figure 3. The evolution of the net total directional spillovers

Figure 3 shows the evolution of the net total directional spillovers. Steers was consistently a net transmitter of shocks at the 0.95 and 0.5 quantiles and (over certain sub-periods) a net receiver of shocks at the 0.05 quantile. The same observation applies to heifers. Young bulls and cows were largely net receivers of shocks at the median and the upper extremes and net transmitters at the lower extremes of the joint distribution of returns.

5. Conclusions

The intensity and the mode of price links for commodities related in the physical and/or the quality space contain potentially useful information about the functioning (efficiency) of their respective markets. This work has investigated the links among qualitatively differentiated wholesale beef meat markets in the UK using the QVAR connectedness approach.

The full-sample analysis suggests that the strength of total connectedness depends critically on the magnitude but not on the sign of price shocks; the four markets are tightly linked to each other under large positive or negative shocks but loosely so under small shocks (regardless of sign). This pattern of connectedness may explained by the presence of transaction costs that create "wedges" (thresholds) around individual prices; large price shocks in a given market surpass such thresholds and evoke responses to other markets in the network whereas small shocks do not (e.g., Meyer & von Cramon Taubadel, 2004; Serra *et al*., 2006). The strength of connectedness for market pairs is closely related to beef quality; for example, the markets for steers and heifers are more tightly linked to each other relative to those of steers and cows. This is in line with the results of Fousekis & Grigoriadis (2017) and Fousekis (2022) for coffee beans and olive oil, respectively. The network's internal structure is quantile-dependent. Strong evidence of asymmetric connectedness exists at the median and at the upper extremes of the joint distribution of returns; the asymmetric pattern, invariably, points to higher-quality beef meats as net transmitters of innovations to the lower-quality ones. This, in turn, implies that the higher-quality beef meats are more likely to shape the evolution of beef prices in the UK relative to lower-quality ones. The finding is consistent with those in Kim & Seong (2022) for organic and conventional milk in Austria and Fousekis (2022) for olive oil; it contrasts, however, with that in Dolgopolova & Roosen (2018) for organic and conventional milk in Germany.

The dynamic (rolling-windows) analysis, generally, confirmed the results of the static one and provided additional insights. Total connectedness under extreme large price shocks has been fairly stable over time; it rose, however, dramatically at the median and at the lower extremes in economic turmoil (the COVID-19 pandemic, the outbreak of the war in Ukraine, and the period with very high inflation rates in the UK). Besides being quantile-dependent, the network's internal structure has been time-varying as well. The four markets, especially in periods of economic turmoil, tended to interchange roles as net transmitters or net receivers of shocks.

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APPENDIX

Table A.1. Results from the Application of the KPPS Unit Root Test

Natural Logarithms of prices				
Statistics	Steers	Heifers	Young Bulls	Cows
With a constant only	4.394	4.382	4.339	4.376
With trend	0.236	0.238	0.172	0.244
Price log-returns				
Statistics	Steers	Heifers	Young Bulls	Cows
With a constant only	0.151	0.238	0.172	0.244
With trend	0.087	0.079	0.05	0.04

Note*:* The log-returns are calculated as $\ln(P_{it}/P_{it-1})$ where P_{it} is the price steers, heifers, young bulls or cows. The critical values are 0.463 and 0.146 for the test with a constant only and for the test with a deterministic trend, respectively.

Table A.2. Descriptive Statistics and Tests on the Distributions of Price Log-Returns

Statistics	Steers	Heifers	Young Bulls	Cows
Mean	0.001	0.001	0.001	0.002
Standard Deviation	0.007	0.007	0.011	0.017
Min	-0.021	-0.024	-0.047	-0.086
Max	0.024	0.023	0.032	0.065
Skewness	0.157 (0.29)	0.306 (0.04)	-0.203 (0.167)	-0.308 (0.04)
Kurtosis	1.407 (<0.01)	1.156 (<0.01)	1.429 (<0.01)	3.632 (<0.01)
Normality	0.976 (<0.01)	0.978 (<0.01)	0.983 (<0.01)	0.956 (<0.01)

Note: p-values in parentheses; obtained using the Wald statistic (Patton, 2013) and block bootstrap (Politis &nd Romano, 1994) with 2500 replications.

[i] https://www.gov.uk/government/statistics/historical-statistics-notices-on-the-number-of-cattle-sheep-and-pigs-slaughtered-in-the-uk-2023/
[ii] For technical details on the derivation of the GFEVD for the QVAR model please consult Ando *et al*. (2022).
[iii] https://ahdb.org.uk/beef/gb-deadweight-cattle-prices-by-region
[iv] Diebold & Yilmaz (2014) and Ando *et al*. (2022) have offered evidence that the results from dynamic analysis are quite robust to the choice of the window length.