Dynamic connectedness of dairy futures prices in the US

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Abstract

This work investigates the strength and the mode of linkages among dairy futures prices in the US using the TVP-VAR connectedness approach and daily observations on class III milk, cheese, butter, and dry whey during 2014 to 2023. The overall connectedness is not high but it tends to increase under the influence Of important market events. The pair of markets (Class III milk, cheese) are tightly linked to each other but they exhibit weak connectivity to those of butter and dry whey. Class III milk and cheese are the price risk connectors in the four-market network. Class III milk is, in addition, the main net price risk transmitter. "Selfhedging" of dairy manufacturers' profits is only viable for Class III milk and cheese.

Keywords: *Connectedness*; *Price risk*; *US dairy futures*; *Asymmetry*

JEL Classification: Q11, G13, C5

1. Introduction

The US is the second cow milk producer in the world and a major exporter of dairy commodities (United States Department of Agriculture (USDA), 2023). According to the International Dairy Foods Association, in 2021, the US dairy sector supported more than 3 million jobs and contributed 3.5 per cent of the US GDP[1]. The main export markets for the US dairy industry are Mexico, Southeast Asia, Canada, China, and the Middle East and North African (MENA) countries[2]. Dairy commodities prices in the US have been quite volatile making, thus, price-risk management difficult (MacDonald et al., 2020). It is not surprising, therefore, that price interrelationships in the US dairy sector are of keen interest to dairy farmers, raw milk processors, participants in dairy futures markets, policy-makers, and research economists.

A number of earlier empirical works have focused on vertical price linkages using bivariate models. Kinnucan and Forker (1987), employing Houck's (1977) approach, investigated the relationships between milk prices at the farm level and those of fluid milk, butter, cheese, and ice cream at the retail level. They found that retail prices adjusted more rapidly and fully to increases in farm prices than to decreases. Chavas and Mehta (2004), relying on a modified VAR model, analyzed the association between butter prices at the wholesale and retail levels. They reported that co-movement tended to be stronger (weaker) under wholesale (retail) price increases. Capps and Sherwell (2007), using a modified Error Correction Model, examined milk price transmission between the farm and the retail level.

[1] https://www.idfa.org/news/u-s-dairy-industrys-economic-impact-totals-753-billion

[2] https://www.usdec.org/research-and-data/market-information/top-charts-x1507

Their results provided evidence of asymmetry under increasing prices. Awokuse and Wang (2009), employing both Threshold Autoregressive and Momentum Threshold Autoregressive models, found that the relationship between milk and butter prices was asymmetric whereas that of milk and cheese prices was symmetric.

The aforementioned works have offered certain useful insights into the operation of the dairy markets in the US pointing to potential inefficiencies and welfare losses due to asymmetric and/or incomplete price transmission. However, bivariate models fail to take into account that dairy markets constitute a pool (network) involving complex commodity linkages[3]. Raw milk is processed into different products some of which may be substitutes (e.g., cheese and butter) while others are complements in production (e.g., dry whey is a by-product of cheese manufacturing). Moreover, to prevent raw milk prices from falling into levels threatening the viability of dairy farms, a number of geographical areas in the US operate "marketing orders" under which dairy manufacturers pay a harmonized price for milk depending on its intended use.[4] Given both vertical and horizontal price relationships as well as the presence of public intervention, multivariate modelling is certainly preferable.

Against this background, the present work revisits price linkages in the US dairy sector using the Time Varying Parameter-VAR-Connectedness Approach (TVPVAR-CA) (Antonakakis et al., 2019; and Antonakakis et al., 2020). The TVP-VARCA brings together the static Connectedness model (Diebold and Yilmaz, 2014) and the dynamic TVP-VAR model (Koop and Korobilis, 2014). The static Connectedness model has two distinct advantages relative to its alternatives: (a) It develops a set of directional spillover measures that offer a detailed characterization of the interactions among the stochastic processes (here prices) of interest. It is, thus, a system-wide approach to connectedness closely related to the theory of directed and weighted networks; (b) It provides a natural framework for investigating asymmetric linkages. The TVP-VAR model allows for a robust characterization of the dynamic evolution of connectedness (i.e., of the network dynamics) by: (a) Ensuring an accurate determination of changes in parameter values over time; (b) Alleviating the potential influence of outliers on outcomes; (c) Dispensing with the need to discard initial sample observations and to set arbitrary rolling-window sizes.

The empirical analysis here utilizes futures prices of the four dairy commodities traded on the Chicago Mercantile Exchange (CME), namely: Class III milk, cheese, butter, and dry whey. The linkages among these four prices are important for hedgers and speculators in the respective futures markets. Collins (2000) noted that profits of firms with multiple commodity endowments (such as the raw milk processing ones) are to some degree "self-hedged" provided that input and output prices are positively correlated. An implication of "self-hedged" profits is that

[3] The same applies to earlier works by Serra and Goodwin (2003), Rezitis (2019), and Ben Abdallah et al. (2020) on the Spanish, and Finnish, and the Hungarian dairy sectors, respectively.

[4] For details see https://www.clal.it/en/?section=latte_usa

attempts to hedge the price of one commodity in isolation may actually increase the overall level of risk. The empirical results, therefore, are likely to offer guidance as to the appropriate price risk management strategies.

The TVP-VAR-CA has been employed, among others, by Antonakakis et al. (2019) to analyze monetary spillovers, Antonakakis et al. (2020) to determine risk transmission in foreign exchange rates, and by Broadstock et al. (2022) to evaluate the role of green bonds in fixed-income investment portfolios. To the best of my knowledge, this is the first work that utilizes the TVP-VAR-CA to investigate price linkages across farm commodities futures markets[5]. In what follows, section 2 presents the analytical framework and section 3 the data and the empirical model. Section 4 presents and discusses the empirical results while section 5 offers conclusions.

2. Analytical framework

Let $X_t = (X_{1,t},\ X_{2,t}, ..., X_{n,t})$ (with t=1, … , T) be a n- dimensional stationary stochastic process. The TVP-VAR-CA model consists of the following two equations:[6]

$$X_t = \Phi_t X_{t-1} + \varepsilon_t, \text{ with } \varepsilon_t \sim \mathrm{N}(0, \Omega_t) \qquad (1),$$

where ε_t is a nx1 dimensional error vector and Φ_t and Ω_t are nxn dimensional parameter matrices, and

$$vec(\Phi_t) = vec(\Phi_{t-1}) + \zeta_t, \quad \text{with} \quad \zeta_t \sim \mathrm{N}(0, \Xi_t) \qquad (2),$$

where ζ_t and $vec(\Phi_t)$ are n^2x1 dimensional vectors and Ξ_t is a n^2xn^2 parameter matrix (e.g., Antonakakis *et al*., 2018; Broadstock *et al*., 2022). The transition equation (2) has a random-walk structure that is highly effective in capturing time-varying parameters accurately. The time-varying variance terms Ω_t and Ξ_t are included to account for time-varying conditional heteroscedasticity (common for high-frequency data of financial time series).

[5] The only empirical work that is somehow related to the present is the one by Fan et al. (2023) that focused on price volatility linkages among Class III milk, cheese butter, price whey, and the S&P GSCI index. However, the earlier work relied on the standard (static) connectedness model by Diebold and Yilmaz (2014).

[6] The exposition, for simplicity, assumes a first-order VAR.

The building blocks of time-varying connectedness measures are the elements of the normalized Generalized Forecast Error Variance (GFEV) matrix of X_t (obtained from the Vector Moving Average representation of the TVP-VAR through Wold's representation theorem). In particular, for a given forecast horizon $H \in Z_+$ and a given time period *t* the mxm dimensional normalized GFEV (Θ) can be expressed concisely as

$$\Theta_t(\mathrm{H}) = [\theta_{ij,t}(\mathrm{H})] \qquad (i, j = 1, 2, \ldots, n) \qquad (3).$$

The element $\theta_{ij,t}(\mathrm{H})$ (with $i \neq j$) gives the percentage of the forecast error for the *i*th stochastic process at time t and forecast horizon H that can be attributed to shocks/innovations to process j (or equivalently, the *spillover* from *j* to *i*). The difference

$$NPDC_{ij,t}(\mathrm{H}) = \theta_{ij,t}(\mathrm{H}) - \theta_{ji,t}(\mathrm{H}) \qquad (4),$$

is the *net pair directional spillover* (net pairwise directional connectedness); when negative (positive) the process i is a net receiver (transmitter) of shocks from (to) process *j* at *t* and H. The sum

$$TO_{i,t}(\mathrm{H}) = \sum_{\substack{i=1, \\ i \neq j}}^{n} \theta_{ij,t}(\mathrm{H}) \qquad (5)$$

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

$$FROM_{i,t}(\mathrm{H}) = \sum_{\substack{j=1, \\ i \neq j}}^{n} \theta_{ij,t}(\mathrm{H}) \qquad (6)$$

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

$$NTDC_{i,t}(\mathrm{H}) = TO_{i,t}(\mathrm{H}) - FROM_{i,t}(\mathrm{H}) \qquad (7)$$

is the *net total directional spillover* (connectedness); when positive (negative) process i is a net transmitter (receiver) of shocks to (from) the remaining n-1 processes. The ratio of the sum of the off-diagonal elements to the sum of all elements of the normalized GFEV matrix

$$TCI_t(\mathrm{H}) = \sum_{\substack{i,j=1 \\ i \neq j}}^{n} \theta_{ij,t}(\mathrm{H}) / \mathrm{n} \qquad (8),$$

(which lies on (0,1)) stands for the *total connectedness index*; it gives the percentage of the variability of the n-dimensional system that can be attributed cross-spillovers. Higher values of TCI indicate that the stochastic processes are more tightly linked to each other.

3. The data and the empirical models

The data are front-month daily futures prices of Class III milk, cheese, butter, and dry whey from 1/1/2014 to 31/10/2023 measured in $ per pound[7]. Class III milk is used primarily in cheese manufacturing (cream cheese, other spreadable cheese, and hard cheese). In 2022, of the raw milk used for produced dairy commodities in the US 54% was Class III, 27% Class I (intended primarily for beverages), 9% Class II (intended primarily for soft products), and 10% Class IV (intended primarily for butter and nonfat dry milk).

Figure 1 shows the evolution of the four futures prices. All series have been quite volatile and none of them has exhibited any clear upward or downward trend. The evolution of Class II milk price is very similar to that of cheese.

[7] The data for Class III milk, cheese, and butter have been obtained from Yahoo Finance whereas that for dry whey from Nasdaq.

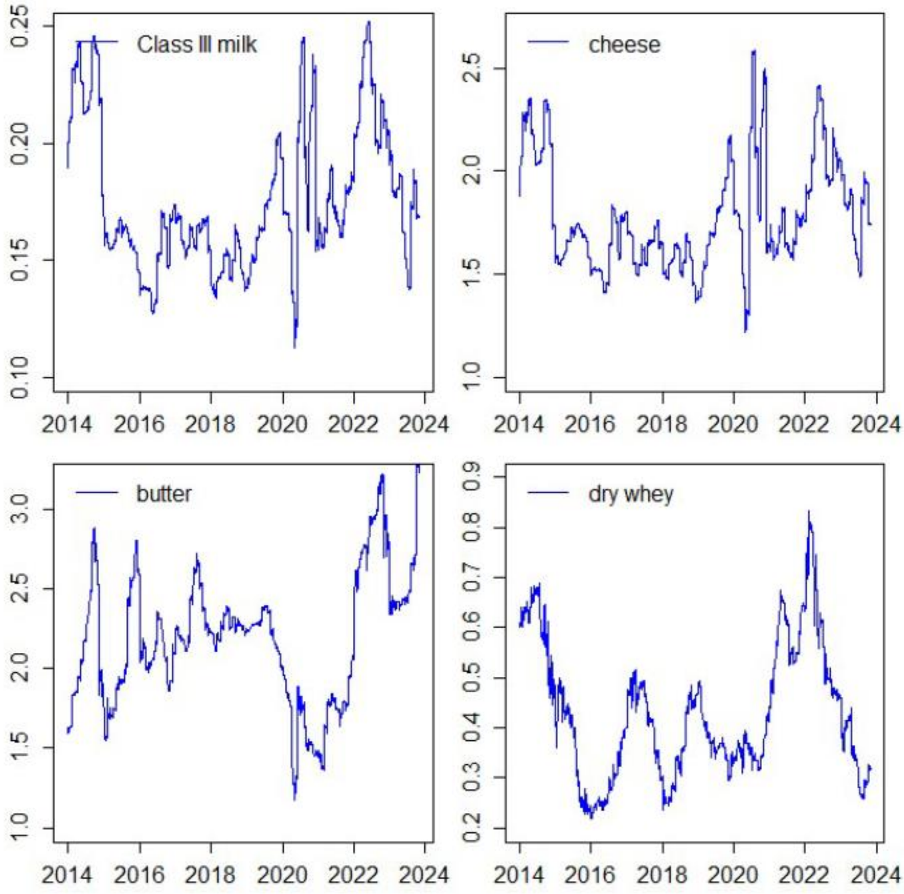

Figure 1. Dairy commodities futures (in $ per pound)

This is a direct result of the operation of the Federal Milk Marketing Order (FMMO) scheme; cheese carries the highest weight in the calculation of the minimum Class III milk price[8]. The natural logarithms of all futures prices are not stationary but their respective log returns are[9]. Therefore, the subsequent analysis relies on log-returns. Table 1 reports Pearson unconditional and partial correlation coefficients.

The unconditional coefficients range from 0.009 for the pair (butter, dry whey) to 0.988 for the pair (Class III milk, cheese). Partial correlation coefficients (Kim, 2015) quantify the linear association between two stochastic processes when conditioned for one or more confounding variables avoiding, thus, spurious correlation.

[8] The relevant formula is $p_m=9.64(p_m)+0.42(p_B)+5.86(p_d)-2.82$, where p, c, b, and d are the spot prices of milk, cheese, butter, and, dry whey respectively (Fan et al., 2023). The minimum Class III milk prices are reported on Wednesdays and on, every reporting day, the closing futures price of Class III milk on the CME should be identical to the spot price under the FMMO scheme; on the remaining week days the minimum Class III milk price and the closing futures price may deviate from each other
(Fan et al., 2023).

[9] The properties of the price series have been verified using the KPPS test. The results are available upon request.

Table 1. Unconditional and partial Pearson correlation coefficients

Pair of commodities returns	Unconditional (1)	Conditional (2)	Difference =(1)-(2)
(Class III milk, cheese)	0.988	0.987	0.001
	(<0.01)	(<0.01)	(0.783)
(Class III milk, butter)	0.442	0.387	0.055
	(<0.01)	(<0.01)	(0.669)
(Class III milk, dry whey)	0.042	0.137	-0.095
	(0.04)	(<0.01)	(<0.01)
(cheese, butter)	0.392	-0.325	0.718
	(<0.01)	(<0.01)	(<0.01)
(cheese, dry whey)	0.027	-0.132	0.155
	(0.265)	(<0.01)	(<0.01)
(butter, dry whey)	0.009	-0.053	0.062
	(0.695)	(0.09)	(<0.01)

Note: *p*-values in parentheses; obtained using block bootstrap (Politis and Romano, 1994) with 1000 replications).

Except for the pair (Class milk III, cheese), there are very large differences between unconditional and partial correlations. For three pairs in particular, namely, (cheese, butter), (cheese, dry whey), and (butter, dry whey) the sign of partial correlation coefficient is negative.

It is obvious that bi-variate modelling is not suitable for investigating the linkages between the diary futures prices in the US; to avoid biased estimates of connectedness, one has to conduct TVP-VAR-CA analysis on all four prices considered together in the same model. The negative sign of the partial correlation coefficient for pair (cheese, dry whey) may be attributed to the fact that dry whey is a by-product of cheese manufacturing. As the price of cheese goes up its supply increases and so does the supply of dry whey. Then, unless the demand for dry whey increases at a pace no lower than that for cheese, the increase in cheese price will exercise downward pressure on dry whey price. The negative sign for the pair (cheese, butter) is admittedly more difficult to explain. These two commodities are, for the period considered here, traded intensively on the international markets where they face stiff competition from EU and New Zealand producers; thus, demand and supply conditions outside the US may have a strong influence on their prices. Two relevant issues in implementing empirically a TVP-VAR-CA model are the selection the forecast horizon and the lag-length. In earlier works, values of H in the range [10, 20] have been employed. Here, after some initial experimentation, H has been set equal to 10. The optimal length (2) has been determined using the Akaike Information Criterion (AIC).[10] Single and multiple coefficients tests have been conducted using a Wald-type statistic

$$\Pi = (R\hat{C})'(R\hat{V}_C R')^{-1}(R\hat{C}) \qquad (9),$$

[10] The experimentation results turned out to very robust. In particular, the average dynamic TCI values for H=5, 10, 15, and 20 were 37.065, 37.069, 37.07, and 37.071, respectively.

where R is the restrictions' matrixr, C is the parameters' vector, and $\hat{V}_C$ is the bootstrap estimate of their variance-covariance matrix (Patton, 2013). Under a null, Π follows the χ^2 distribution with degrees of freedom equal to the number of restrictions.

4. The empirical results

Table 2 presents the averaged dynamic connectedness measures[11]. The diagonal elements stand for own-connectedness while the off-diagonal ones for pair spillovers; the off-diagonal row sums are total directional spillovers FROM others whereas the off-diagonal column sums are total directional spillovers TO others; the bottom-right element (in boldface) is total connectedness. The own-connectedness estimates are the largest individual elements in Table 2 ranging from 45.25 per cent for Class III milk to 90.36 per cent for dry whey. The TCI value is 37.15 suggesting that slightly more than 1/3 of the GFEV is due to innovation spillovers and the rest is due to idiosyncratic shocks. Class III milk and cheese (in this order) are, by far, the prices with the highest total directional TO and FROM spillovers.

From a networkwide perspective, therefore, these two commodities are more important for the propagation of shocks relative to butter and dry whey; thus, they may be viewed as price risk connectors (Nguyen et al., 2020). The market for dry whey is the one that exhibits the lowest degree of connectedness with the other three. The net directional spillovers are positive and statistically significant for Class III milk and cheese and negative and statistically significant for butter and dry whey suggesting that Class III milk and cheese are net transmitters whereas butter and dry whey are net receivers of price shocks. Fan et al. (2023) reported that (by far) the most important market in the price volatility network was that of cheese followed by the market of Class IIL milk whereas the contributions of butter and dry whey markets to connectedness were trivial. All average dynamic net pair connectedness measures (Table 3) are statistically significant. Class III milk is a net transmitter of price shocks to the other three commodities and cheese to dry way and butter. Dry whey is, in all cases, a net receiver of price shocks. The derived demand theory (Marshall, 1920) predicts that prices are first established at the final product markets and they are transmitted subsequently upstream to the intermediate or primary good markets. At the same time, the FMMO scheme ties (one Wednesdays) the futures price of Class III milk to the prices of cheese, butter and dry whey.

The pattern of net transmission of price shocks with respect to Class III milk appears to contrast with the predictions of the derived demand theory and to the objectives of the public management policies for the dairy sector. According to Adrangi et al. (2006), price shocks may be transmitted (or equivalently information may flow) more intensively downstream than upstream in a supply chain when the market structure changes along a continuum of vertically interrelated markets.

[11]The estimations have been carried out using the package ConnectednessApproch in R (Gabauer, 2022). Each average measure is the sum of the respective values over all observations divided by sample size.

This may be relevant for the US dairy markets as well. Raw milk is a bulky and perishable commodity making it, thus, difficult and expensive to transport. Consequently, raw milk markets are local or (at best) regional in geographical scope (Saitone and Sexton, 2017). Milk processing is dominated by a few very large firms (Kelloway and Miller, 2021). At the same time, concentration in food retailing has been increasing (Zeballos et al., 2023). Therefore, buyer and (or) seller power may be present at the different stages of the US dairy supply chain. The average connectedness measures in Tables 2 and 3 may inadvertently mask dynamics and influences of specific events shaping the linkages among dairy futures prices.

Table 2. Averaged dynamic connectedness (%)

Commodity	Class III milk	Cheese	butter	dry whey	Total directional FROM others
Class III milk	45.25 (<0.01)	42.31 (<0.01)	10.75 (<0.01)	1.68 (<0.01)	54.75 (<0.01)
Cheese	42.70 (<0.01)	45.63 (0.01)	10.26 (<0.01)	1.41 (<0.01)	54.37 (<0.01)
Butter	14.19 (<0.01)	13.30 (<0.01)	70.16 (<0.01)	2.35 (<0.01)	29.84 (<0.01)
Dry whey	3.49 (<0.01)	2.90 (<0.01)	3.25 (<0.01)	90.36 (<0.01)	9.64 (<0.01)
Total directional TO others	60.38 (<0.01)	58.51 (<0.01)	24.26 (<0.01)	5.44 (<0.01)	
Net total directional	5.63 (<0.01)	4.15 (<0.01)	-5.58 (<0.01)	-4.20 (<0.01)	
					Total connectedness
					37.15 (<0.01)

Note: *p*-values in parentheses; obtained using block bootstrap (Politis and Romano, 1994) with 1000 replications).

Table 3. Average dynamic net pair directional connectedness (%)

Pair of commodities returns	Test statistic	Pair of commodities returns	Test statistic
(Class III milk, cheese)	0.39 (0.05)	(cheese, butter)	3.04 (<0.01)
(Class III milk, butter)	3.44 (<0.01)	(cheese, dry whey)	1.49 (<0.01)
(Class III milk, dry whey)	1.81 (<0.01)	(butter, dry whey)	0.9 (<0.01)

Note: The test statistic is spillover from the first minus spillover from the second commodity in the pair : *p*-values in parentheses; obtained using block bootstrap (Politis and Romano, 1994) with 1000 replications).

In the following, the present work exploits the full potential of the TVP-VAR-CA by presenting richer time-varying measures from the fully dynamic connectedness network. A four-variate model TVP-VAR-CA model produces a large statistics; to avoid a clutter with figures and in line with Broadstock et al. (2022), the presentation here is restricted to TCI, the net total directional spillovers (NTDC), and the net pair spillovers (NPDC). Figure 2 shows the evolution of the TCI. The measure fluctuates between a low of 20.24 to a high of 66.84 and it exhibits a large number of local peaks and troughs. The highest peak occurred around the big drop in dairy prices in early 2015 following a sizable reduction of China's dairy imports. The lowest value occurred in June 2022. It is interesting that two of the higher peaks occurred between early April and early July 2020 suggesting that "panic buying" (Wolf et al., 2021) in the early phase of the Conid-19 pandemic due to the disruption of supply chains and the lockdowns, worked towards tighter linkages among dairy commodities prices. Another peak (although somehow less pronounced) occurred in February 2022 with the outbreak of the war Ukraine; in the last case, the concerns were about energy cost, availability of cow feed and fertilizers, as well as about the level of Belarussian and Ukrainian dairy exports[12].

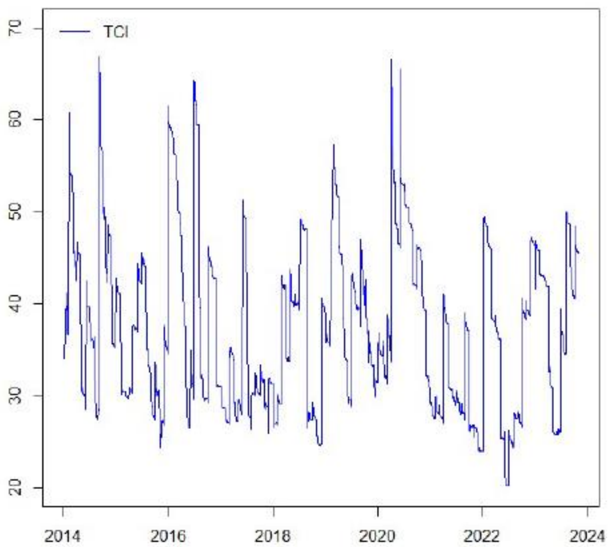

Figure 2. The evolution of the total connectedness index (TCI)

Figure 3 presents the evolution of the NTDCs. In line with has been already transpired from Table 2, the NTDCs are (in the large majority of sample points) positive for Class III milk and cheese and negative for butter and dry whey. Also, it appears that during the early phase of the Covid-19 pandemic the importance of Class III, cheese and butter as net transmitters of price risk to the other dairy markets increased.

[12] https://www.tridge.com/news/milk-prices-rise-as-war-in-ukraine-threatens-suppl

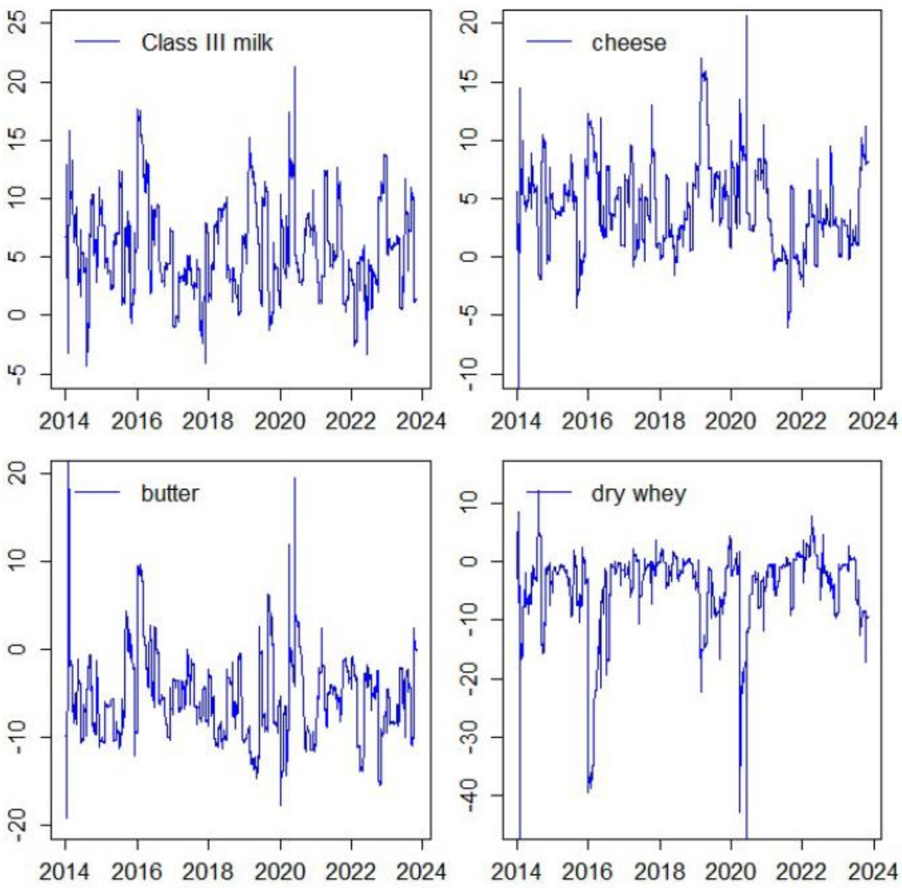

Figure 3. The evolution of net total directional connectedness (NTDC)

Figure 4 shows the evolution of the NPDCs. In large majority of sample points Class III milk have been a net transmitter of price risk to cheese, butter, and dry whey and cheese to butter and dry whey. However, butter and dry whey very often alternated roles as net receivers and transmitters of price risk.

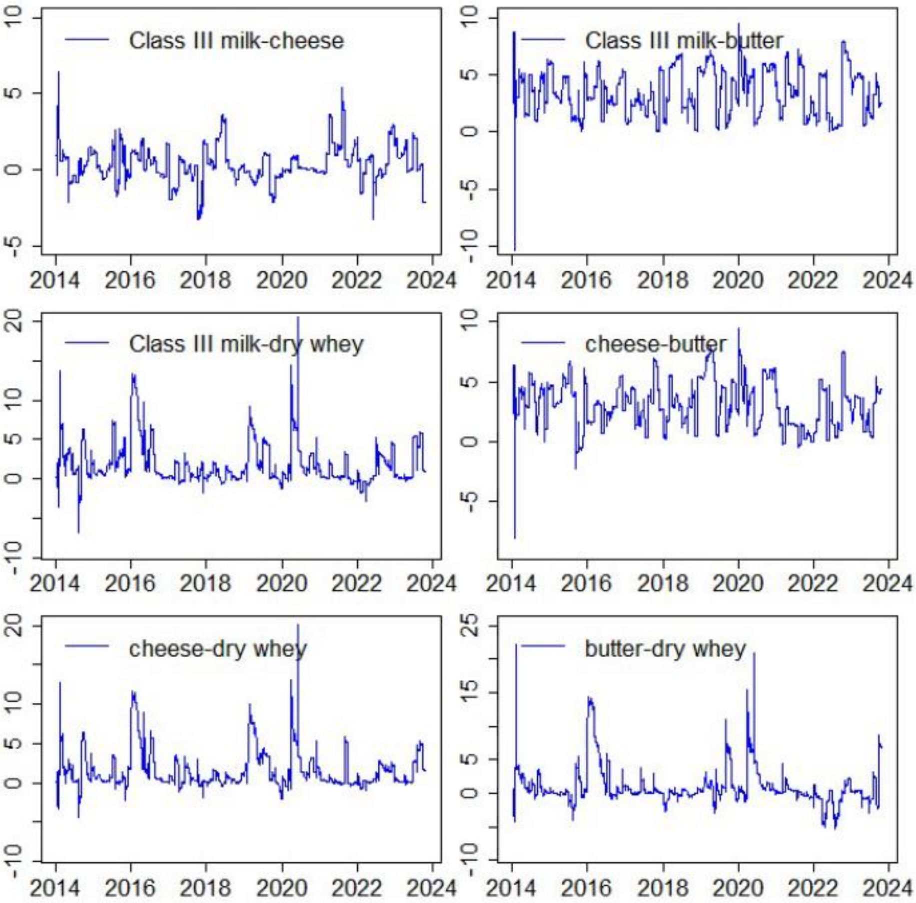

Figure 4. The evolution of net pair directional connectedness (NPDC)

5. Conclusions

The dairy sector is an important component of the US economy while the vertical and horizontal price interrelationships among dairy commodities attract the close attention of producers, policy-makers, and futures markets traders. The objective of the present work has been to investigate the intensity and the pattern of price connectedness among the four dairy commodities traded on the CME. The analysis has relied on the flexible TVP-VAR Connectedness model and on daily futures prices of Class III milk, cheese, butter, and dry whey.

The empirical findings suggest:

(a) The overall level of connectedness among all four commodities is not high; almost 2/3 of the forecast error variance is explained by idiosyncratic price shocks. The prices of Class III milk and cheese are linked tightly together but they exhibit a rather weak connectedness to those of butter and cheese. From a networkwide perspective, the futures markets of Class III milk and cheese are, by far, the most important propagators of price shocks.

(b) There are bi-directional spillovers among all four markets. However, they tend to be strongly asymmetric. Class III milk (the raw/farm commodity) is a net transmitted of price risk to all three processed commodities. Vertically in the dairy supply chain, therefore, the information appears to flow more intensively forward than backward. Horizontally, the information flows more intensively from cheese to

butter and to dry whey and from butter to dry whey.
(c) All measures of dynamic connectedness show considerable volatility over time suggesting that the strength and the mode of linkages are sensitive to the developments in the relevant markets. Major events (such as the drop of dairy prices in 2015, the Covid-19 pandemic, and the war in Ukraine), at least in their respective initial phases, led to higher market connectivity.
(d) The weak spillovers between Class III milk and cheese on the one side and butter and dry whey on the other along with a number of negative partial correlations suggest that dairy manufacturers' profits from all four commodities considered together are not "self-hedged". "Self-hedging" appears to be viable only for the pair (Class III milk, and cheese). For butter and dry whey, however, protection against price risk will probably require individual trading on the respective futures markets or the use of other forward arrangements.

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