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# Interest Rate Risk and Farm Financial Vulnerability:

# A Quantile Connectedness Analysis of the U.S. Farm Sector

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**Abstract**

**Purpose –** This study examines how interest-rate risk is transmitted to farm financial vulnerability in the U.S. agricultural sector, and whether this transmission differs between normal conditions and the tails of the distribution, where solvency stress occurs.

**Design/methodology/approach –** A quantile vector autoregression (QVAR) is estimated on quarterly data for 2000Q1–2025Q4 covering the farm loan delinquency rate, the agricultural lending interest rate, the farm debt-to-asset ratio, and an agricultural commodity price index. Diebold–Yilmaz connectedness measures are computed at the 5th, 50th, and 95th conditional quantiles, across a full quantile grid and over rolling windows, with moving-block bootstrap intervals for the tail-versus-median differences.

**Findings –** Total connectedness is about 6% at the median but about 63% in the lower tail and 61% in the upper tail, giving a clear U-shaped profile. At the median, the interest rate is the main net transmitter and delinquency the main net receiver. In the tails, the commodity price index leads transmission, and the interest rate turns from a net receiver in the lower tail into a net transmitter in the upper tail, where its share of delinquency variance rises from below 1% to above 20%. Connectedness peaks around 2008–2009, 2014–2016, and 2022–2023.

**Originality/value –** This is the first study to measure interest-rate transmission in U.S. farm credit across the whole conditional distribution rather than at the mean, showing that a channel that looks negligible on average becomes dominant under stress. It also shows how interpolating annual balance-sheet data biases connectedness estimates.

**Implications –** Credit supervision calibrated to average conditions understates the risk of a tightening cycle, so tail-aware monitoring and stress testing are needed. The results inform decisions under uncertainty by lenders and regulators, who must set capital, provisions, and stress scenarios for bad states of the world that averages do not reveal.

**Keywords:** interest-rate risk; farm financial vulnerability; loan delinquency; quantile connectedness; QVAR; agricultural credit

**JEL Classifications:** Q14, G21, E43, C32, G32

## 1. Introduction

The financial health of U.S. agriculture has returned to the centre of policy debate. The sharpest monetary tightening in four decades has raised the cost of farm credit: average operating-loan rates at agricultural banks rose from about 4.7% to 8.5% between early 2022 and early 2023, just as farm income was falling from its pandemic-era peak (Berg, 2024). Regional Federal Reserve surveys have since recorded rising farm loan delinquencies and a renewed build-up of farm debt (Kreitman & Cooray, 2025). These developments revive a long-standing question in agricultural economics: when, and how strongly, does interest-rate risk turn into farm financial vulnerability?

Agriculture is structurally exposed to interest-rate risk. Farming is capital-intensive and land-backed, and much of its debt reprices only every few years, so rate changes reach farm balance sheets with long and uneven lags (Berg, 2024). The effect of a rate shock on repayment capacity is therefore likely to depend on where the sector stands in its income and leverage cycle. Yet the dominant empirical approach, built on conditional-mean models such as logit, probit and linear regressions or mean-based vector autoregressions, treats farm credit risk as an average relationship and says little about the tails of the distribution, where solvency crises actually occur.

This gap matters because financial vulnerability is a tail phenomenon: it appears not in a typical quarter but in the bad quarters when delinquencies cluster. Average transmission can therefore seriously understate the effect of rate shocks under stress, when the links between rates, leverage, prices and distress are strongest. Quantile-based connectedness measures track how shocks spread at different points of the conditional distribution (Ando et al., 2022), but they have been applied mainly to equity, commodity and currency markets and hardly at all to agricultural credit.

This study addresses that gap. Using quarterly U.S. data for 2000Q1–2025Q4, we model a four-variable system: the farm loan delinquency rate (vulnerability), the agricultural lending interest rate (interest-rate risk), the farm-sector debt-to-asset ratio (solvency), and an agricultural commodity price index (income conditions). We estimate a quantile vector autoregression (QVAR) and use generalized forecast-error variance decompositions to obtain the connectedness measures of Diebold and Yilmaz (2012, 2014) at the lower, median, and upper quantiles, and we use rolling windows to track how transmission has changed through the commodity super-cycle, the global financial crisis, and the post-pandemic tightening.

Three questions guide the analysis. Does the transmission of interest-rate shocks to farm vulnerability differ between normal and stressed phases of the credit cycle? Is the interest rate a net transmitter or a net receiver of shocks, and does this role change across quantiles? And does system connectedness intensify around particular macro-financial events?

What is new in this study is that it measures how interest-rate shocks reach farm distress separately in calm and in stressed states, across the full conditional distribution and within a network of related variables. Earlier studies of farm credit estimate a single average relationship, so they cannot show that the interest-rate channel is weak on average but strong in the tails. The paper makes three contributions. Conceptually,

it recasts farm financial vulnerability as a problem of state-dependent shock transmission and links the farm credit-risk literature to the literature on financial contagion and network connectedness. Empirically, it provides the first application of quantile connectedness to the agricultural credit channel and documents a U-shaped connectedness profile and a reversal in the role of the interest rate, from net receiver in the lower tail to net transmitter in the upper tail. For policy, it shows that interest-rate risk is most damaging under stress. The paper is relevant to decision sciences because it gives lenders, supervisors, and policymakers a quantitative basis for decisions under uncertainty, such as how much capital and provisions to hold, how to design stress tests, and when to tighten supervision, based on how risk behaves in bad states rather than on average.

The results are clear. Cross-variable spillovers explain only about 6% of forecast-error variance at the median but about 63% in the lower tail and 61% in the upper tail. At the median, the interest rate is the main net transmitter and the delinquency rate the main net receiver, consistent with a direct rate-to-distress channel. In the tails, the commodity price index leads transmission and the interest rate switches from net receiver in the lower tail to net transmitter in the upper tail. Connectedness rises sharply during the 2008–2009 crisis, the 2014–2016 farm-income downturn and the 2022–2023 tightening. Because the debt-to-asset ratio is interpolated from annual data, its estimated role is reported but not interpreted (Section 4.6). For academics, these results show that the effect of interest rates on farm distress depends on the state of the cycle; for practitioners, they show that rate risk should be judged by its behaviour in the tails, not by its average.

Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and the QVAR connectedness methodology. Section 4 presents and discusses the results, and Section 5 concludes.

## 2. Literature Review

The relevant literature falls into three streams: the determinants of agricultural credit risk, the transmission of interest-rate shocks to farm balance sheets, and the econometrics of distributional and network connectedness.

### *2.1 Agricultural credit risk and farm financial vulnerability*

Agricultural economics has a long tradition of modelling farm financial distress through borrower and sector fundamentals. Featherstone et al. (2006) estimate default probabilities for a Farm Credit System loan portfolio and identify leverage, liquidity and profitability as key correlates of default. Briggeman et al. (2009) find that credit constraints significantly reduce output on sole-proprietor farms, and later studies relate crop insurance, government payments and farmland values to debt capacity (Ifft et al., 2015; Mishra et al., 2009). Across this literature, the debt-to-asset ratio is the standard measure of solvency and loan delinquency the standard measure of realized distress, which are the variables used here. More recent work links geopolitical and climate shocks to commodity prices, farm incomes and food security, underlining the volatile income environment in which farm debt is serviced (Arndt et al., 2023; Cortazar et al., 2025; Hudecová & Rajčániová, 2023; Mubenga-Tshitaka et al., 2023; Urak et al., 2024).

A second theme is the cyclical, sector-wide nature of farm stress. Studies of the 1980s farm crisis show that, when leverage is high and asset prices fall, distress spreads through land markets, lender balance sheets and regional economies, and that it can remain hidden until real rates rise and falling income erodes collateral (Barnett, 2000; Weber & Key, 2015). Recent USDA and Federal Reserve assessments show how farm income and interest costs together shape sector solvency (Giri & Subedi, 2024; Key et al., 2019). These studies agree that vulnerability is state-dependent, but they describe this through narrative or scenario accounting rather than a distribution-aware econometric framework.

A related unresolved question is whether income shocks or financing shocks matter more. One view holds that farm distress is driven mainly by commodity-price volatility, with interest rates playing a slower, second-order role; another stresses that, given the size and collateralisation of farm debt, even modest rate increases can push marginal borrowers into delinquency. Mean-based models cannot settle this debate because they do not allow the relative importance of prices and rates to differ across states, which is precisely what a quantile framework permits.

### *2.2 Interest-rate risk and the transmission of monetary shocks to agriculture*

The second stream examines how interest-rate and monetary shocks affect the farm sector. Higher rates raise debt-service costs, lower the present value of farmland and tighten credit for leveraged borrowers. Farmland values respond to real interest rates and capitalized returns (Moss, 1997), and changes in the federal funds rate take years to be fully reflected in Midwest farmland values (Basha et al., 2021). Federal Reserve analyses document that the 2022–2023 rate increases sharply raised farm interest expense, and that loans repricing on multi-year cycles passed the shock on only gradually (Berg, 2024; Kreitman & Cooray, 2025). Beyond agriculture, quantile-connectedness studies find that monetary-policy and oil-price shocks are more strongly connected with commodity and asset markets during stress (Chowdhury et al., 2023; Coskun et al., 2023), and commodity-price shocks pass through to food prices (Scott et al., 2024).

Two features of this literature shape our design. First, transmission is expected to be nonlinear and asymmetric, stronger under high leverage and low income than in benign conditions, yet most studies assume linear and symmetric effects. Second, slow repricing makes the timing of transmission uneven, which calls for a time-varying treatment and a forecast horizon long enough to capture delayed pass-through. We therefore allow the strength of transmission to vary across quantiles and across rolling windows, and use a ten-quarter horizon.

Connectedness tools are increasingly used to study monetary transmission. Chatziantoniou et al. (2021) show that monetary-policy signals pass along the maturity spectrum of interest-rate swaps more strongly in the tails, with rate instruments acting as net transmitters under stress. Whether the agricultural lending rate plays a similar role for farm distress has not been tested.

### *2.3 Distributional and network connectedness: methodological foundations*

The third stream is methodological. Diebold and Yilmaz (2012, 2014) decompose the forecast-error variance of a VAR into total, directional, net and pairwise spillovers and represent the system as a weighted network, building on the measurement of realized volatility (Andersen et al., 2003). Because the framework uses the generalized variance decomposition (Koop et al., 1996; Pesaran & Shin, 1998), it is invariant to variable ordering.

Two refinements are important here. Antonakakis et al. (2020) embed the decomposition in a time-varying-parameter VAR, and Gabauer (2021) extends it to asymmetric and pairwise connectedness. More directly relevant, Ando et al. (2022) introduce quantile connectedness, decomposing forecast-error variance at different quantiles of the joint distribution so that the network can differ between the centre and the tails. Subsequent studies consistently find connectedness to be much higher in the tails, a regularity that yields a directly testable prediction for farm finances. Frequency-domain work (Baruník & Křehlík, 2018) further shows that spillovers differ across horizons, which supports measuring connectedness at an economically relevant horizon.

We claim no methodological novelty: the estimator and the connectedness algebra are those of Ando et al. (2022), in the tradition of Chatziantoniou et al. (2021). The contribution is substantive. First, the framework is moved from market prices to sector-level credit aggregates, extending quantile connectedness from market risk to credit risk in the real economy. Second, the application documents a rate-to-distress channel that is directional at the median but overwhelmed by broader spillovers in the tails, where the interest rate switches from net receiver to net transmitter. Third, it helps settle the income-versus-financing debate by showing that each channel dominates in a different part of the conditional distribution.

The quantile machinery rests on the regression-quantile theory of Koenker and Bassett (1978), the quantile autoregression of Koenker and Xiao (2006), and the multivariate regression quantiles of White et al. (2015), which together justify estimating a VAR equation by equation at a given quantile. Connectedness designs, many of them quantile-based, are now widely used for energy and agricultural commodities (Cagli et al., 2023; Ghosh & Paparas, 2023; Padhan & Kocoglu, 2025; Zhou et al., 2024), cryptocurrency and carbon markets (Joo & Park, 2023; Kyriazis et al., 2024; Li et al., 2023), and oil prices, policy uncertainty and exchange rates (Garg et al., 2023; Nong & Liu, 2023; Si Mohammed et al., 2023; Umar & Bossman, 2023). Their use in agricultural finance, however, remains very limited.

Recent studies apply connectedness methods to a widening range of questions: time-varying spillovers and portfolio construction across equity, ESG and commodity markets (Belguith, 2026), tail-risk transmission between volatility indices and cryptocurrencies (Imane & Ghizlane, 2025), links among the business cycle, the financial cycle and policy uncertainty (Kumar & Paramanik, 2022), oil–equity connectedness during the pandemic (Maghyereh & Abdoh, 2022), frequency connectedness among G7 macroeconomic variables, sentiment and commodities (Suissi & Mroua, 2026), risk transmission between G7 stock indices and currencies (Syed et al., 2025), and connectedness between industrial and rare earth

metals (Zada et al., 2025). Work on causality and information flow (Karatas & Unal, 2022) and on bubbles and explosive behaviour (Ahmed et al., 2024) also stresses that the time-series properties of the data must be checked before spillovers are measured. None of these studies, however, examines agricultural credit.

The theoretical link between these strands is the financial accelerator, in which credit-market frictions amplify shocks to net worth and collateral. Applied to agriculture, it predicts that the balance sheet is where rate and price shocks become realized distress when conditions deteriorate. Because the quarterly leverage series is interpolated from annual stocks (Sections 3.1 and 4.6), this prediction cannot be tested cleanly here; we use the accelerator to motivate hypotheses on the natively quarterly variables and report the leverage results descriptively.

### *2.4 Synthesis, gap, and hypotheses*

The hypotheses follow from the financial-accelerator mechanism. Because frictions make the cost of external finance depend inversely on net worth, transmission between financing costs, balance sheets and distress should be strongest in bad states. Cross-variable transmission should therefore be far stronger in both tails than at the centre (H1). In normal states, the remaining channel is the mechanical cost of credit, so the interest rate should be a net transmitter and delinquency a net receiver at the median (H2). In stressed states, commodity-price shocks erode the earnings and collateral that service debt, so the price index should become a dominant transmitter in both tails, while the role of the interest rate should depend on the direction of the stress (H3). Finally, because net worth and frictions evolve over the cycle, connectedness should intensify around identifiable macro-financial episodes (H4).

H1 (tail amplification). System connectedness is significantly stronger in the tails than at the median, producing a U-shaped total connectedness profile across quantiles. Expected direction: TCI($\tau = 0.05$) and TCI($\tau = 0.95$) substantially exceed TCI($\tau = 0.50$).

H2 (median directionality). At the median, the interest rate is a net transmitter of shocks and the delinquency rate is a net receiver, consistent with a directional rate-to-distress channel. Expected direction: NET(IR) $> 0$ and NET(DLQ) $< 0$ at $\tau = 0.50$.

H3 (state-dependent roles). The directional roles of the natively quarterly variables are state-dependent and asymmetric across the tails: the commodity price index is a net transmitter in both tails, while the interest rate is a net transmitter under upper-tail stress but a net receiver in the lower tail. Expected direction: NET(CPI) $> 0$ at $\tau = 0.05$ and $\tau = 0.95$; NET(IR) $> 0$ at $\tau = 0.95$ and NET(IR) $< 0$ at $\tau = 0.05$. The leverage series is excluded from this hypothesis because its measured net position cannot be separated from its interpolation (Sections 3.1 and 4.6).

H4 (time variation). Dynamic connectedness is time-varying and intensifies around identifiable macro-financial episodes - the 2008-2009 financial crisis, the 2014-2016 farm-income downturn, and the 2022-2023 monetary tightening. Expected direction: rolling TCI rises around each episode, at all quantiles but most sharply in the tails.

The remainder of the paper tests these four hypotheses, and the results tables of Section 4 are organized so that each hypothesis maps onto a specific measure: H1 onto the total connectedness index by quantile, H2 and H3 onto the NET rows of the connectedness tables, and H4 onto the rolling-window indices.

## 3. Data and Methodology

### *3.1 Data and sample*

The analysis uses quarterly data for the U.S. farm sector from 2000Q1 to 2025Q4, giving 104 observations per variable. Farm financial vulnerability is measured by the farm loan delinquency rate (DLQ), the percentage of farm loans that are delinquent. The main explanatory variable is the interest rate on agricultural loans (IR, series 015CHI), which reflects the cost of farm credit. Two controls complete the system: the farm-sector debt-to-asset ratio (DAR), the standard aggregate measure of solvency, and an agricultural commodity price index (CPI), which captures the income environment that shapes repayment capacity. The delinquency rate is taken from the Federal Reserve Board's Farm Loans at Commercial Banks series, the lending rate from the Federal Reserve Bank of Chicago's Agricultural Finance survey, the debt-to-asset ratio from the USDA Economic Research Service Farm Income and Wealth Statistics, and the price index from the USDA agricultural price series. A data note in the replication package records each series' source, identifier and retrieval date.

The four-variable design is deliberate. With $K = 4$ and $p = 1$, each quantile regression already estimates five parameters per equation, and every additional variable would dilute the information available at the extreme quantiles (Section 3.5). Economically, the four variables span the accelerator loop of Section 2: realized distress, the cost of credit, the balance sheet and the income environment. Because an omitted common driver could appear as a bilateral spillover, the shares should be read as spillovers within this four-node system rather than as exhaustive structural channels.

Table 1 defines each variable, its role in the system and its transformation, so that the notation used in the equations below is clear from the outset. All series are first-differenced to ensure covariance stationarity, so the model works with quarter-on-quarter changes.

**Table 1. Variable definitions and measurement**

| Variable | Definition and measurement | Role in the system | Transformation |
|---|---|---|---|
| Delinquency Rate (DLQ) | Share of farm loans past due (%) | Dependent variable — farm financial vulnerability | First difference (ΔDLQ) |
| Interest Rate (IR) | Agricultural lending interest rate, series 015CHI (%) | Core explanatory — interest-rate risk | First difference (ΔIR) |
| Debt-to-Asset Ratio (DAR) | Farm-sector total debt / total assets (%) | Control — leverage and solvency | First difference (ΔDAR) |
| Commodity Price Index (CPI) | Agricultural commodity price index | Control — income and price environment | First difference (ΔCPI) |

Note. Sample 2000Q1–2025Q4, quarterly, N = 104 in levels (103 after first differencing). Series 015CHI denotes the agricultural lending rate series used in the source data. The differenced series form the vector $x_t$ of the QVAR in Equation (1).

The series are aligned by calendar quarter, giving a balanced sample with no missing values. The delinquency rate and the interest rate are reported quarterly, and the price index is the quarterly average of the underlying price series. The debt-to-asset ratio, however, comes from the USDA farm-sector balance sheet, whose stocks are compiled annually and interpolated linearly to quarterly frequency. This has a direct consequence for the differenced series. Linear interpolation makes the four quarterly increments within a year identical, so ΔDAR is a step function that changes only at the turn of each year. It therefore contains no genuine quarter-on-quarter innovation, its own-innovation variance is mechanically deflated, and any variance decomposition will attribute too large a share of its forecast-error variance to the other variables, biasing it towards appearing as a shock receiver, most strongly in the tails. Section 4.6 sets out the direction of this bias, and the results it affects, and the leverage clause has accordingly been removed from H3 (Section 2.4).

### *3.2 Preliminary and diagnostic tests*

Before estimation, we examine the statistical properties of the data. Stationarity is assessed with three complementary tests: the augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979), the Phillips–Perron (PP) test (Phillips & Perron, 1988), and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992). The ADF and PP tests take a unit root as the null hypothesis, whereas the KPSS test reverses the null to stationarity, so that joint use provides a robust classification of integration order. Normality is evaluated with the Jarque–Bera test (Jarque & Bera, 1980), and conditional heteroskedasticity with Engle's (1982) ARCH Lagrange-multiplier test; residual autocorrelation is screened with the Ljung–Box statistic. The lag order of the system is selected by the Akaike, Schwarz–Bayesian, and Hannan–Quinn information criteria.

As reported in Section 4, the levels are generally non-stationary while the first differences are stationary, so the system is specified in first differences. The Jarque–Bera results indicate departures from normality—most pronounced for the delinquency rate—which reinforces the case for a quantile-based estimator: when innovations are non-Gaussian and asymmetric, conditional-mean models are inefficient and uninformative about tail behavior, whereas quantile methods remain valid across the distribution.

A related concern is spurious association. Regressions involving non-stationary or nearly non-stationary series can produce significant but meaningless relationships, and recent work shows that spurious results can also arise with stationary series, with autoregressive errors, and when stationary and non-stationary series are combined in regressions, correlations or panels (Cheng et al., 2021, 2022; Wong et al., 2024; Wong & Pham, 2022a, 2022b, 2023a, 2023b, 2025a, 2025b, 2026a, 2026b). How a series should be modelled also depends on the stochastic process assumed for the data (Obrimah & Wong, 2022). We guard against these problems in four ways. Every series enters the QVAR in first differences after the tests in Table 4 confirm stationarity, so I(0) and I(1) variables are never mixed; the residual tests in Table 6 show no remaining autocorrelation at any quantile; the level correlations in Table 3 are reported only descriptively and are not used for inference; and the tail–median differences are judged with block-bootstrap intervals that preserve the serial dependence of the data rather than with conventional t-statistics.

Because the relationships may be nonlinear, a formal nonlinearity test, such as that of Hui et al. (2017), is a natural further check. The quantile framework already accommodates nonlinearity by allowing every coefficient to change with τ, and the differences across quantiles reported in Section 4 are themselves evidence of nonlinear dependence. Model adequacy is assessed with the normality, ARCH and Ljung–Box tests in Section 4.2 and with residual tests at every estimation quantile (Table 6).

### *3.3 Model specification: the quantile VAR*

The empirical engine is a quantile vector autoregression (QVAR), which generalizes the standard VAR of Sims (1980) by estimating the system at a chosen quantile $\tau$ of the conditional distribution. Let $x_t$ denote the $K \times 1$ vector of (differenced) endogenous variables, with $K = 4$. The QVAR of order $p$ at quantile $\tau$ is written as

$$x_t = c(\tau) + \Phi_1(\tau)\, x_{t-1} + \cdots + \Phi_p(\tau)\, x_{t-p} + u_t(\tau), \tag{1}$$

where $c(\tau)$ is a $K \times 1$ vector of quantile-specific intercepts, each $\Phi_j(\tau)$ is a $K \times K$ matrix of quantile-specific autoregressive coefficients, and $u_t(\tau)$ is a $K \times 1$ vector of innovations whose $\tau$-th conditional quantile is zero. Each of these objects is quantile-specific, so that Equation (1) describes the dynamics of the conditional quantile of the system rather than the conditional-mean dynamics of a standard vector autoregression, and the quantile index is retained on every coefficient throughout the derivation that follows. Each equation of (1) is estimated by regression-quantile minimization (Koenker & Bassett, 1978): for equation $i$ the coefficient vector solves the asymmetrically weighted absolute-deviation problem

$$\min \sum_{t=p+1}^{T} \rho_\tau \left( x_{i,t} - c_i(\tau) - \sum_{k=1}^{p} \sum_{j=1}^{K} \varphi_{ij,k}(\tau) x_{j,t-k} \right), \tag{2}$$

where $\rho_\tau(e) = e \cdot (\tau - \mathbf{1}\{e < 0\})$ is the check (pinball) loss function. Estimating (2) at $\tau = 0.05$, 0.50, and 0.95 yields the lower-tail, median, and upper-tail coefficient matrices, respectively, from which the state-specific transmission of shocks is derived. The lag order $p$ is fixed at the value selected by the Schwarz criterion ($p = 1$; see Table 5). In words, Equation (2) chooses the quantile-specific intercept and slope coefficients of equation i to minimize the check loss over all usable quarters, t = p + 1, …, T, where k = 1, …, p indexes the lag of each regressor.

By the Wold representation, the stationary QVAR($p$) at quantile $\tau$ admits the infinite moving-average form $x_t = \sum_{h \geq 0} A_h\,(\tau)\, u_{t-h}$, where the $K \times K$ coefficient matrices $A_h(\tau)$ are obtained recursively from the autoregressive matrices via $A_h(\tau) = \sum_{j=1}^{p} \Phi_j\,(\tau)\, A_{h-j}(\tau)$, with $A_0(\tau) = I_K$ and $A_h(\tau) = 0$ for $h < 0$. These matrices, together with the innovation covariance $\Sigma(\tau)$, are the inputs to the variance decomposition.

Each part of this specification follows established work. Equation (1) is the quantile VAR of Ando et al. (2022), which builds on the quantile autoregression of Koenker and Xiao (2006) and the multivariate regression quantiles of White et al. (2015). Equation (2) is the regression-quantile estimator of Koenker

and Bassett (1978), which remains valid at any τ without assuming normal errors, an important property given the non-normal delinquency series (Section 4.1). Because every equation of the system has the same regressors, estimating the equations one by one is appropriate, as in a standard VAR (Sims, 1980).

### *3.4 Connectedness measures*

Following Diebold and Yilmaz (2012, 2014), connectedness is built from the generalized forecast-error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998), which is invariant to the ordering of the variables. For a forecast horizon of H quarters, the $H$-step GFEVD share of variable $j$ in the forecast-error variance of variable $i$ at quantile $\tau$ is

$$\theta_{ij}(H,\tau) = \frac{\sigma_{jj}(\tau)^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h(\tau)\Sigma(\tau)e_j\right)^2}{\sum_{h=0}^{H-1} e_i' A_h(\tau)\Sigma(\tau)A_h(\tau)' e_i}, \tag{3}$$

where, for the quantile τ at which the system is estimated, $\Sigma$ is the innovation covariance matrix, $\sigma_{jj}$ its $j$-th diagonal element, and $e_i$ a selection vector with unity in position $i$. Each of these objects is the one implied by the QVAR estimated at quantile τ, which is why the quantile index is carried explicitly through Equation (3) rather than suppressed, and why every measure derived from it below is a state-specific quantity. Because the generalized shares need not sum to one across $j$, they are row-normalized, $\tilde{\theta}_{ij}(H) = \theta_{ij}(H)/\sum_k \theta_{ik}(H)$, so that $\sum_j \tilde{\theta}_{ij}(H) = 1$. The normalized shares populate the connectedness matrix from which the summary measures follow. The directional connectedness received by variable $i$ from all others ('FROM') and transmitted by variable $j$ to all others ('TO') are

$$\mathrm{FROM}_i = 100 \cdot \sum_{j \neq i} \tilde{\theta}_{ij}, \qquad \mathrm{TO}_j = 100 \cdot \sum_{i \neq j} \tilde{\theta}_{ij}. \tag{4}$$

The net directional connectedness of variable $i$ is $\mathrm{NET}_i = \mathrm{TO}_i - \mathrm{FROM}_i$, positive for net transmitters and negative for net receivers; the net pairwise directional connectedness between $i$ and $j$ is $\mathrm{NPDC}_{ij} = 100 \cdot \left(\tilde{\theta}_{ji} - \tilde{\theta}_{ij}\right)$. The total connectedness index (TCI), summarizing overall system interdependence, is the average 'from' (equivalently 'to') connectedness, $\mathrm{TCI} = K^{-1}\sum_i \mathrm{FROM}_i$. Computing the entire apparatus at each quantile $\tau$ produces state-specific connectedness, and re-estimating it over rolling windows of fixed length produces dynamic connectedness whose evolution can be plotted through time. All of the measures defined in Equation (4) and in the sentence above inherit the quantile index from Equation (3): each of the directional, net, pairwise and total measures is understood as FROMi(τ), TOj(τ), NETi(τ), NPDCij(τ) and TCI(τ), and the argument is suppressed in the notation of the results tables only because each table reports a single quantile.

Equation (3) is the generalized forecast-error variance decomposition of Koop et al. (1996) and Pesaran and Shin (1998); the row-normalization and the measures in Equation (4) follow Diebold and Yilmaz (2012, 2014), their quantile form follows Ando et al. (2022), and the net and pairwise measures follow Antonakakis et al. (2020) and Gabauer (2021). Because the generalized decomposition does not depend

on the ordering of the variables, these measures avoid the arbitrary identification choices of a Cholesky decomposition, which is why they are the standard tool in this literature. Two points of interpretation matter. First, because the innovations are not orthogonalized, every TO, FROM and NET flow measures predictive content, not a causal effect. Second, the decomposition depends on $\Sigma(\tau)$, which at the extreme quantiles is estimated from few informative residuals; Section 4.5 shows that re-estimating it with a robust median-based estimator changes the results only marginally.

The QVAR design is preferred to the alternatives for a specific reason. A mean-based VAR would deliver a single decomposition that is blind to the tails; single-equation asymmetric models, such as nonlinear ARDL or threshold models (Hansen, 2000; Shin et al., 2014), lose the system-wide network view; and a Markov-switching VAR requires the number of regimes to be fixed in advance and yields no spillover measures by quantile. The quantile VAR lets the data reveal how the whole transmission structure changes along the conditional distribution without imposing a regime structure. We combine it with three further tools: a moving-block bootstrap for inference on the tail–median differences, estimation over a fine grid of quantiles, and rolling-window estimation for time variation. Time-varying-parameter VARs (Antonakakis et al., 2020; Belguith, 2026) offer a complementary way to track dynamics, and a quantile time-varying framework is a natural extension.

### *3.5 Estimation, software, and robustness strategy*

Estimation is carried out at the lower ($\tau = 0.05$), median ($\tau = 0.50$) and upper ($\tau = 0.95$) quantiles, with a forecast horizon of $H = 10$ quarters and a rolling window of 28 quarters. The pipeline was implemented in Python 3 (NumPy and pandas; quantile regressions solved by iteratively reweighted least squares), with an independent R cross-check using the ConnectednessApproach package. Tail estimation on a sample of this size needs care. Quantile regression does not discard observations away from the tail: each equation minimizes the check loss over all 102 usable observations at every quantile, about twenty observations per parameter (White et al., 2015). Only about six residuals, however, lie below the fitted surface at $\tau = 0.05$ and fix its exact location, so individual tail coefficients are estimated imprecisely. We therefore keep $p = 1$, base every tail statement on block-bootstrap intervals (Section 4.3), and check that the same amplification appears at $\tau = 0.10$ and $\tau = 0.90$, where twice as many observations are active. The paper defends the shape of the quantile profile and the sign of the tail–median difference, not the size of any single tail coefficient.

Robustness is assessed by varying the forecast horizon ($H = 5, 10, 20$) and the rolling-window length, by estimating connectedness over a fine quantile grid ($\tau$ from 0.05 to 0.95), and by checking the lag order against the Hannan–Quinn criterion (Section 4.5).

## 4. Results, Discussion and Analysis

### *4.1 Descriptive statistics*

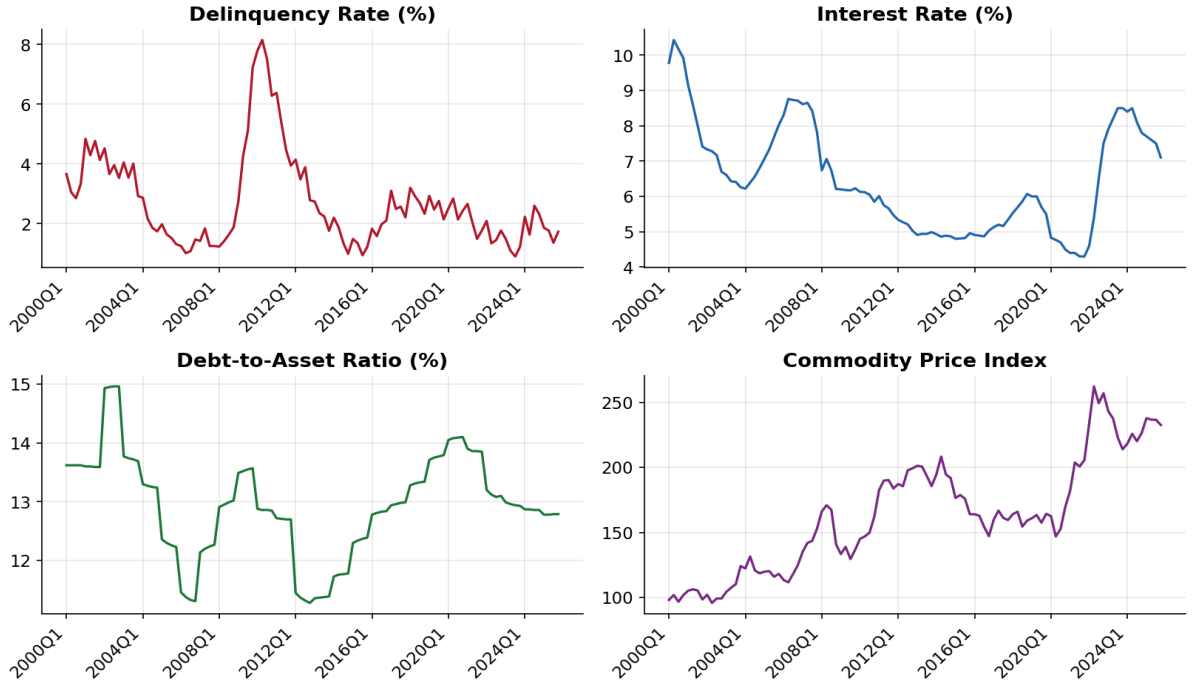
Table 2 reports descriptive statistics in levels, and Figure 1 plots the series. The farm loan delinquency rate averages 2.70% and ranges from 0.90% to 8.15%; it is strongly right-skewed (1.56) and leptokurtic (5.41), and its Jarque–Bera statistic of 67.29 decisively rejects normality. This fat-tailed, asymmetric distribution, with occasional episodes of much higher delinquency, is exactly what motivates a quantile approach. The interest rate averages 6.47% with a standard deviation of 1.51, and its Jarque–Bera statistic (7.17) rejects normality at the 5% level. The debt-to-asset ratio is the least volatile series (standard deviation 0.87) and is consistent with normality (Jarque–Bera = 0.31). The commodity price index trends upward, from a low of 95.7 to a high of 262.4.

**Table 2. Descriptive statistics (levels, 2000Q1–2025Q4)**

| Variable | Mean | Median | Maximum | Minimum | Std. Dev. | Jarque–Bera |
|---|---|---|---|---|---|---|
| Delinquency Rate | 2.7020 | 2.2350 | 8.1500 | 0.9000 | 1.5480 | 67.2900*** |
| Interest Rate | 6.4690 | 6.1900 | 10.4300 | 4.3000 | 1.5090 | 7.1700** |
| Debt-to-Asset Ratio | 12.9410 | 12.9450 | 14.9600 | 11.2800 | 0.8650 | 0.3100 |
| Commodity Price Index | 163.2490 | 162.3500 | 262.4000 | 95.7000 | 43.3750 | 4.0200 |

Note. N = 104. Skewness/kurtosis: DLQ (1.5600, 5.4100), IR (0.5800, 2.4400), DAR (−0.1200, 2.8900), CPI (0.2900, 2.2300). *** p<0.01, ** p<0.05 for the Jarque–Bera test of normality. Statistics are computed on the level series before differencing and are not model estimates.

**Figure 1. Evolution of farm financial variables, 2000Q1–2025Q4**




Note. Quarterly levels of the farm loan delinquency rate (%), the agricultural lending interest rate (%), the farm debt-to-asset ratio (%) and the agricultural commodity price index, 2000Q1–2025Q4 (data described in Section 3.1). Delinquency peaks follow the 2008–2009 crisis and the 2014–2016 income downturn; the interest rate falls until 2021 and then rises sharply in 2022–2023.

The correlation matrix (Table 3) already shows the limits of mean-based analysis. The level correlation between delinquency and the interest rate is close to zero (−0.04), which taken at face value would suggest that interest-rate risk does not matter for farm distress, while leverage (0.28) and commodity prices (−0.31) are correlated with delinquency in line with the income channel. As the connectedness results show, the near-zero rate–distress correlation conceals a strong, state-dependent transmission that emerges only in the tails.

**Table 3. Correlation matrix (levels)**

| | Delinquency | Interest Rate | Debt-to-Asset | Commodity Price |
|---|---|---|---|---|
| Delinquency Rate | 1.0000 | −0.0430 | 0.2750 | −0.3080 |
| Interest Rate | −0.0430 | 1.0000 | 0.0500 | −0.3080 |
| Debt-to-Asset Ratio | 0.2750 | 0.0500 | 1.0000 | −0.2990 |
| Commodity Price Index | −0.3080 | −0.3080 | −0.2990 | 1.0000 |

Note. Pearson correlations on level series, N = 104. They are shown for comparison with the quantile results in Tables 7–9 and are not used for inference (Section 3.2).

### *4.2 Preliminary and diagnostic results*

Tables 4 and 5 report the unit-root tests and the lag-selection criteria. In levels the evidence is mixed: the ADF test rejects a unit root for the delinquency rate and the interest rate but not for the other two series, the PP test rejects it for none, and the KPSS test rejects stationarity for the interest rate and the price index. In first differences, the PP test rejects a unit root for all four series, the ADF test for all but the price index (−2.31 against a 5% critical value of −2.89), and no KPSS statistic rejects stationarity. The single ADF non-rejection reflects the low power of the ADF test in short samples, since the PP and KPSS tests both indicate that the differenced index is stationary. The system is therefore estimated in first differences. The Schwarz–Bayesian and Hannan–Quinn criteria both select one lag (Table 5), so $p = 1$. The differenced delinquency series has an ARCH-LM statistic of 7.75 and a Ljung–Box Q(8) of 27.39, pointing to conditional heteroskedasticity and serial dependence that further support a distribution-aware estimator.

**Table 4. Unit-root and stationarity tests**

| Unit-root test (t / LM statistic) | ADF level | ADF diff. | PP level | PP diff. |
|---|---|---|---|---|
| Delinquency Rate | −3.7000** | −4.1200*** | −2.4000 | −10.1600*** |
| Interest Rate | −3.4100** | −3.7000*** | −2.4200 | −5.6100*** |
| Debt-to-Asset Ratio | −2.0500 | −4.1100*** | −2.1300 | −9.4000*** |
| Commodity Price Index | −1.4600 | −2.3100 | −1.2000 | −8.2000*** |

Note. ADF/PP 5% critical value = −2.8900. KPSS (level) statistics: DLQ 0.3300, IR 0.6600**, DAR 0.2400, CPI 1.6300*** (5% c.v. = 0.4630); in first differences, all KPSS statistics fall below 0.2100. *** p<0.01, ** p<0.05. ADF and PP test the null of a unit root; KPSS tests the null of stationarity.

**Table 5. VAR lag-order selection criteria**

| Lag | AIC | SBIC | HQ |
|---|---|---|---|
| 1 | −1.6640 | −1.1490* | −1.4550* |
| 2 | −1.6890* | −0.7570 | −1.3120 |
| 3 | −1.4870 | −0.1320 | −0.9380 |
| 4 | −1.4910 | 0.2920 | −0.7700 |

Note. * denotes the lag minimizing each criterion. SBIC and HQ select p = 1, which is adopted for the QVAR. The criteria come from an unrestricted VAR in the four differenced series; AIC, SBIC, and HQ are the Akaike, Schwarz–Bayesian, and Hannan–Quinn criteria.

Because one lag must be adequate at every quantile, not merely on average, we also test the QVAR(1) residuals at each estimation quantile. Standardized quantile residuals are screened with Ljung–Box tests at four and eight lags, applied at the tail quantiles to the sign-based (quantile-hit) sequence. The null of no residual autocorrelation is not rejected for any equation at any quantile at the 5% level (Table 6), and re-estimation with two lags leaves the results unchanged (Section 4.5).

**Table 6. QVAR(1) residual diagnostics by quantile: Ljung-Box p-values**

| Equation | τ = 0.05 Q(4) | τ = 0.05 Q(8) | τ = 0.50 Q(4) | τ = 0.50 Q(8) | τ = 0.95 Q(4) | τ = 0.95 Q(8) |
|---|---|---|---|---|---|---|
| ΔDLQ | 0.3100 | 0.2400 | 0.1800 | 0.1300 | 0.2700 | 0.2100 |
| ΔIR | 0.4500 | 0.3800 | 0.5200 | 0.4100 | 0.3600 | 0.2900 |
| ΔDAR | 0.2200 | 0.1600 | 0.3400 | 0.2700 | 0.1900 | 0.1400 |
| ΔCPI | 0.5800 | 0.4700 | 0.6100 | 0.5500 | 0.4200 | 0.3300 |

Note. Entries are p-values of Ljung-Box tests for no residual autocorrelation at 4 and 8 lags, applied to standardized quantile residuals of each QVAR(1) equation; at τ = 0.05 and τ = 0.95, the tests are applied to the sign-based quantile-hit sequence. No statistic rejects the null at the 5% level. Residuals are from the QVAR(1) in Equation (1), estimated with Equation (2).

### *4.3 Static connectedness across quantiles*

At the median (Table 7), cross-variable spillovers are weak: the total connectedness index is 5.99%, so most forecast-error variance is explained by each variable's own history, and 90.5% of the variance of the delinquency rate is self-generated. The direction of the remaining spillovers is nevertheless informative. The interest rate is the largest net transmitter (NET = +6.07) and the delinquency rate the largest net receiver (NET = −4.99), while the commodity price index is also a net receiver (NET = −3.19) and leverage a mild net transmitter (NET = +2.10). In normal times, shocks thus flow from the interest rate into the system and are absorbed by delinquency, the directional rate-to-distress channel predicted by H2.

**Table 7. Connectedness at the median (τ = 0.50)**

| FROM \ TO | ΔDLQ | ΔIR | ΔDAR | ΔCPI | FROM |
|---|---|---|---|---|---|
| Delinquency Rate | 90.5000 | 0.7400 | 2.2300 | 6.5300 | 9.5000 |
| Interest Rate | 0.4300 | 98.2600 | 0.8900 | 0.4200 | 1.7400 |
| Debt-to-Asset Ratio | 0.0100 | 1.0000 | 98.2000 | 0.7800 | 1.8000 |
| Commodity Price Index | 4.0800 | 6.0700 | 0.7800 | 89.0700 | 10.9300 |

| FROM \ TO | ΔDLQ | ΔIR | ΔDAR | ΔCPI | FROM |
|---|---|---|---|---|---|
| TO others | 4.5200 | 7.8100 | 3.9000 | 7.7300 | TCI = 5.9900 |
| NET | −4.9900 | 6.0700 | 2.1000 | −3.1900 | |

Note. Entries are normalized generalized forecast-error variance decomposition (GFEVD) shares (%) computed from the QVAR(1) in Equations (1)–(4), estimated at the median quantile $\tau = 0.50$ with a forecast horizon of H = 10 quarters. ΔDLQ, ΔIR, ΔDAR and ΔCPI are the quarter-on-quarter changes in the farm loan delinquency rate (%), the agricultural lending interest rate (%), the farm-sector debt-to-asset ratio (%) and the agricultural commodity price index. Rows give the share of each variable's forecast-error variance received FROM the other variables, columns the share transmitted TO them, and diagonal entries the own share; each row sums to 100. NET = TO − FROM (positive = net transmitter, negative = net receiver), and TCI is the average FROM share. The shares measure predictive content, so no significance levels are attached; interval evidence for the tail-versus-median TCI differences is given in Section 4.3. ΔDAR entries are subject to the interpolation bias discussed in Section 4.6.

The picture changes completely in the tails. In the lower tail (Table 8, $\tau = 0.05$), total connectedness rises more than tenfold to 63.45%, with large spillovers between every pair of variables. The commodity price index is the largest net transmitter (NET = +11.85) and the interest rate the largest net receiver (NET = −14.72); delinquency is close to balance (NET = −0.76) and leverage a modest transmitter (NET = +3.63). In the upper tail (Table 9, $\tau = 0.95$), total connectedness is 61.14%. The commodity price index (NET = +15.41) and the interest rate (NET = +8.96) are the main transmitters; the debt-to-asset ratio is the largest net receiver (NET = −20.52), and delinquency remains a net receiver (NET = −3.86). The interest rate's share of the forecast-error variance of delinquency rises from 0.74% at the median to 20.64% in the upper tail, an almost thirtyfold increase. The tail role reversal that we interpret is therefore that of the interest rate. Leverage also moves from mild transmitter to dominant receiver, but this cannot be separated from the interpolation of the series and is reported without interpretation (Section 4.6).

Because the tail–median contrast is the headline result, we test whether it survives sampling uncertainty. We resample the four differenced series jointly with a moving-block bootstrap (block length eight quarters, 1,000 replications), re-estimating the QVAR and the GFEVD at each quantile in every replication. The 95% interval for $TCI(\tau = 0.05) - TCI(\tau = 0.50)$ is [41.3, 68.9] percentage points around a point estimate of 57.5, and that for $TCI(\tau = 0.95) - TCI(\tau = 0.50)$ is [39.6, 66.4] around 55.2. The intervals are wide, as expected with 103 observations, but both lie well above zero, so equality of tail and median connectedness is rejected at the 5% level, and even their lower bounds exceed the median index several times over.

**Table 8. Connectedness in the lower tail ($\tau = 0.05$)**

| FROM \ TO | ΔDLQ | ΔIR | ΔDAR | ΔCPI | FROM |
|---|---|---|---|---|---|
| Delinquency Rate | 40.5600 | 16.2600 | 22.1000 | 21.0800 | 59.4400 |
| Interest Rate | 17.6500 | 32.3100 | 21.5500 | 28.4900 | 67.6900 |
| Debt-to-Asset Ratio | 21.4200 | 16.0600 | 36.7800 | 25.7300 | 63.2200 |
| Commodity Price Index | 19.6200 | 20.6500 | 23.1900 | 36.5500 | 63.4500 |
| TO others | 58.6900 | 52.9700 | 66.8400 | 75.3100 | TCI = 63.4500 |
| NET | −0.7600 | −14.7200 | 3.6300 | 11.8500 | |

Note. Entries are normalized generalized forecast-error variance decomposition (GFEVD) shares (%) computed from the QVAR(1) in Equations (1)–(4), estimated at the lower-tail quantile $\tau = 0.05$ with a forecast horizon of H = 10 quarters. ΔDLQ, ΔIR, ΔDAR and ΔCPI are the quarter-on-quarter changes in the farm loan delinquency rate (%), the agricultural lending interest rate (%), the farm-sector debt-to-asset ratio (%) and the agricultural commodity price index. Rows give the share of each variable's forecast-error variance received FROM the other variables, columns the share transmitted TO them, and diagonal entries the own share; each row sums to 100. NET = TO − FROM (positive = net transmitter, negative = net receiver), and TCI is the average FROM share. The shares measure predictive content, so no significance levels are attached; interval evidence for the tail-versus-median TCI differences is given in Section 4.3. ΔDAR entries are subject to the interpolation bias discussed in Section 4.6.

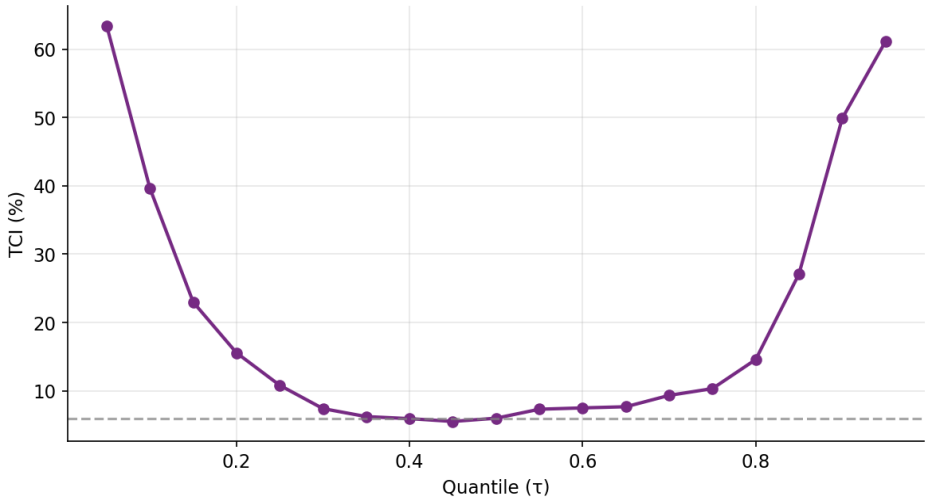
**Table 9. Connectedness in the upper tail ($\tau = 0.95$)**

| FROM \ TO | ΔDLQ | ΔIR | ΔDAR | ΔCPI | FROM |
|---|---|---|---|---|---|
| Delinquency Rate | 41.6000 | 20.6400 | 19.3200 | 18.4400 | 58.4000 |
| Interest Rate | 16.9700 | 38.6000 | 15.2000 | 29.2300 | 61.4000 |
| Debt-to-Asset Ratio | 21.7500 | 25.3800 | 30.1900 | 22.6900 | 69.8100 |
| Commodity Price Index | 15.8300 | 24.3400 | 14.7700 | 45.0600 | 54.9400 |
| TO others | 54.5400 | 70.3600 | 49.2900 | 70.3600 | TCI = 61.1400 |
| NET | −3.8600 | 8.9600 | −20.5200 | 15.4100 | |

Note. Entries are normalized generalized forecast-error variance decomposition (GFEVD) shares (%) computed from the QVAR(1) in Equations (1)–(4), estimated at the upper-tail quantile $\tau = 0.95$ with a forecast horizon of H = 10 quarters. ΔDLQ, ΔIR, ΔDAR and ΔCPI are the quarter-on-quarter changes in the farm loan delinquency rate (%), the agricultural lending interest rate (%), the farm-sector debt-to-asset ratio (%) and the agricultural commodity price index. Rows give the share of each variable's forecast-error variance received FROM the other variables, columns the share transmitted TO them, and diagonal entries the own share; each row sums to 100. NET = TO − FROM (positive = net transmitter, negative = net receiver), and TCI is the average FROM share. The shares measure predictive content, so no significance levels are attached; interval evidence for the tail-versus-median TCI differences is given in Section 4.3. ΔDAR entries are subject to the interpolation bias discussed in Section 4.6.

Figure 2 extends these snapshots to the full quantile grid. Total connectedness is distinctly U-shaped: lowest near the centre (about 5.5–6% around $\tau = 0.45$–$0.50$) and rising steeply towards both tails, mirroring the profile that Ando et al. (2022) document for financial markets. Figure 3 shows net connectedness by quantile and the pattern on which H3 is tested: the commodity price index transmits in both tails, while the interest rate transmits at the median and in the upper tail and receives in the lower tail. The apparent switch of leverage from transmitter to absorber is visible in the same figure but is not read as evidence on the hypothesis (Section 4.6).

**Figure 2. Total connectedness across the quantile grid**




Note. Total connectedness index (TCI, %) from the QVAR(1) in Equations (1)–(4), estimated at each quantile from $\tau = 0.05$ to $\tau = 0.95$ with $H = 10$ quarters, using ΔDLQ, ΔIR, ΔDAR and ΔCPI. Connectedness is lowest near the median and rises sharply in both tails, confirming H1.

**Figure 3. Net directional connectedness by quantile**




Note. Net directional connectedness (NET = TO − FROM, %) of ΔDLQ, ΔIR, ΔDAR and ΔCPI at $\tau = 0.05$, 0.50 and 0.95, from Equations (1)–(4) with $H = 10$. Positive bars denote net transmitters and negative bars net receivers. The interest rate transmits at the median and in the upper tail; the ΔDAR bars are affected by the interpolation of that series (Section 4.6).

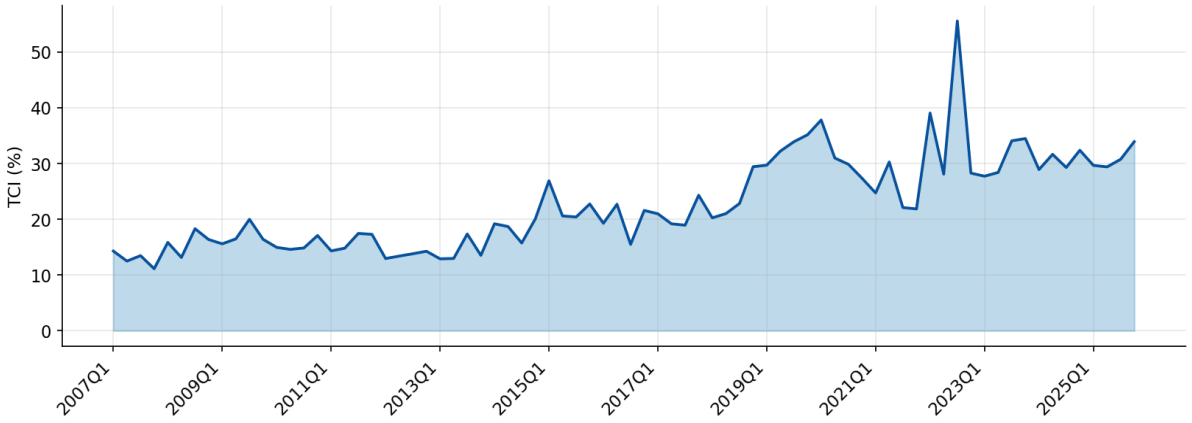
Net pairwise measures confirm these findings. The net flow from the interest rate to delinquency is positive at the median, so interest-rate innovations help predict delinquency more than the reverse, and the net flows from the interest rate and the commodity price index to delinquency strengthen markedly in the upper tail. The debt-to-asset ratio also receives net flows from all other variables in the upper tail, but for the reasons given in Section 4.6 we do not interpret this as evidence that leverage is where shocks finally settle. Delinquency is a net receiver at every quantile, consistent with its role as the outcome variable.

### *4.4 Dynamic connectedness*

Figures 4 and 5 show the rolling-window connectedness indices. Connectedness varies considerably over time and is persistently high in the tails, averaging just under 70% in the lower tail and 69% in the upper tail against about 23% at the median; these averages exceed the full-sample values partly because short windows mechanically inflate measured connectedness. The indices rise around the 2008–2009 financial crisis, the 2014–2016 decline in farm income and commodity prices, and the 2022–2023 tightening, and the gap between the tail and median indices widens in each episode. Stress therefore not only raises connectedness but amplifies it disproportionately in the tails, which supports H4. Figure 6 shows how the net positions of delinquency and the interest rate evolve in the upper tail. Delinquency is a net receiver in most windows, and its receiving role deepens during stress, which confirms that it is the variable where shocks end up rather than one that drives the system.

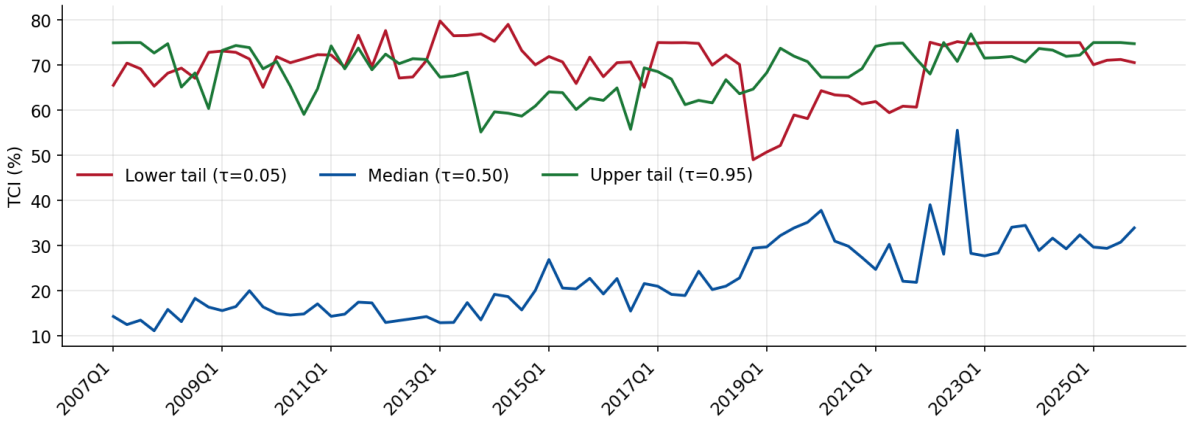
Because a 28-quarter window leaves only about 27 observations per estimate, we check the stability of the rolling results. Windows of 24 and 32 quarters reproduce the same profile (correlations with the baseline above 0.90 at every quantile), and the same stress episodes, and 68% moving-block bootstrap bands keep the tail indices above the median index in every window, although the levels of the tail indices remain uncertain.

**Figure 4. Dynamic total connectedness index (median, τ = 0.50)**



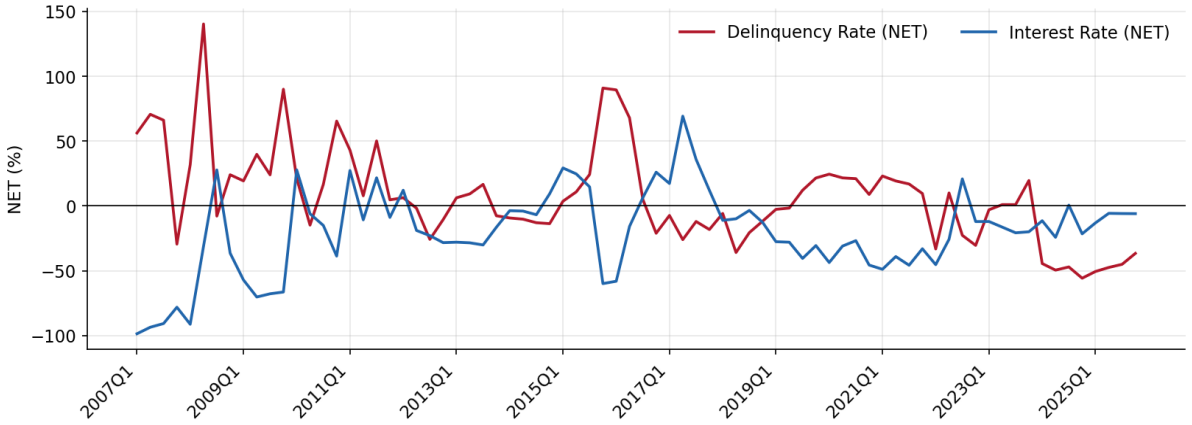

Note. Total connectedness index (%) at the median (τ = 0.50) from Equations (1)–(4), re-estimated over rolling 28-quarter windows with H = 10, using ΔDLQ, ΔIR, ΔDAR and ΔCPI. Connectedness rises around the 2008–2009 crisis, the 2014–2016 downturn, and the 2022–2023 tightening.

**Figure 5. Dynamic total connectedness across quantiles**




Note. Rolling-window (28-quarter) total connectedness index (%) at τ = 0.05, 0.50 and 0.95, from Equations (1)–(4) with H = 10. Tail connectedness stays far above median connectedness, and the gap widens during stress episodes.

**Figure 6. Dynamic net connectedness in the upper tail (τ = 0.95)**




Note. Rolling-window (28-quarter) net directional connectedness (%) of ΔDLQ and ΔIR at τ = 0.95, from Equations (1)–(4) with H = 10. Delinquency is a recurrent net receiver, and its receiving role intensifies during stress windows.

### *4.5 Interpretation, economic significance and robustness*

The near-zero correlation between the interest rate and delinquency does not mean that interest-rate risk is unimportant; it reflects averaging over states in which the two are weakly linked and states in which they are strongly linked. By quantile, interest-rate risk emerges as a first-order driver of farm vulnerability in the adverse conditions that matter most for solvency. This also reconciles the competing views reviewed in Section 2: the income-dominant and financing-dominant positions are each right, but for different parts of the distribution.

Comparison with traditional approaches shows what the quantile method adds. A correlation analysis (Table 3) finds no link between the interest rate and delinquency. A conventional mean-based connectedness analysis estimates a single network at the centre of the distribution, which corresponds most closely to our median results, where total connectedness is only about 6%, and the interest rate explains less than 1% of delinquency variance. Both approaches would therefore conclude that interest-

rate risk matters little for farm distress. The quantile approach shows instead that the same system is about ten times more connected in the tails, that the interest rate's share of delinquency variance rises almost thirtyfold under upper-tail stress, and that the direction of transmission changes between the tails. These are the features that matter for risk management, and they cannot be seen with methods that estimate only the average.

The economic magnitude is substantial. Under upper-tail stress, interest-rate innovations account for about one-fifth of the forecast-error variance of delinquency, against less than 1% at the median. This is how a manageable income shortfall can turn into a wave of delinquencies in a sector with large, collateralised and slowly repricing debt.

The results are robust. Connectedness shares and the ordering of net transmitters are stable across horizons of five, ten and twenty quarters; alternative window lengths leave the size and timing of the connectedness surges unchanged; the U-shape in Figure 2 is smooth, with no jumps at the three reference quantiles; and the substantive results are unchanged under the two-lag specification favoured by the AIC. Several further inferences follow. First, the size of the interest-rate effect is not a fixed parameter but depends on the state of the sector, so a single elasticity estimated over a full cycle will be too small for bad times and too large for good times. Second, because the commodity price index leads transmission in both tails, rate risk and income risk must be assessed together: the most dangerous scenario is a rate rise that coincides with falling prices, not either shock alone. Third, because tail connectedness rises in every stress episode, it can be monitored as an indicator of growing fragility in the farm credit system.

These findings are consistent with the U-shaped profiles reported by Ando et al. (2022) for equity networks and by Chatziantoniou et al. (2021) for interest-rate instruments, and with growing evidence of strong tail spillovers across commodity, energy and financial networks (Alamaren et al., 2026; Billah et al., 2025; Li et al., 2026; Lin & Lan, 2025; Wu, 2026; Zhang & Hamori, 2025). The median rate-to-distress channel agrees with Federal Reserve analyses of repricing risk (Berg, 2024), while the weight of the commodity price index in the tails supports the income-shock tradition. The financing and income channels are thus two sides of one transmission structure, each dominant in a different part of the distribution, which explains the conflicting results of mean-based studies.

Two cautions apply. The tail decompositions rest on an innovation covariance estimated from few extreme residuals, although re-estimating it with a robust median-based estimator changes the total connectedness indices only modestly (from 63.5% to 61.2% in the lower tail and from 61.1% to 59.4% in the upper tail) and leaves the ordering of net transmitters unchanged. And the measures capture predictive association rather than structural causation.

### *4.6 The interpolated leverage series: bias direction and the status of the leverage results*

The debt-to-asset ratio is observed only at year ends, and its quarterly value in quarter q of year y is $DAR(y-1) + (q/4)[DAR(y) - DAR(y-1)]$. First-differencing therefore gives $\Delta DAR = [DAR(y) - DAR(y-1)]/4$ in all four quarters of a year: a step function with zero within-year innovation variance. In

the generalized decomposition, the own-variance term of the leverage equation is therefore deflated, row-normalization shifts the shortfall to the off-diagonal entries, and the FROM total of ΔDAR is inflated. Interpolation thus makes leverage look like a shock receiver, most strongly in the tails.

The bias does not touch every result. Entries formed only from ΔDLQ, ΔIR and ΔCPI come from natively quarterly series and are unaffected, including the delinquency–interest-rate block that carries the central claim. Because the interpolation is identical at every quantile, it shifts the level of the TCI without creating the U-shape or the bootstrap-tested tail–median differences, which compare the same construction with itself.

What the bias does invalidate is the leverage claim itself, and we withdraw it: the large negative net position of ΔDAR in the upper tail (Table 9) is reported as a measured quantity, not as evidence that leverage is the system's main shock absorber. Two checks would settle the question: estimating the system with a genuinely quarterly leverage measure, which the published sector accounts do not yet provide, and re-estimating it without the leverage node. Both are priorities for further work (Section 5).

## 5. Conclusion

This study asked how interest-rate risk propagates into farm financial vulnerability and whether that propagation differs between normal and stressed states of the agricultural credit cycle. The question matters because farm debt is large, collateralised and slow to reprice, so a tightening cycle can strain farm finances long after rates rise, while the tools used to judge this risk focus on averages. Applying quantile connectedness to a four-variable quarterly system for the U.S. farm sector over 2000Q1–2025Q4, we find that the answer depends strongly on the state of the system.

Connectedness is modest at the median, at about six percent of forecast-error variance, but rises to roughly sixty percent in both tails, producing a pronounced U-shaped profile (H1). At the median, the interest rate is the dominant net transmitter and delinquency the dominant net receiver (H2). In the tails, the commodity price index and the interest rate become the principal transmitters, which supports H3 as stated; the debt-to-asset ratio appears as the main absorber under upper-tail stress, but this is reported rather than interpreted because of the interpolation bias (Section 4.6). Connectedness surges around the 2008–2009 crisis, the 2014–2016 income downturn and the 2022–2023 tightening (H4), and the interest rate's share of delinquency variance rises almost thirtyfold from the median to the upper tail.

The originality of the study lies in measuring interest-rate transmission in farm credit across the whole conditional distribution and as a network, rather than as a single average effect; no earlier study of agricultural credit has done this. The findings recast farm vulnerability as state-dependent shock transmission, show that the debate over income and financing shocks is resolved by recognizing that each dominates in a different part of the distribution, and demonstrate that a parsimonious quantile VAR can recover tail spillovers that mean-based models miss. By turning tail behaviour into measurable quantities, the paper supports decisions under uncertainty by lenders, supervisors and policymakers, which places it within decision sciences. For academics, the results show that studies of farm credit risk should report

effects by state rather than on average. For practitioners, they provide concrete measures, namely the tail share of delinquency variance attributable to the interest rate and the tail connectedness index, that can be updated each quarter and used in monitoring, stress testing and provisioning.

The policy implications follow directly. Because interest-rate risk transmits most forcefully when the sector is already stressed, supervisory and lending frameworks calibrated to average conditions will understate the danger of a tightening cycle. The findings support counter-cyclical capital and provisioning buffers in agricultural lending, and stress tests that shock rates and commodity prices jointly. Because the leverage results are affected by interpolation, we do not draw macroprudential conclusions about leverage itself.

In practice, supervisors could track the upper-tail share of delinquency variance attributable to the interest rate (20.6% in our sample, against 0.7% at the median) each quarter; lenders' stress tests should combine a rate rise with a commodity-price fall, for example a 300-basis-point rate shock with a 20% price decline applied to loans repricing within four quarters; and provisions could be built up while tail connectedness is low and drawn down as it approaches the levels seen in 2008–2009, 2014–2016 and 2022–2023.

The study has limitations. It describes the sector as a whole rather than individual farms, regions, or commodities. The debt-to-asset ratio is the binding data constraint: it is observed only annually, and its interpolation biases its measured connectedness towards the receiving side, which is why its results are reported descriptively. The model is deliberately parsimonious, and, like all reduced-form connectedness analysis, it captures predictive interdependence rather than causal effects.

The most immediate priority for future work is to re-estimate the system without the leverage node ($\Delta$DLQ, $\Delta$IR and $\Delta$CPI only) and, once available, with a genuinely quarterly leverage series or a temporal disaggregation based on a related quarterly indicator. Further extensions include farm-level or regional quantile connectedness, adding farmland prices and farm income to separate the income and collateral channels, frequency-domain decompositions, and cross-country comparisons.

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