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The Australian Journal of
Agricultural and
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Australian Journal of Agricultural and Resource Economics, 66, pp. 383–399

Tail price risk spillovers along the US beef and pork supply chains

Panos Fousekis and Dimitra Tzaferi[†]

The objective of this paper was to investigate the intensity and the pattern of tail price risk spillovers in the US beef and pork industries. To this end, it estimates *CoVaR* functions for directly linked market pairs (farm–wholesale and wholesale–retail) along the relevant supply chains using quantile regressions. Over the total sample (1980–2020) and two sub-samples (1980–1999 and 2000–2020), the beef industry appears to exhibit a higher degree of price risk connectedness relative to the pork industry. Positive and negative tail price events are transmitted between markets with the same intensity. However, tail price events (irrespective of sign) are likely to spillover with greater intensity backwards in the supply chain than forwards. This pattern of transmission may be a cause of concern about the efficiency of alternative meat marketing arrangements as risk-sharing instruments.

Key words: Meat, the United States, prices, risk connectedness, asymmetry.

JEL classifications: Q11, C5

1. Introduction

Price relationships in vertically linked meat markets have long been of keen interest to agricultural economists, consumers, farmers and policymakers. This is not accidental. The extent and the pattern of price transmission contain potentially valuable information about the efficiency and the distribution of welfare (equity) along supply chains (e.g. Goodwin & Holt, 1999; Hahn, 1990; Lawrence, 2010; Panagiotou, 2021; Saitone & Sexton, 2017; USDA, 2019a).

Since the mid-1980s, the US meat sector has experienced major structural changes that increased dramatically concentration and vertical coordination. Here are some examples. In 1978, the average pig farm had an inventory of 115, while in 2012, it had an inventory of 1043 animals. In 1980, cattle slaughtering had a concentration ratio, four biggest firms (CR4) of 26 and in 2012 of 70. In 1992, the CR4 in grocery retailing was 17, while in 2014, it was 38. In 2016, 2.5 per cent of hogs were transacted via spot or cash markets compared with almost 90 per cent in 1990; the rest were sold under alternative marketing arrangements (AMAs) such as forward or formula contract, packer/processor owned production contract and packer sold (e.g. Adjemian

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doi: 10.1111/1467-8489.12455

et al., 2016; Saitone & Sexton, 2017; USDA, 2019a, 2019b). The motivation for higher concentration has been the gains from scale and scope economies, while that for increased vertical coordination has been the efficiencies resulting from operating capital-intensive plants with an adequate and timely flow of the main (farm) input with desired characteristics (e.g. Adjemian et al., 2016; Saitone & Sexton, 2017; Ward, 2010).[1] The processes, however, of concentration and vertical coordination have raised concerns about their potential implications for market power abuses, the viability of small farms and the overall performance of the system.[2] In 1999, the US Congress passed the Livestock Mandatory Reporting (LMR) Act mandating the collection of meat prices at the farm and wholesale level to facilitate transparent price discovery and to provide livestock industry stakeholders with comparable levels of information.[3] There have been also several civil lawsuits for alleged violations of Section 1 of the Sherman Act (Ward, 2010).[4]

The intensity and the pattern (symmetric or asymmetric) of price transmission along the meat supply chain in the United States and in several other developed countries have been investigated over the last 25 years with a variety of econometric and statistical tools. Most empirical studies (e.g. Abdulai, 2002; Bakucs & Ferto, 2005; Chang & Griffith, 1998; Fousekis et al., 2016; Goodwin & Harper, 2000; Goodwin & Holt, 1999; Panagiotou, 2021; Pozo et al., 2021) have relied on cointegration analysis. Among the models employed have been the Asymmetric Vector Error Correction Model (VECM), the Threshold VECM and the Non-linear Autoregressive Distributed Lag (NARDL). Much fewer studies have employed Copulas (e.g. Emmanouilides & Fousekis, 2014, 2015). The empirical results vary with the quantitative tool employed, the market levels, the time period and the country considered. A potential limitation of cointegration analysis is its focus on the relationship between random variables (here, prices at different levels of the supply chain) around the mean of their joint distribution. However, there is no *a priori* reason to assume that extreme, moderate and weak price shocks in one market level are transmitted with the same strength

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[1] Most pork is under vertical control, either through vertical integration or through production contracts. On the contrary, vertical control is less popular in the beef market. The main reasons are the longer beef life cycle, the multiple stages of production, the disperse geographic concentration and the reliance on land (Norwood and Lusk, 2018).

[2] Saitone and Sexton (2017) and Panagiotou and Stavrakoudis (2018) are among the recent works on market power in the US food supply chain and its implications for prices and welfare.

[3] From 1946 to 2001, price information was collected by the USDA on a voluntary basis.

[4] As far as the most recent cases are concerned, in 2019, a group of fed cattle producers, a meat wholesaler and beef consumers filed an antitrust class-action lawsuit claiming that the four largest meat packers have conspired to fix, decrease and stabilise fed cattle prices paid to producers and to fix, increase and stabilise wholesale and retail price of beef paid by buyers since 2015 (https://www.dtnpf.com/agriculture/web/ag/news/farm-life/article/2019/04/24/class-action-points-cattle-price). In 2018, a group of consumers also filed a lawsuit alleging that food companies schemed to collectively raise pork prices since 2009 (https://www.nationalhogfarmer.com/business/pork-companies-face-price-fixing-lawsuit).

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to another market level. At the same time, cointegration analysis requires strong distributional assumptions. Copulas allow for the intensity of connectedness to vary across a joint distribution. Their empirical usefulness, however, is constrained due to the "curse of dimensionality" and the need to select among different copula families and a very large number of functional forms (e.g. Nagler & Czado, 2016).

Against this background, the objective of the present work was to provide further insights into price relationships in the US beef and pork industries. To this end, it relies on the notion of conditional value at risk (*CoVaR*) and on quantile regression analysis. The *CoVaR* is a well-known and popular measure of tail risk conditional upon an adverse shock, while the quantile regression is robust to outliers and it does not require restrictive distributional assumptions. The concept of *CoVaR* and quantile regressions has been employed to study the contagious nature of tail events by Hautsch et al. (2015) for publicly traded US financial companies, by Adrian and Brunnermeier (2016) for four financial sectors in the United States, and by Borri (2019) and Nguyen et al. (2020) for cryptocurrencies.

Cattle production is the single largest segment of the US agriculture, while pork production is also among the most important farm industries (in the most recent years, taken together, cattle and pork production contribute about 23 per cent of farm net cash receipts). None of the earlier empirical studies has investigated tail price risk spillovers in the US meat sector.

The empirical analysis here places special emphasis on potential asymmetries associated with the qualitative nature (positive versus negative) and the origins (e.g. farm versus wholesale) of price shocks. Moreover, by investigating tail price risk spillovers in different sub-samples, it attempts to shed light on the question of whether the increased concentration and vertical coordination over the last 20 years have had an impact on the strength and the pattern of price risk transmission. In what follows, Section 2 presents the analytical framework and Section 3 the data, the empirical models and the results. Section 4 offers conclusions and suggestions for future research.

2. Analytical framework

Let p_{it} be the price of commodity i at time t, and $r_{it} = \ln(p_{it}/p_{it-1})$ be the log return. The unconditional lower tail value at risk $\left(VaR_{it}^{q,L}\right)$ is the maximum value of r_{it} at confidence level 1-q, that is the q-quantile of the unconditional log return distribution.

$$q = \Pr\left(r_{it} \leq VaR_{it}^{q,L}\right), \tag{1}$$

with $0 < q \leq 0.5$. Intuitively, $VaR_{it}^{q,L}$ corresponds to the maximum r_{it} in a bad state of the world. Let also r_{jt} be the log return of commodity j over the same

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period. The lower tail conditional value at risk for commodity i given that j is in a bad state of the world $\left(CoVaR^{q,L}_{it/jt}\right)$ is the q-quantile of the conditional probability distribution of r_{it}

$$q = \Pr\left(r_{it} \leq VaR^{q,L}_{it} / r_{jt} \leq VaR^{q,L}_{jt}\right) \tag{2}$$

(e.g. Adrian & Brunnermeier, 2016; Borri, 2019).

An ideal approach to implement lower tail $CoVaR$ empirically is the standard linear quantile regression model of Koenker and Bassett (1978). Hautsch et al. (2015) and Nguyen et al. (2020) propose estimating a quantile regression model of the form.

$$VaR^{q,L}_{it} = \alpha^{q,L}_{i} + \beta^{q,L}_{i} E^{q,L}_{jt} + \gamma^{q,L}_{i} P'_{it} + u_{it}, \tag{3}$$

where $E^{q,L}_{jt}$ is loss exceedance in r_{jt} (defined as $E^{q,L}_{jt} = 0\,(r_{jt})$ for $r_{jt} > (\leq)\, VaR^{qL}_{jt}$, P'_{it} is a vector of other relevant right-hand-side variables, and u_{it} is the error term. Parameter estimates are obtained by minimising

$$\frac{\sum_{t=1}^{T} \rho_q\left(VaR^{q,L}_{it} - W'_{it}\xi^{q,L}_{i}\right)}{T}, \tag{4}$$

where $\xi^{q,L}_{i} = \left(\alpha^{q,L}_{i},\ \beta^{q,L}_{i},\ \gamma^{q,L}_{i}\right)$, $W'_{it} = \left(1,\ E^{q,L}_{jt},\ P'_{it}\right)$ and $\rho_q = (q - I(u < 0))$, a piecewise linear check (loss) function.

The coefficient $\beta^{q,L}_{i}$ in (3) measures the vulnerability of r_{it} at quantile q to lower tail risk in r_{jt} (i.e. the lower tail risk in-degree for commodity i or, equivalently, the lower tail risk out-degree for commodity j). If $\beta^{q,L}_{i} = 0$, there are no lower tail risk spillovers from commodity j to i at tail threshold q; if $\beta^{q,L}_{i} > 0$, values of r_{jt} below $VaR^{q,L}_{jt}$ tend to increase the probability of observing values of r_{it} below $VaR^{q,L}_{it}$; if $\beta^{q,L}_{i} < 0$, shocks to r_{jt} below $VaR^{q,L}_{it}$ are more likely to affect parts of the r_{it} distribution that lie above its q-quantile. When $\beta^{q,L}_{i} \neq 0$, commodity j is a lower tail risk transmitter for i and commodity i is a lower tail risk receiver from commodity j (e.gHautsch et al., 2015; Nguyen et al., 2020).

The estimation of upper tail $CoVaR$ is facilitated when noting that.

$$q = \Pr\left(r_{it} \geq VaR^{1-q,U}_{it}\right) = \Pr\left(-r_{it} \leq -VaR^{q,L}_{it}\right) \tag{5}$$

which suggests that in the corresponding quantile regression model, the dependent variable is $-VaR^{q,L}_{it}$ and the loss exceedance regressor is defined as

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$E_{jt}^{q,L} = 0\ (-r_{jt})$ for $-r_{jt} > (\leq) - VaR_{jt}^{qL}$. The coefficient of loss exceedance, denoted as $\beta_i^{1-q,U}$, measures the vulnerability of r_{it} at quantile q to upper tail risk in r_{jt}. Again, $\beta_i^{1-q,U} = 0$ suggests the absence of upper tail risk spillovers from j to i at tail threshold q, while $\beta_i^{1-q,U} > (<)\ 0$ implies that values of r_{jt} above the 1-q-quantile of its unconditional distribution tend to increase (decrease) the likelihood of observing values of r_{it} above its $VaR_{it}^{1-q,U}$. Therefore, $\beta_i^{1-q,U} \neq 0$ indicates that commodity j is an upper tail risk transmitter for i and commodity i is an upper tail risk receiver from commodity j.

With regard to tail price risk connectedness, of particular importance appear to be: (a) the relative intensity of spillovers at symmetric lower and upper quantile thresholds (i.e. q and 1-q) and (b) the relative intensity of tail risk in- and tail risk out-degrees. The sign and the statistical significance of the difference $\beta_i^{q,L} - \beta_i^{1-q,U}$ provide information on whether the price of commodity i tends to be more vulnerable to the downswings or to the upswings of market j. The sign and the statistical significance of the difference $\beta_i^{q,L} - \beta_j^{q,L}$ (or $\beta_i^{1-q,U} - \beta_j^{1-q,U}$) provide information on the tail risk net-degree; a positive difference implies that commodity i is a net receiver of tail price risk from j (Barunik et al., 2016; Nguyen et al., 2020).

3. Data, empirical models, and empirical results

3.1 Data and empirical models

The data for the empirical analysis are monthly prices at the farm, the wholesale and the retail level. They have been obtained by the ERS-USDA and refer to the period 1980–2020.[5] Figure A.1 and Figure A.2 present the logarithmic price ratios (wholesale to farm and retail to wholesale) for the beef and the pork industry, respectively. For beef, the wholesale-to-farm price ratio has remained fairly stable until 2014, and since then, it has exhibited a strong upward trend; the retail-to-wholesale price ratio has shown a generally upward trend over 1980–2020. For pork, the dynamics of the wholesale-to-farm price ratio have been qualitatively similar to those for beef; the retail-to-wholesale price ratio has increased at a very fast pace over 1980 to 2000, and it has shown a tendency for stabilisation since then. Table A.1 and Table A.2 in the Appendix present descriptive statistics of log returns at the three levels

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[5] The data that support the findings of this work are available by the ERS-USDA at https://www.ers.usda.gov/data-products/meat-price-spreads/Hahn et al. (2009) and Pozo et al. (2021) have expressed concerns that meat prices at the retail level (supplied to the USDA by the BLS) may not reflect accurately what consumers actually pay and they have recommended the use of scanner quantity-weighted data, instead. Scanner price data were collected by the USDA only from 2001 (monthly) and from 2007 (weekly) to 2012. In any case, the monthly BLS data series have been utilised in the overwhelming majority of relevant empirical studies (e.g. Awokuse and Wang, 2009; Kim and Ward, 2013; Fousekis et al., 2016; Panagiotou, 2021).

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of beef and pork supply chains, respectively. All but one (return at the farm level in the beef industry) series exhibit excess kurtosis. Returns at the farm level in both industries are symmetric, while the return series at the wholesale level of the beef industry is negatively skewed. The remaining four series exhibit positive skewness. The null of normality is strongly rejected everywhere but for the log returns of beef at the farm level. Also, return volatility at the retail level tends to be much smaller relative to those at the farm and at the wholesale level (especially in the pork industry).

Price shocks originating from the farm (retail) level are transmitted to the retail (farm) level only indirectly, which means through the wholesale level. In contrast, price transmission for the pairs of markets farm–wholesale and wholesale–retail is a direct one. Given the presence of indirect links in a three-level supply chain, it makes absolute sense to focus on market pairs involving direct links only.[6] Also, following Nguyen et al. (2020), the P vector in (3) (and in the corresponding model for the upper tail $CoVaR$) is set equal to a vector of lagged values of the relevant dependent variable. The presence of loss exceedance (E_t) on the right hand side of (3) may raise questions about potential simultaneity bias. However, as noted by Hautsch et al. (2015) although a highly negative return on price j causes the VaR of the return of price i to rise, it does not necessarily imply a higher loss exceedance for i because the relationship between a specific quantile and the conditional distribution of exceedances, given a fixed threshold, is not known; consequently, the potential effect of simultaneity bias (if it exists at all) is expected to be much weaker than in the classical mean regression model, and thus, it can be safely ignored.[7]

The empirical models have been estimated in R with four lower and four upper quantile thresholds (0.05, 0.10, 0.25 and 0.45).[8] The number of lags for the returns variable has been determined using the Bayesian information criterion (BIC). The p-values for individual vulnerability (β) coefficients and for symmetry tests have been obtained, as in Patton (2013), using bootstrap with 2500 replications and a Wald-type test, the statistic of which, under the null hypothesis, follows the χ^2 with degrees of freedom equal to the number of restrictions. The test statistic is $\Omega = (\prod \hat{C})'(\prod \hat{V}_C \prod)^{-1}(\prod \hat{C})$, where Π is the restrictions' vector, C is the parameters' vector, and $\hat{V}_C$ is the bootstrap estimate of their variance–covariance matrix.

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[6] Exactly, the same choice has been made by Emmanouilides and Fousekis (2015) and Bumpass et al. (2019) in their empirical analyses of the US beef and the US gasoline supply chains, respectively.

[7] Nguyen et al. (2020) found that their empirical results were very robust to the choice of the exceedance variable (contemporaneous or lagged by one period).

[8] The 0.05 upper quantile threshold is the value above which lies 5 per cent of the distribution of r_{it} (or equivalently, the value below which lies 95 per cent of the distribution of r_{it}). Similar are the interpretations for the 0.10, 0.25 and 0.45 upper thresholds.

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3.2 Empirical results

Table 1 shows the tail price risk spillovers for the pair of beef markets farm and wholesale along with the results from the symmetry tests. The tail price risk connectedness coefficients (β) are everywhere positive and strongly statistically significant. This suggests that an increase in price risk, either at the lower or at the higher tails, at the farm (wholesale) level works towards higher price risk at the wholesale (farm) level. The null of symmetry with respect to the state of a market (downswing vs upswing) cannot be rejected at the 5 per cent level (or less); exactly, the same holds for the symmetry between tail price risk in- and risk out-degrees.

Table 2 shows the results for the pair of beef markets wholesale and retail. Again, the β coefficients are everywhere positive and strongly statistically significant and the symmetry with respect to market crashes and booms cannot be rejected at the conventional levels. The estimates of the tail risk net-degree are negative and in all but one case significant at the 1 per cent level or less. This result suggests that both at the lower and at the upper tails, the wholesale market is net price risk receiver, whereas the retail market is net price risk transmitter.

Table 3 presents the results for the pair of pork markets farm and wholesale. An important difference here (relative to the same pair of the beef industry) is that tail risk net-degree is, in most cases, negative and statistically significant, indicating that both at the upper and at the lower tails, the farm market is likely to be more vulnerable to price risk at the wholesale market than the other way round.

Table 4 shows the results for the pair of pork markets wholesale and retail. The β coefficients for spillovers from the wholesale to the retail market at the lower tails are not significant at the conventional levels, whereas the large majority at the upper tails are. This implies that lower tail price risk is not transmitted from the wholesale to the retail market (i.e. price decreases at the wholesale level are not reflected at the retail level), whereas upper tail price risk is. The tail risk net-degree is again negative and mostly significant providing evidence that both at the upper and at the lower tails, price shocks are transmitted with higher intensity backwards (i.e. to the wholesale market) than forwards (i.e. to the retail market).

An additional insight about tail price risk spillovers that can be obtained from comparing the findings in Tables 1–4 (especially the significance of the corresponding β coefficients) is that while the pair of markets farm and wholesale in the beef and the pork industries appear to have similar degrees of connectedness, this is not the case with the pair wholesale and retail. For this pair, the beef industry exhibits far stronger connectedness relative to the pork industry.

As noted in Introduction, there are several empirical works on vertical price transmission in the US beef and pork industries. Goodwin and Holt (1999), applying a TVECM to the beef supply chain, found that there is

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Table 1 BEEF: Tail risk spillovers, farm and wholesale levels (1980–2020)

Quantile	From farm to wholesale			From wholesale to farm			Tail risk net-degree	
	Lower (1)	Upper (2)	Vulnerability with respect to tail (3) = (1)-(2)	Lower (4)	Upper (5)	Vulnerability with respect to tail (6) = (4)-(5)	Lower (7) = (1)-(4)	Upper (8) = (2)-(5)
0.05	0.84 (0.12)	0.87 (0.58)	−0.03 (0.99)	0.55 (<0.01)	0.47 (<0.01)	0.08 (0.71)	0.29 (0.60)	0.40 (0.80)
0.10	0.76 (0.01)	0.87 (<0.01)	−0.11 (0.78)	0.71 (<0.01)	0.56 (<0.01)	0.15 (0.44)	0.05 (0.90)	0.31 (0.33)
0.25	0.82 (<0.01)	0.87 (<0.01)	−0.05 (0.54)	0.93 (<0.01)	0.79 (<0.01)	0.14 (0.27)	−0.11 (0.31)	0.08 (0.32)
0.45	1.10 (<0.01)	1.12 (<0.01)	−0.02 (0.84)	1.14 (<0.01)	0.94 (<0.01)	0.20 (0.12)	−0.04 (0.71)	0.16 (0.07)

Note: p-values in parentheses.

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Table 2 BEEF: Tail risk spillovers, wholesale and retail levels (1980–2020)

Quantile	From wholesale to retail			From retail to wholesale			Tail risk net-degree	
	Lower (1)	Upper (2)	Vulnerability with respect to tail (3) = (1)-(2)	Lower (4)	Upper (5)	Vulnerability with respect to tail (6) = (4)-(5)	Lower (7) = (1)-(4)	Upper (8) = (2)-(5)
0.05	0.46 (0.01)	0.28 (<0.01)	0.18 (0.35)	1.25 (0.01)	2.44 (<0.01)	−1.19 (0.14)	−0.79 (0.06)	−2.16 (<0.01)
0.10	0.29 (0.12)	0.27 (<0.01)	0.02 (0.91)	1.58 (<0.01)	2.54 (<0.01)	−0.96 (0.19)	−1.29 (0.01)	−2.28 (<0.01)
0.25	0.14 (<0.01)	0.24 (<0.01)	−0.10 (0.22)	1.57 (<0.01)	1.72 (<0.01)	−0.15 (0.76)	−1.42 (<0.01)	−1.48 (<0.01)
0.45	0.17 (<0.01)	0.21 (<0.01)	−0.04 (0.54)	1.52 (<0.01)	1.51 (<0.01)	0.01 (0.98)	−1.35 (<0.01)	−1.30 (<0.01)

Note: p-values in parentheses.

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Table 3 PORK: Tail risk spillovers, farm and wholesale levels (1980–2020)

Quantile	From farm to wholesale			From wholesale to farm			Tail risk net-degree	
	Lower (1)	Upper (2)	Vulnerability with respect to tail (3) = (1)-(2)	Lower (4)	Upper (5)	Vulnerability with respect to tail (6) = (4)-(5)	Lower (7) = (1)-(4)	Upper (8) = (2)-(5)
0.05	0.85 (<0.01)	1.51 (0.01)	−0.66 (0.26)	0.99 (0.20)	1.07 (0.16)	−0.08 (0.94)	−0.14 (0.87)	0.44 (0.69)
0.10	0.58 (<0.01)	0.49 (0.02)	0.08 (0.75)	1.13 (<0.01)	1.35 (<0.01)	−0.22 (0.58)	−0.56 (0.10)	−0.85 (0.02)
0.25	0.54 (<0.01)	0.58 (<0.01)	−0.04 (0.68)	1.52 (<0.01)	1.72 (<0.01)	−0.19 (0.27)	−0.98 (<0.01)	−1.14 (<0.01)
0.45	0.64 (<0.01)	0.66 (<0.01)	−0.02 (0.73)	1.92 (<0.01)	1.95 (<0.01)	−0.03 (0.89)	−1.28 (<0.01)	−1.29 (<0.01)

Note: p-values in parentheses.

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Table 4 PORK: Tail risk spillovers, wholesale and retail levels (1980–2020)

Quantile	From wholesale to retail			From retail to wholesale			Tail risk net-degree	
	Lower (1)	Upper (2)	Vulnerability with respect to tail (3) = (1)-(2)	Lower (4)	Upper (5)	Vulnerability with respect to tail (6) = (4)-(5)	Lower (7) = (1)-(4)	Upper (8) = (2)-(5)
0.05	0.09 (0.28)	0.43 (0.06)	−0.34 (0.16)	0.62 (0.42)	3.27 (0.44)	−2.65 (0.54)	−0.52 (0.48)	−2.84 (0.51)
0.10	0.01 (0.83)	0.14 (0.43)	−0.12 (0.50)	1.01 (0.04)	0.92 (0.38)	0.09 (0.94)	−1.00 (0.03)	−0.79 (0.46)
0.25	0.04 (0.21)	0.07 (<0.01)	−0.03 (0.45)	1.01 (0.01)	0.95 (<0.01)	0.06 (0.89)	−0.97 (0.01)	−0.88 (<0.01)
0.45	0.04 (0.35)	0.11 (<0.01)	−0.07 (0.09)	1.19 (<0.01)	1.13 (<0.01)	0.06 (0.87)	−1.15 (<0.01)	−1.02 (<0.01)

Note: p-values in parentheses.

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bidirectional price transmission for the pair of markets farm and wholesale but unidirectional from the wholesale to retail level (i.e. the price shocks at the retail level were largely confined into the retail market). The identified asymmetries, however, were modest in magnitude and probably not economically significant. Pozo et al. (2021), employing again a TVECM to the US beef sector, concluded that price transmission is symmetric. Emmanouilides and Fousekis (2015), using bivariate copula models, reported that price shocks for the pair farm and wholesale were well connected both at the lower and at the upper tails, while price shocks for the pair wholesale and retail were connected only at the lower tails. Fousekis et al. (2016), relying on a NARDL model, obtained evidence of asymmetric price transmission under which positive shocks were transmitted forward with greater intensity relative to negative ones. Hahn (1990), employing a Generalized Switching Model of the pork industry, reported that all prices along the chain showed greater sensitivity to positive than to negative price shocks. Goodwin and Harper (2000), using a TVECM, failed to detect asymmetric price transmission. Panagiotou (2021), relying on a NARDL model, found that transmission of positive stocks takes place at a higher speed and magnitude compared with negative ones.

To investigate whether the structural changes have had an impact on the intensity and the pattern of tail price risk connectedness, the same *CoVaR* models have been estimated for the sub-periods 1980–1999 and 2000–2020. The first sub-period involves considerably lower levels of concentration and vertical integration relative to the second one.[9]

Tables A.3 and A.4 in the Appendix present the empirical results for the pair of beef markets farm and wholesale, and for the sub-periods 1980–1999 and 2000–2020, respectively. The most notable differences between the two sets of estimates are that price risk spillovers at the very extreme quantiles (0.05 and 0.10) are not statistically significant in the second sub-period and that while in 1980–1999, there is certain evidence of asymmetry with respect to the market where price shocks are originated, this is not the case in 2000–2020. The decrease in the statistical significance of the β coefficients is, *ceteris paribus*, an indication of weaker market connectedness in the second sub-period. Tables A.5 and A.6 in the Appendix present the empirical results for the pair of beef markets wholesale and retail, and for the sub-periods 1980–1999 and 2000–2020, respectively. One observes that in the second sub-period, risk spillovers from retail to wholesale markets are all strongly statistically significant and that the limited evidence of asymmetry with respect to the source of price shocks in 1980–1999 has been considerably

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[9] In principle, the use of rolling windows could provide more detailed information. Initial attempts to employ rolling windows of typical lengths for monthly data (e.g. four to 6 years) have not been very successful. In particular, statistical inference at the very low and the very high tails failed very often due to the small number of observations at these parts of the joint distributions. Increasing the window length (e.g. eight to ten years) mitigated the problem at the expense, however, of detail.

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strengthened in 2000–2020 (at both the lower and the upper tails, price risk spillovers from the retail market to the wholesale market exceed those in the opposite direction). The increase in the statistical significance of the β coefficients points to a higher market connectedness in the second sub-period. Moreover, the strengthening of the tail risk asymmetry is an indication that in the most recent years, it has become easier for retailers to shift price risk backwards in the beef supply chain.

Tables A.7 and A.8 in the Appendix present the empirical results for the pair of pork markets farm and wholesale, and for the sub-periods 1980–1999 and 2000–2020, respectively. The findings for the two sub-periods are qualitatively the same. Tables A.9 and A.10 in the Appendix present the empirical results for the pair of pork markets wholesale and retail, and for the sub-periods 1980–1999 and 2000–2020, respectively. Whereas in the first sub-period almost all β coefficients are strongly statistically significant, less than a handful of them are statistically significant in the second sub-period. This is a clear indication that the degree of connectedness between the two markets has decreased substantially over 2000–2020. Emmanouilides and Fousekis (2014) arrived at very similar conclusions about the changes in the degree of connectedness along the US pork supply chain, using bivariate copula models.

4. Conclusions and suggestions for future research

The strength and the pattern of price transmission along food supply chains may contain important information about pricing strategies, market efficiency and welfare distribution. The objective of this study has been to investigate tail price risk connectedness in the US beef and pork industries. This has been pursued by estimating *CoVaR* functions for 1980–2020 and for two sub-periods (1980–1999 and 2000–2020).

The total-sample measures of conditional price risk vulnerability suggest that:

- The pair of markets farm and wholesale in the beef industry are strongly interconnected to each other. The intensity of price risk spillovers does not depend on the sign of shocks or on the market of origin. The pair of markets wholesale and retail are also strongly interconnected, but the wholesale market appears to be more vulnerable to price risk in the retail market for both positive and negative shocks. Several researchers (e.g. Chang & Griffith, 1998; Griffith et al., 1991) noted that marketers may practise price levelling (wholesalers and retailers tend to hold their prices relatively stable when faced with increasing or decreasing input procurement costs), something that may, in turn, lead to destabilisation of farm prices. The findings here offer no evidence of price levelling in the US beef sector. At the same time, the higher vulnerability of the wholesale market to price risk at the retail level may be interpreted as either that retailers

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have the power to shift price risk backwards or that wholesalers are in a better position to sustain risk relative to retailers. The former interpretation is in line with evidence from food marketing chains, indicating that retailers have been gaining marketing power at the expense of wholesalers (e.g. Crespi et al., 2012).

- The pair of markets farm and wholesale in the pork industry also shows a high degree of connectedness. This is not the case, however, with the wholesale and retail levels where lower tail price risk is not transmitted from the former to the latter (an indication of inefficiency). At the same time, there is considerable evidence that the farm and the wholesale markets are more vulnerable to price risk in the wholesale and the retail market, respectively. Farmers are very unlikely to be in a relatively better position to sustain price risk than slaughterers and processors. Therefore, the asymmetry of tail price risk transmission for the pair farm and wholesale probably reflects the presence of market power.

The sub-sample(-period) analysis of conditional price risk vulnerability suggests that:

- For beef, the strength of connectedness between the farm and the wholesale levels has somehow decreased in the second sub-period. The asymmetry of risk from retail to wholesale has increased in the second sub-period.
- For the pair of markets farm and wholesale in the pork industry, the results in the two sub-periods are qualitatively very similar. Tail price risk spillovers for the pair retail–wholesale, however, have almost disappeared in the second period.

It appears that there are two aspects of our empirical findings that may cause concerns about the efficiency of the US meat markets. The first is the decrease in risk connectedness over the second sub-period. Both Goodwin and Holt (1999) and Goodwin and Harper (2000) suggested that the structural changes were likely to lead to a better functioning of the US meat markets. The second is the shift of price risk from the wholesale to the farm level. The alternative marketing arrangements (AMAs) are supposed to be, among other things, instruments of risk-sharing. The economic theory of contracts (e.g. Varian, 1992) predicts that, in an efficient risk-sharing, economic agents capable of sustaining risk more easily assume a greater part of it. It is hard to imagine that meat processors and wholesalers (multinational corporations with diversified activities) are in a more difficult position to deal with price risk relative to individual farmers.

There are two potential avenues for future research. The first may involve the investigation of tail price risk spillovers in other vertical food chains. The second may focus on spatially related farm commodities in an attempt to identify central markets (i.e. markets that tend to be price risk transmitters) and markets that are mainly price risk receivers.

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Conflict of interest

The authors have no conflict of interest to declare.

Data availability statement

The data that support the findings of this study are available by the ERS-USDA at https://www.ers.usda.gov/data-products/meat-price-spreads/.

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Appendix S1 Table A1. BEEF: Summary statistics and tests on the distributions of logarithmic price returns.

Appendix S1 Table A2. PORK: Summary statistics and tests on the distributions of logarithmic price returns.

Appendix S1 Table A3. BEEF: Tail risk spillovers. Farm and wholesale levels (1980–1999).

Appendix S1 Table A4. BEEF: Tail risk spillovers. Farm and wholesale levels (2000–2020).

Appendix S1 Table A5. BEEF: Tail risk spillovers. Wholesale and retail levels (1980–1999)

Appendix S1 Table A6. BEEF: Tail risk spillovers. Wholesale and retail levels (2000–2020).

Appendix S1 Table A7. PORK: Tail risk spillovers. Farm and wholesale levels (1980–1999).

Appendix S1 Table A8. PORK: Tail risk spillovers. Farm and wholesale levels (2000–2020).

Appendix S1 Table A9. PORK: Tail risk spillovers. Wholesale and retail levels (1980–1999).

Appendix S1 Table A10. PORK: Tail risk spillovers. Wholesale and retail levels (2000–2020).

Appendix S1 Figure A1. BEEF: Logarithmic price ratios.

Appendix S1 Figure A2. PORK: Logarithmic price ratios.

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