Market connectedness in the US beef supply chain

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Abstract

This work investigates market connectedness in the US beef industry using alternative measures of spillovers and information about prices at the farm, the wholesale, and the retail level over 1990 to 2019. The empirical results suggest that connectedness in the system of markets farm and wholesale is stronger relative to that of wholesale and retail. They also imply that, although there are statistically significant price spillovers both upstream and downstream, the spillovers from farm to wholesale level and from wholesale to the retail level tend to exceed those in the opposite directions.

Keywords: *Market connectedness, price spillovers, US beef industry*
JEL classification: Q11, C5.

Introduction

Vertical price linkages along food supply chains has been the subject of a large number of theoretical (e.g. Gardner, 1975; Azzam, 1999; Fousekis, 2008; Xia, 2009) and empirical (Heien, 1980; Kinnucan and Forker, 1987; Chang and Griffith, 1998; Goodwin and Holt, 1999; Sexton and Zhang, 2000; Goodwin and Harper, 2000; Lass, 2005; Gervais, 2011; Emmanouilides and Fousekis, 2015, Fousekis *et al.*, 2016; Madau *et al.*, 2016; Dong *et al.*, 2018) works in agricultural economics. The interest of professional economists, consumers, and policy makers appears to be well justified. The intensity and the pattern of price relations at the different levels of a food supply chain reflect the underlying structure, conduct, and performance of the relevant industry and, as such, they may contain important information with regard to the efficiency and the equity in the food marketing system (e.g. Vavra and Goodwin, 2005; European Commission, 2009; Saitone and Sexton, 2017).

An industry that has attracted a lot of attention over the last 30 years is the beef supply chain in the US. This for three main reasons. First, it is quite complex and heterogeneous exhibiting a diversity of products, enterprises, and markets. Second, it constitutes the single largest segment of the US agriculture (with net cash receipts of 67 billion dollars in 2017 or about 12 percent of the total); Third, it has often times come under the scrutiny of antitrust authorities because of buyers' market strategies and of very high levels of concentration in beef slaughtering, packing, and retailing (e.g. Ward, 2010; Saitone and Sexton, 2017)[2].

The empirical analysis of price interrelationships in the US beef industry has been conducted with a variety of statistical and econometric tools including tests of causality, linear, non-linear, and threshold cointegration as well as copulas (e.g. Heien, 1980;

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[2] Among the market strategies that may inhibit price spillovers are price leveling and captive supplies (e.g. Chang and Griffith, 1998; Emmanouilides and Fousekis, 2015). The CR4 values in 2012 for animal slaughtering (expect poultry), meat processed from carcass, and retailing in the US were 60.7, 32.8, and 38, respectively (Saitone and Sexton, 2017).

Chang and Griffith, 1998; Lass, 2005; Emmanouilides and Fousekis, 2015; Fousekis *et al.*, 2016). The findings vary depending on the methodology employed and on the time period considered. Nevertheless, most studies appear to agree that prices along the US beef supply chain are more likely to be transmitted from upstream (farm level/cattle feedlots) to downstream (beef packing and retailing) than in the opposite direction. Also, studies often report some evidence of asymmetric price transmission where positive shocks upstream tend to be transmitted downstream with higher intensity or speed relative to negative ones.

The presents work revisits the issue of price linkages in the US beef industry using the notion of *market connectedness* and time series (monthly) data over 1990 to present. The term market connectedness refers to the extent to which price shocks in one or more markets *spillover* to other markets. Diebold and Yilmaz (2012), employing forecast error variance decomposition (FEVD) from a generalized vector autoregression (VAR) model, proposed a number of alternative measures of market connectedness (or, equivalently, of price spillovers) that are capable of providing a very detailed description of how price shocks are transmitted between and among the elements of a system of potentially interrelated markets.

The spillover measures by Diebold and Yilmaz (2012) have been fruitfully applied in financial economics to evaluate connectedness of horizontally related stock and commodity markets (e.g. Barunik *et al*., 2016; Belke and Dubova, 2018; Barunik and Krehlik, 2018; Shu and Chang, 2019; Xu *et al*., 2019; Barunik and Kocenda, 2019; Pham, 2019; Shahzad *et al*., 2019; Aromi and Clements, 2019). It appears, however, that they have not found yet their way in the study of either horizontally (spatially) or vertically related food markets. 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.

Methodology

Let a covariance stationary N-variable VAR(p) process

$$(1) \qquad y_t = \sum_{k=1}^{p} \Phi_k y_{t-k} + \varepsilon_t,$$

where $e_t \sim (0, \Sigma)$ is a vector of *i.i.d* disturbances. The moving average representation of y_t is $y_t = \sum_{k=0}^{\infty} B_k \varepsilon_{t-k}$, where B_k are NxN coefficient matrices obtained as $B_k = \sum_{k=0}^{p} \Phi_k B_{k-p}$ (with B_0 being an identity). The forecast error variance decomposition (FEVD) allows one to assess the fraction (share) of the H-step ahead error variance in forecasting variable y_i that can be attributed to shocks in variable y_j $(i, j = 1, 2, ..., N)$. Koop *et al.* (1996) and Pesaran and Shin (1998) proposed a generalized VAR approach attaining a FEVD that is independent of the ordering of variables. With that approach the variance shares are calculated as

$$(2) \qquad \theta_{ij}(H) = \frac{\sigma_{jj} \sum_{h=0}^{H-1} (e_i' B_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h \Sigma B_h' e_i)},$$

where σ_{jj} is the standard deviation of the error term for the *j*th equation; when $i = j\ (i \neq j)$ (1) gives the own- (cross-) variance share.

Under the generalized VAR, the sum of elements in each row of the variance decomposition matrix, $\left[\theta_{ij}(H)\right]$, is not equal to 1. To address this problem Diebold and Yilmaz (2012) normalized each entry of $\left[\theta_{ij}(H)\right]$ by the row sum as

$$(3) \qquad \tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\theta_{ij}(H)}.$$

Moreover, using (2), Diebold and Yilmaz (2012) developed a number of spillover measure (indices) capable for describing different aspects of the connectedness among and between the individual elements of the *N*-variable y_t process. By aggregating the measures of pairwise connectedness shown in (3), Diebold and Yilmaz (2012) arrived at the (*total connectedness*) *total spillover* index

$$(4) \qquad S(H) = 100\ \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}}{N}$$

capturing the contribution of spillovers from stochastic shocks across all members of y_t to the total variance. The *directional spillovers* provide further insights into the underlying transmission mechanism by identifying how individual elements affect the overall system as well as how the system affects the individual elements. In particular, the directional spillover index of shocks received by y_i from all other variables in the system is obtained as

$$(5) \qquad S_{i.}(H) = 100\ \frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}}{N}$$

whereas that of shocks transmitted by y_i to all other variables in y_t is obtained as

$$(6) \qquad S_{.i}(H) = 100\ \frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ji}}{N}.$$

The *net spillover index* for y_i is the difference between the two respective directional spillover indices,

$$(7) \qquad S_i = S_{.i}(H) - S_{i.}(H)$$

and it measures the net spillover contribution of y_i to the remaining *N*-1 variables. Finally, the *net pairwise spillover index* is obtained as

$$(8) \qquad S_{ij}(H) = 100\ \frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{N}$$

and it captures the net spillover of variable y_i to variable y_j. Observe that when the process y_t consists of only two variables the net spillover from variable 1 to 2 equals the negative of the net spillover from variable 2 to 1.

The data, the empirical models, and the empirical results

The data are monthly prices (in cents per pound, retail weight equivalent) at the farm (feedlots), the wholesale (processing and packaging), and at the retail level. They are obtained from the ERS-USDA[3] and they refer to the period January 1990 to August 2019. Figure 1 presents the evolution of the natural logarithms of the three prices over the period under study. All series appear to exhibit, generally, upwards trends. The relationships between prices at the different levels of the beef supply chain, however, tend to vary over time. For example, the ratio of the wholesale to farm price is about 1.25 in 2000, 1.1 in 2015, and 1.35 in 2018. Similarly, the ratio of the retail to wholesale price is about 1.8 in 1995, 1.5 in 2004, and 2.1 in 2017. Both ratios, however, generally exhibit upwards trends over the entire sample (especially that of retail to wholesale).

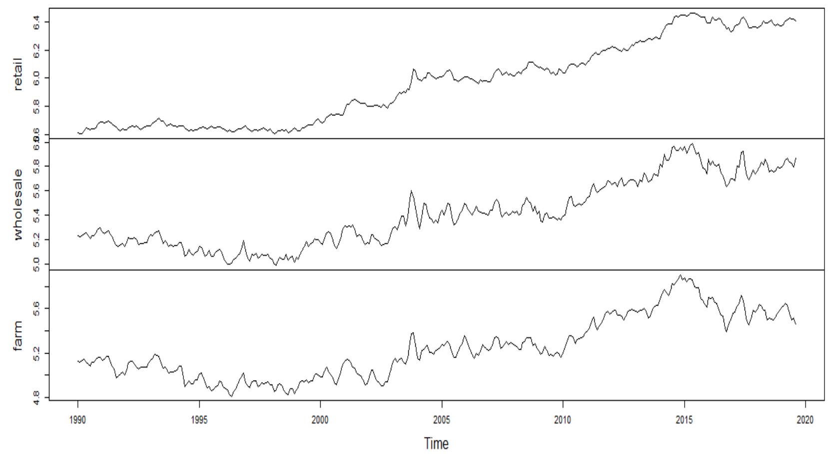


Figure 1. The natural logarithms of prices at the different levels of the US supply chain

Table 1 shows the results of the DF-GLS tests on the weak stationarity for the logarithmic prices and the logarithmic price returns (computed as $r_{it} = \ln(p_{it} / p_{it-1})$, where p_{it} denotes the price at level i of the beef supply chain in time period t). The logarithmic levels are non-stationary but the logarithmic returns are. The logarithmic prices, therefore, are I(1) time series. Table 2 shows summary statistics and the results of statistical tests on the distribution for each logarithmic price returns series. The standard deviation (i.e. the price volatility) for the farm and the wholesale market is 2.5 times that for the retail market suggesting that the retail market is far less risky relative to the other two. At the farm level, price returns exhibit negative skewness but they are mesokurtic and normal at the conventional levels of significance. At the wholesale level, price returns are symmetric, leptokurtic and they depart from normality. At the

[3] https://www.ers.usda.gov/data-products/meat-price-spreads/

retail level, price returns exhibit positive skewness, they are leptokurtic, and non-normal.

Table 1. The results of weak stationarity (DF-GLS) tests

	Farm	Wholesale	Retail
		On logarithmic price levels	
Test with			
Constant	-0.53	0.49	1.60
Trend	-1.43	-1.35	-1.58
		On logarithmic price returns	
Constant	-5.34***	-5.38***	-1.92*
Trend	-4.78***	-4.95***	-3.60***

Note: The critical values for the test with a constant are -2.57, -1.94, and -1.62 at the 1%, the 5%, and the 10% level, respectively; The critical values for the test with a rend are -3.48, -2.89, and -2.57 at the 1%, the 5%, and the 10% level, respectively; *** and * denote statistical significance at the 1 and the 10 percent level, respectively.

Table 2. Summary statistics and tests on the distributions of logarithmic prices

Statistic	Farm	Wholesale	Retail
Mean	0.001	0.002	0.002
Median	0.004	0.003	0.001
Standard Deviation	0.039	0.040	0.016
Minimum	-0.131	-0.140	-0.058
Maximum	0.122	0.126	0.093
1st Quartile	-0.022	-0.024	-0.008
3rd Quartile	0.026	0.025	0.011
Skewness	-0.288	0.112	0.656
	(0.026)	(0.377)	(<0.01)
Kurtosis	0.369	0.849	3.643
	(0.137)	(<0.01)	(<0.01)
Normality	0.993	0.990	0.962
	(0.104)	(0.012)	(<0.01)

Note: The *p*-values for skewness, kurtosis, and normality have are obtained using the tests by d'Agostino (1970), Anscombe and Glynn (1983), and Shapiro and Wilks (1965), respectively.

Price shocks emanating from the farm (retail) level may be transmitted to retail (farm) level only indirectly, that is, through the wholesale level. Price shocks from the wholesale level may be transmitted to the retail and to the farm level directly. Given that the price link between the farm and the retail level is only an indirect one, it makes perfect sense to analyze price spillovers along the beef supply chain by considering two separate systems of markets (i.e. the system involving the farm and the wholesale levels and the system involving the wholesale and the retail levels)[4]. Table 3 presents the results of Johansen's cointegration test by market system. Farm and wholesale prices are cointegrated at the 10(5) percent level on the basis of the Trace (Eigenvalue) test;

[4] Exactly the same approach was adopted by Emmanouilides and Fousekis (2015), Fousekis *et al*. (2016), and Bumpass *et al*. (2019) in their analyses of the US beef and the US gasoline supply chains, respectively.

wholesale and retail prices at cointegrated (at the 1 percent level) regardless of the test type employed.

Table 3. Results of Johansen's cointegration tests on logarithmic prices

	Farm and Wholesale		**Wholesale and Retail**	
Type of test	Number of cointegrating vectors	Test statistic	Number of cointegrating vectors	Test statistic
Trace	0	18.62*	0	33.45***
	1	2.21	1	6.71
Eigenvalue	0	16.40**	0	26.73***
	1	2.21	1	6.71

Note: ***, **, and * denote statistical significance at the 1, the 5, and the 10 percent level, respectively. The optimal lag lengths in cointegration analysis are 2 and 4 for the farm-wholesale and wholesale-retail pair, respectively; they are determined using the Schwartz Criterion (SIC)

Taken together, the findings from the stationarity and the cointegration tests imply that the two VAR(p) models for the analysis of price spillovers in the US beef supply chain should be specified as VECM (p) ones; that is, the y variables appearing in (1) should be the logarithmic price returns and each individual equation should include, in addition, an ECM term to capture disequilibrium effects (e.g. Lutkepohl and Reimers, 1992; Krehlik, 2018).

The final step with regard to model specification concerns the selection of the forecast horizon (H). Often times researchers compute the FEVD at different values of H to assess the sensitivity of the results to forecast horizon (e.g. Fousekis and Klonaris, 2002; McKenzie *et al*., 2009; Barunik and Kocenda, 2019). Higher values of H imply that market participants have more time to make adjustments to shocks and, typically, they are associated with higher degrees of market connectedness. To select the most appropriate values for H, this study utilizes information about the time of cattle slaughtering. The large majority of cattle are slaughtered at age between 18 and 36 months and very small percentages at ages less than 12 and over 40 months[5]. It appears, therefore, that values of H equal to 6, 18, and, 36 provide reasonable approximations for the potential of adjustments in the short-, the intermediate- and the long-run, respectively.

All estimations are carried out in *R* software using the package *frequencyConnecteness* (Kreklik, 2018)[6]. Table 4 shows the (normalized) price spillovers for the pair of markets farm and wholesale across the entire sample and for the three forecast horizons. For H=6, 42.07 percent of the total forecast variance in the system of these two markets comes from price spillovers; the remaining 57.93 percent is due to the effect of own-price shocks (that means, shocks that stem from and contained within individual markets). As expected, the total spillover index rises, although slowly, with the forecast horizon. The price spillovers from the farm to the wholesale market for the different values of H are between 24.4 and 24.75 implying that the shocks in

[5] See for example *fao.org3/T02796/T02796.htm*, *agriland.ie/farming-news/are-irish-cattle-being-killed at-younger-ages/* , and *ausiessabattoirs.com.facts.age-slaughtred*.
[6] *https://github.com/tomaskrehlik/frequencyConnectedness*

upstream (farm) prices explain about 49 percent of the forecast variance in the downstream (wholesale) prices[7]. The price spillovers from the wholesale to the farm market are between 17.3 and 23 implying that the shocks in downstream (wholesale) prices explain about 42 percent of the forecast variance in the upstream (farm) prices. Also, for all values of *H* considered, the price spillover from the farm to the wholesale market exceeds that from the wholesale to the farm one. The difference between the two directional measures, however, is statistically significant only for *H*=6. On the basis of the entire sample (static analysis), therefore, one may conclude that in the short-run there is strong evidence that the wholesale (farm) market is a net recipient (contributor) of price shocks; in longer runs, however, the impacts of price shocks from the farm and the wholesale level on the total variance are similar to each other. Table 5 shows the spillovers for the pair of markets wholesale and retail across the entire sample and for the three forecast horizons. For *H*=6, 33.95 percent of the total variance in the system of the two markets comes from price spillovers; the remaining 66.05 percent reflects the influence of own-price shocks. For *H*=36, the total spillover index has a value of 41.36 percent. The price spillovers from the upstream (wholesale) market appear to explain about 60 percent of the forecast variance in the downstream (retail) prices whereas those from the retail explain only about 20 percent of the forecast variable in the wholesale prices. For all *H* considered, the difference between the two directional measures (from wholesale minus from retail) is everywhere positive and statistically significant. More importantly, it tends to rise with the value of *H*. The static analysis of spillovers for the system involving the wholesale and the retail markets, therefore, provides strong evidence that the wholesale (retail) level is a net contributor (recipient) of price shocks. The comparison of the values of the total spillover measures indicates that, for all *H*, the pair of markets farm and wholesale exhibits a higher degree of connectedness relative to that of wholesale and retail.

Table 4. Price spillovers in the farm-wholesale system of markets (static analysis)

	Forecast horizon		
	6	18	36
Total spillover	42.07	45.44	47.40
	(<0.01)	(<0.01)	(<0.01)
Directional Spillovers			
From farm to wholesale			
(1)	24.74	24.70	24.42
	(<0.01)	(<0.01)	(<0.01)
From wholesale to farm	17.33	20.74	22.98
(2)	(<0.01)	(<0.01)	(<0.01)
Net spillover =(1)-(2)	7.41	3.95	1.44
	(<0.01)	(0.31)	(0.78)

Note: *p*-values in parentheses. They are obtained as in Patton (2013) using bootstrap with 1000 replications and a Wald-type test which, under the null hypothesis, follows the χ^2 distribution with 1 degree of freedom. The relevant test statistic is $\Phi = (R\hat{\Lambda})'(R\hat{V}_{\Lambda}R')^{-1}(R\hat{\Lambda})$ where R is the restrictions matrix, $\hat{\Lambda}$ is the vector of estimates, and $\hat{V}_{\Lambda}$ is their bootstrap variance-covariance matrix.

[7] For a system of just two markets the percentage of the forecast variable in market (say) 2 explained by price shocks in market (say) 1 is two times the directional spillover from market 1 to market 2.

Table 5. Price spillovers in the wholesale-retail system of markets (static analysis)

	Forecast horizon		
	6	18	36
Total spillover	33.95	37.88	41.36
	(<0.01)	(<0.01)	(<0.01)
Directional Spillovers			
From wholesale to retail (1)	26.08	28.99	31.04
	(<0.01)	(<0.01)	(<0.01)
From retail to wholesale (2)	7.87	8.88	10.33
	(<0.01)	(<0.01)	(<0.01)
Net spillover =(1)-(2)	18.21	20.12	20.71
	(<0.01)	(<0.01)	(<0.01)

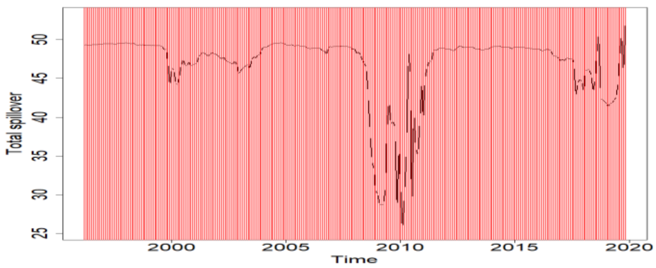
Note: *p*-values in parentheses. They are obtained as in Patton (2013) using bootstrap with 1000 replications and a Wald-type test which, under the null hypothesis, follows the χ^2 distribution with 1 degree of freedom. The relevant test statistic is $\Phi = (R\hat{\Lambda})'(R\hat{V}_{\Lambda}R')^{-1}(R\hat{\Lambda})$ where R is the restrictions matrix, $\hat{\Lambda}$ is the vector of estimates, and $\hat{V}_{\Lambda}$ is their bootstrap variance-covariance matrix.

Further insights about the extent and the pattern of price spillovers in the US beef industry can be obtained through a dynamic analysis. To this end, the present work employs a 72-month rolling window[8]. Figure 2 (panels (a), (b), (c), and (d)) presents the dynamic measures of spillovers for H=18 and for the pair of markets farm and wholesale; to avoid a clutter with diagrams the relevant figures for H=6 and H=36 are delegated to the Appendix. The shadowed areas correspond to periods where a spillover measure is, on the basis of the Wald-type test (Patton, 2013), statistically significant at the 5 percent level (or less). The total spillover index (panel (a)) is statistically significant in all windows. It receives values in the neighborhood of 50 until the mid-2000s and over the last seven years; it exhibits a sharp decline of more than 20 percentage points in sub-periods ending around 2010 followed by a fast recovery. The directional derivative from farm to wholesale (panel (b)) exhibits generally an upwards trend and, at the same time, it shows considerable volatility. The directional derivative from wholesale to farm (panel (c)) exhibits a generally downwards trend and it is quite volatile as well. Both directional derivatives are statistically significant in all windows. The net spillover (from farm minus from wholesale) is statistically significant in 169 out of 285 windows (or in 59.3 percent of the total). In the early 2000s it receives negative and, over a few periods of time, statistically significant values suggesting the farm market is a recipient of prices shocks; since 2005 it is, in the overwhelming majority of windows, positive and mainly statistically significant. The dynamic analysis for the system comprising the farm and the wholesale markets suggest that the lack of statistical significance of the net price spillover for H=18 in Table 4 should be largely attributed to aggregation across time.

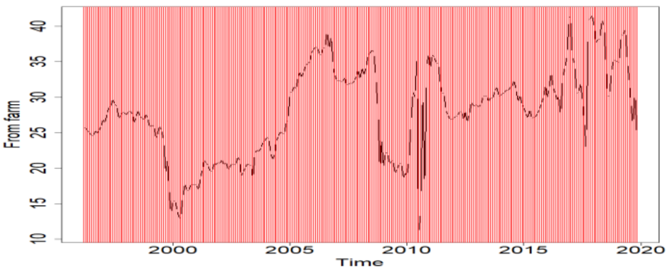
[8] The total number of windows in the sample is 285 (=357-72). The window length is selected in such a way as provide details about the spillover dynamics and, at the same time, to ensure that the empirical models are estimated from an adequate number of observations. The rolling widow length runs from point t-72 to point t. Note that very similar lengths have been selected in earlier empirical studies that used monthly data (e.g. Fousekis *et al*., 2016). Nevertheless, sensitivity analysis is performed with lengths of 84 and 60 without notable changes in the results.

Figure 3 (panels (a), (b), (c), and (d)) presents the dynamic measures of spillovers for H=18 and for the pair of markets wholesale and retail; again, the relevant figures for H=6 and H=36 are delegated to the Appendix. The dynamics of the total spillover index (panel (a)) are, to a large extent, similar to those for the system involving the farm and wholesale markets. The directional derivative from wholesale to retail (panel (b)) varies widely around 30 and it is statistically significant at the 5 percent level (or less) everywhere. The directional derivative from the retail to wholesale (panel (c)) exhibits big fluctuations around 10 and it is statistically significant in 237 out of 285 windows (or in 83.2 percent of the total). The net spillover index receives a few negative and statistically significant values early in the sample and in sub-periods ending around 2010; in the remaining windows it is positive, and predominantly statistically significant.

(a)



(b)



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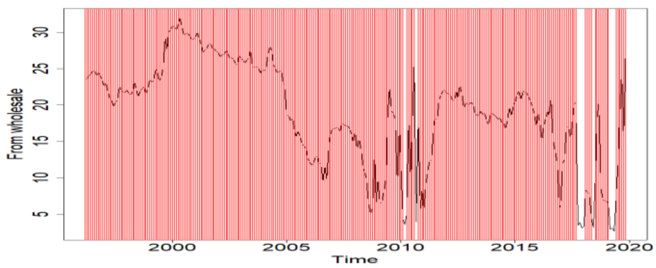

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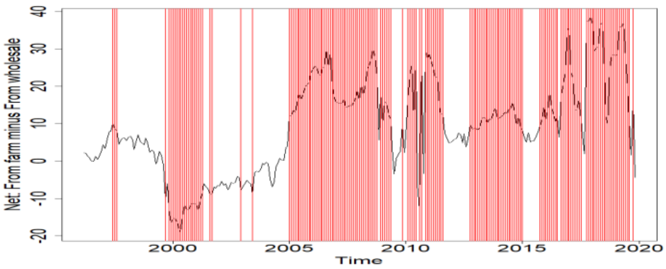

Figure 2. Price spillovers in the farm-wholesale system of markets (dynamic analysis for H=18)

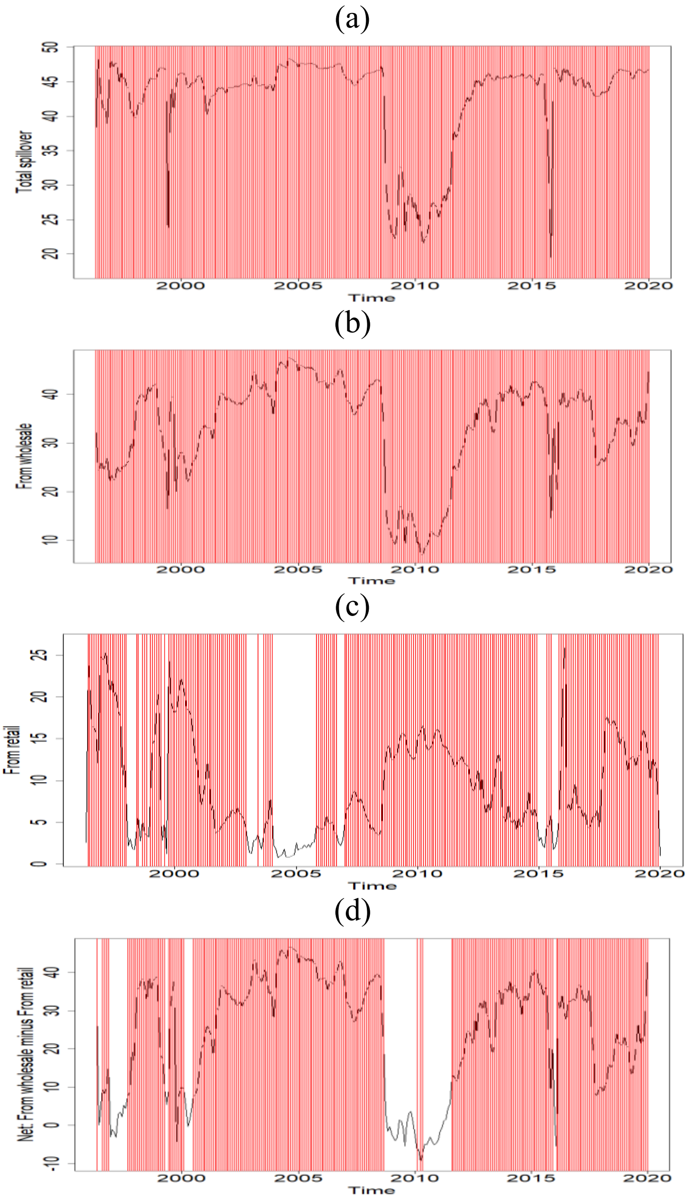

Figure 3. Price spillovers in the wholesale-retail system of markets (dynamic analysis for H=18)

Conclusions

The objective of the present study is to investigate market connectedness in the US beef industry. To this end, it employs spillover measures and monthly data on prices at the farm, the wholesale, and the retail level over 1990 to 2019. The empirical analysis is both static (i.e. across the entire sample) as well as dynamic (i.e. for a large number of rolling time windows (sub-periods)).

The empirical results suggest:

(a) Both systems of markets (the farm-wholesale and the wholesale-retail) are well connected; even in short forecast horizons, price spillovers from one marker to another explain more than one third of the respective forecast error variances.

(b) The measure of total connectedness is consistently higher for the system comprising the farm and the wholesale levels. This finding in line with what was reported in the recent study by Emmanoulides and Fousekis (2015) on price co-movement in the same supply chain over 1990 to 2013.

(c) There are price spillovers both upstream as well as downstream. Chang and Griffith (1998), using a three-price cointegration model of the Australian beef industry, found that the wholesale price was weakly exogenous in the short-run (i.e. it transmitted price shocks to the other two levels but it did not receive price shocks from them). Goodwin and Holt (1999), using two-price cointegration models of the US beef supply chain, found that the price transmission was largely unidirectional with information flowing up the marketing channel from upstream to downstream but not in the opposite direction. Turi (2011), using again two-price cointegration models and data from the US beef industry, reported that in the farm-wholesale market system and in the short run the live cattle price responded to shocks stemming from downstream while the packers' price was weakly exogenous. They also found that in the wholesale-retail market system both prices adjusted to deviations from the long-run equilibrium. Given that weak price exogeneity in the short-run is an indication of inefficiency (e.g. Chang and Griffith, 1998) this study appears to offer more evidence in favor of efficiency relative to the earlier ones.

(d) The farm level and the wholesale level are, in the overwhelming majority of the sub-periods considered, net contributors of spillovers to the wholesale and to the retail level, respectively. This, in turn, appears to be inconsistent with notion that downstream agents practice price leveling by holding their selling prices relatively stable when faced with rising or declining procurement costs.

There are a number of avenues for future research. One may involve the investigation of vertical spillovers in other food supply chains. Another may focus on connectedness among spatially related agricultural and food product markets. Finally, because positive and negative price shocks may be transmitted with different intensity and pattern, it may be useful to identify and quantify potential asymmetries in spillovers among markets. In any case further research on this elaborate topic is certainly warranted.

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APPENDIX

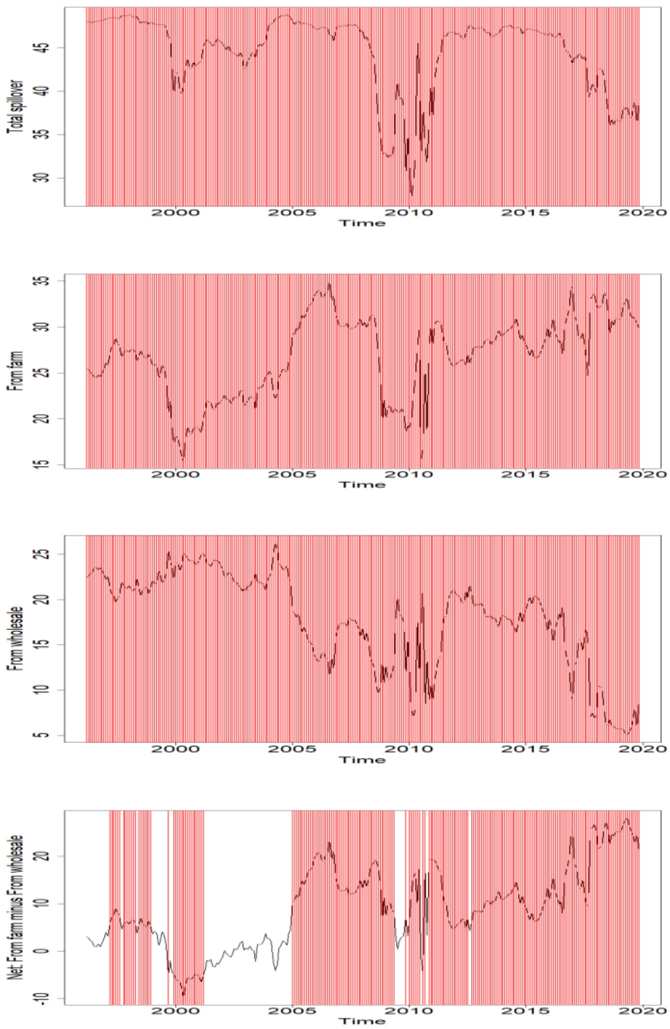

Figure A.1. Price spillovers in the farm-wholesale system of markets (dynamic analysis for H=6)

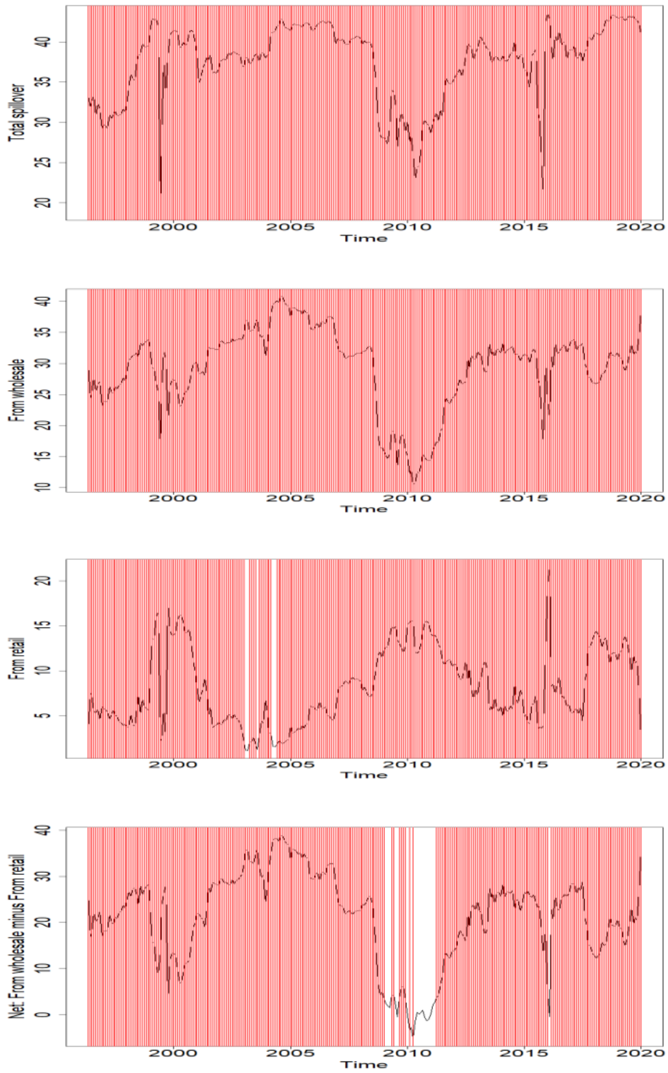

Figure A.2. Price spillovers in the wholesale-retail system of markets (dynamic analysis for *H*=6)

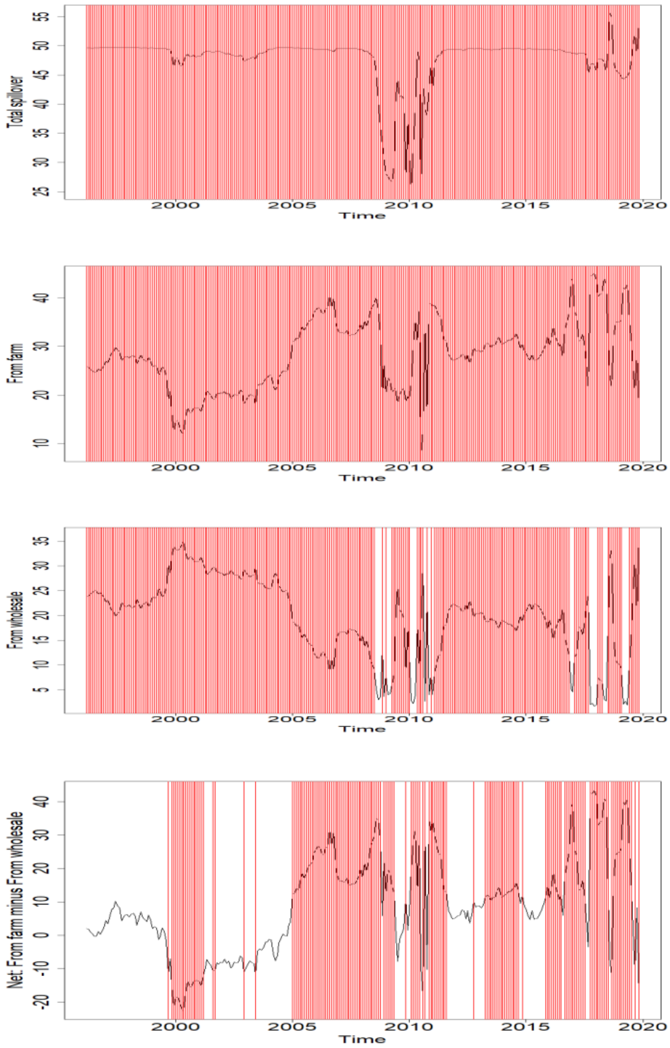

Figure A.3. Price spillovers in the farm-wholesale system of markets (dynamic analysis for *H*=36)

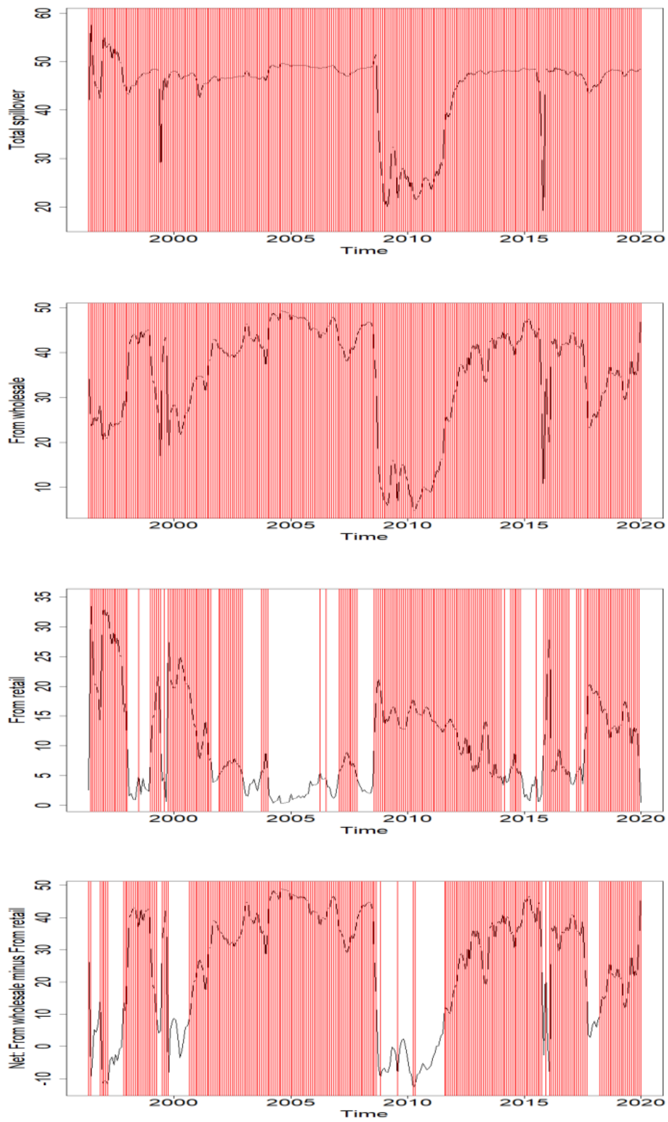

Figure A.4. Price spillovers in the wholesale-retail system of markets (dynamic analysis for *H*=36)