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The Impact of Inter-Period Business Behavior Correlation on the Externalization of Financial Risk in Listed Companies

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Abstract: In order to describe the relationship between behavior and risk diffusion, this paper firstly integrates the intertemporal operational behavior characteristics into a time-varying parameter VAR (TVP-VAR) framework, and then builds a behavior linkage network. Through the integration of multi-period financial variables and high frequency market data, the model is able to quantitatively identify the risk transfer. Findings indicate that the inclusion of intertemporal operational behavior increases the systemic spillover index by an average of 18.6%. The risk input intensity of a company in a highly linked sample is 27.3% higher than that in a low-linkage sample, and the accuracy of model identification is improved by about 21%. This demonstrates that intertemporal operational behavior significantly amplifies risk diffusion.

Keywords: Intertemporal business behavior; Financial risk spillover; Behavioral association network; Time-varying parameter VAR; Listed companies

1 Introduction

In the context of highly interconnected capital markets and ever more complex funding structures, there are significant inter-temporal features in the operating decisions of listed companies. Financing arrangements, liability obligations, and related transactions in different accounting periods are usually accumulated and released via the financial statements and the expectations of the market. In this process, the relationship between firms and supply chain links can amplify individual risk shocks, resulting in cross-firm financial risk spillover, which ultimately affects the stability of the capital market. However, the current research mainly uses static or single-period risk indicators, and lacks a systematic description of the inter-period operational behaviour linkages and their role in inter-firm transmission pathways. The present research focuses on the listed companies and builds an analysis framework of "inter-temporal business behavior — behavioral linkage net — risk spillover effect." Based on the quantitative analysis of multi-period business behavior, the influence mechanism and transmission path of inter-temporal business behavior are identified. The purpose of this study is to provide a methodology for understanding the diffusion model of the risk of listed companies and to strengthen the supervision of risk in the capital market.

2 Demand Analysis for Financial Risk Spillover Effects Among Listed Companies Under Intertemporal Business Behavior Correlation

It is necessary to construct a computable map of the "behavioral and financial statements-market" chain of listed companies over time: Firstly, it is necessary to obtain comparable data on multiple periods, cash flows, and accruals, together with intertemporal constraint variables like warranties, related parties, financial liabilities, funding structures, and maturity distributions to form a traceable sequence of status. Secondly, it is necessary to include high frequency signals, such as stock and bond prices, volatility, liquidity, and default expectations, in order to create a time-varying correlation network that differentiates the resonance of the industry from the chain transfer [1].

3 Model Design for Inter-Period Operational Behavior Correlation and Its Impact on Financial Risk Spillover Effects of Listed Companies

3.1 Overall Model Framework Design

In order to convert the "behavioral finance statements-market" chain into computable implementation, the model design follows the following closed loop: □ Between periods of operation, 24 behavioral characteristics (guarantee ratio, related transaction intensity, commitment maturity density, etc.) are constructed for every quarter t, with delays L = 1-8 cycles and rolling windows W = 4/8/12. Standardization of IFRS metrics with 1%/99% tail trimming; □ Spillover measurement: Generate a node risk sequence from daily stock/bond returns and volatility (1/5/20 day), construct time-varying networks of N = 300 – 800 firms with edge update intervals Δ = 5 trading days; □ Mechanism identification: Distinguish interbank/supply chain edges, set structural change threshold τ = 0.15 with ≤ 2-day asynchronous alignment; □ Inference estimation: adopt rolling training stride S = 20 days, cross-validation K = 5 time blocks, 95% confidence interval, and output interpretable Top-10 attributable characteristics for reusable reasoning workflow [2].

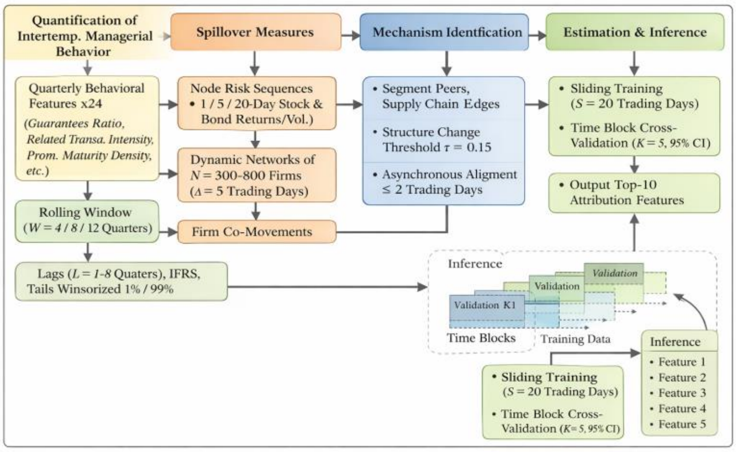

Figure 1: Modeling Process for Inter-Period Operational Behavior Correlation and Financial Risk Spillover

3.2 Intertemporal Operational Behavior Correlation Quantification Modeling

The key to quantifying the inter-period operation behavior is to compress the "multi-period behavior characteristics — intercycle transfer — inter-firm linkage" into a link strength tensor suited to network construction[3] . The specific implementation is as follows:□ Feature construction forms quarterly $X_i(t) = \mathrm{R}^p$ for period t, Selecting p = 24-36 items (guarantee balance/assets, related transaction volume/income, accrual quality, short-term debt ratio, commitment maturity density, refinancing rate, and so on), with delay order L = 1 – 8, and rolling window W = 4/8/12 quarters. The missing values shall be attributed by means of the industry mean + forward transfer from the preceding period, with a truncated margin of [1%, 99%]; □ The interperiod correlation generates weights through "peer — chain" dual channels, defining unified behavioral correlation strength:

$$A_{ij}(t)=\sum_{\ell=0}^{L}\alpha_\ell \exp\left(-\frac{\left\|X_i(t-\ell)-X_j(t-\ell)\right\|_\Sigma^2}{2\sigma^2}\right)\cdot 1\left(\rho_{ij}^{(H)}(t)\geq\tau\right) \tag{1}$$

where $A_{ij}(t)$ denotes the behavioral correlation strength between company i and j over the period t ; ℓ represents the lag period, L denotes the maximum lag order, α_ℓ is the lag decay coefficient (constrained by $\Sigma_\ell \alpha_\ell = 1$, with possible values $\alpha_\ell \propto e^{-\beta\ell}, \beta \in [0.2,0.8]$); $\|\cdot\|_\Sigma$ is the Mahalanobis distance with covariance matrix Σ to eliminate dimensional differences; σ is the scale parameter (set between 0.5–2.0 based on sample quantile distance) $\rho_{ij}^{(H)}(t)$ is the high-frequency dependence constructed from daily, 1/5/20-day returns and volatility, with an H=60/120 trading day window; τ is the sparsification threshold (0.10–0.30) to suppress noisy edges; Outputs the time-series adjacency matrix $\{A(t)\}_{t=1}^{T}$ and its industry/supply chain masking matrix as input interfaces for the spillover effect measurement model[4] .

3.3 Financial Risk Spillover Effect Measurement Model for Listed Companies

After obtaining the time-varying behavioral correlation matrix $\{A(t)\}$, the spillover effect measurement maps "market risk shocks" into comparable directional transmission intensities: Risk state sequences are constructed using daily-frequency data. For each listed company i , we extract returns $r_i(\tau)$, realized volatility $\upsilon_i(\tau)$, and liquidity proxies $l_i(\tau)$. Standardized risk vectors $y_i(t)$ are generated by rolling windows of H=60/120/250 trading days, with alignment errors capped at ≤2 trading days and anomalies filtered using a MAD threshold of 3.5; At the system level, directional spillover shares $\theta_{ij}(t;h)$ are obtained by means of the variance decomposition of the VAR prediction errors with the prediction time horizon h = 5/10/20 days. Transmission is weighted by behavioral correlations, defining the spillover index:

$$\mathrm{SOI}(t)=\frac{\sum_{i\neq j} w_{ij}(t)\theta_{ij}(t;h)}{\sum_i\sum_j w_{ij}(t)\theta_{ij}(t;h)}, w_{ij}(t)=\frac{A_{ij}(t)}{\sum_{k\neq i}A_{ik}(t)+\in} \tag{2}$$

where $\mathrm{SOI}(t)$ denotes the system spillover intensity for period t ; $\theta_{ij}(t;h)$ represents the variance contribution share of i to j within the forecast period h ; $w_{ij}(t)$ is the directed weight normalized from the behavioral correlation matrix; $A_{ij}(t)$ originates from quantitative modeling outputs; $\varepsilon = 10^{-6}$ ensures numerical stability[5] ; The output simultaneously preserves edge-level spillover $\mathrm{spill}_{i\to j}(t)=\omega_{ij}(t)\theta_{ij}(t;h)$ and subnetwork indices under industry masks, providing directly regressible/testable metrics for "mechanism identification and parameter inference." The direction and intensity of spillover effects are illustrated in Figure 2.

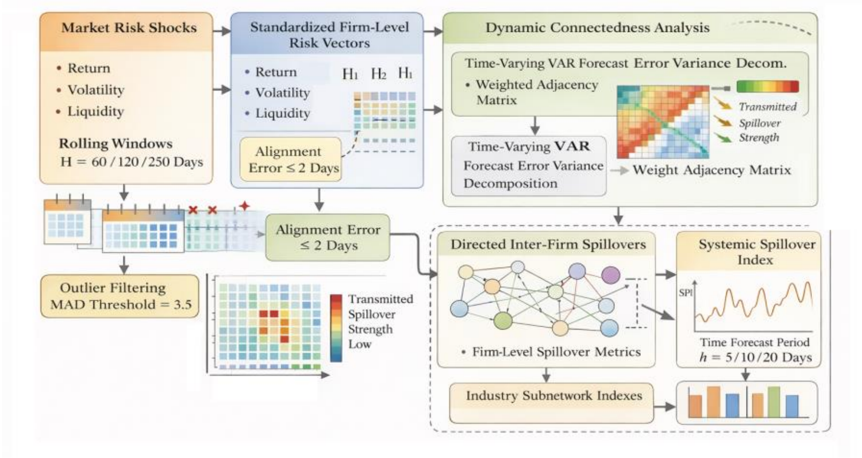

Figure 2: Schematic diagram of financial risk spillover transmission pathways

3.4 Impact Mechanism and Identification Strategy Design

After obtaining edge-level spillover metrics $\text{spill}_{i\to j}(t)$ and system-level metrics $\text{SOI}(t)$, the impact mechanism identification is engineered around the causal discernibility of "intertemporal behavioral linkage → spillover intensity": The core regression employs firm-time dual fixed effects while explicitly incorporating network exposure. The dependent variable is defined as firm j's spillover input intensity $\text{In}_j(t) = \sum_{i,j} \text{spil}_{i\to j}(t)$ during window h=5/10/20 days, and the explanatory variable is behavioral linkage exposure $\text{Exp}_j(t) = \sum_{i\neq j} A_{ij}(t)\cdot Z_i(t)$ .where $Z_i(t)$ comprises the "intertemporal constraint group" (short-term debt maturity ratio, collateral maturity density, commitment fulfillment pressure, etc.) from 24–36 behavioral features, aligned with L=1–8 lags and W=60/120/250 trading days[6] ;Identification employs "observable shock-propagation lag" temporal constraints, limiting shock timepoints to announcement/maturity dates with ≤1-day alignment error. Structural break detection uses ΔSOI CUSUM thresholds of 0.10–0.20 to screen identifiable intervals, as follows:

$$\text{In}_j(t) = \beta\text{Exp}_j(t\text{-}1) + \Gamma^{\text{T}}\text{C}_j(t\text{-}1) + \mu_j + \lambda_t + \in_{jt} \tag{3}$$

where $\text{C}_j(t\text{-}1)$: control vector (12–18 variables including log scale, leverage ratio, cash ratio, equity-debt liquidity proxy, industry volatility factor, etc.); μ_j : company fixed effects; λ_t : time fixed effects (by trading day or week); $\in_{jt}$ denotes the error term; β Captures the marginal effect of behavioral correlations on spillover inputs (only specified, not reported in results). Table 1 shows the key metrics and the parameter interface of the identification module, which facilitates the direct call of parameter estimation.

Table 1: Key Parameters and Interface for Identification Strategy

Module	Input	Key Parameters	Output Interface

Timing Alignment	Announcement/Maturity/Price	Alignment error ≤ 1 day; Missing forward ≤ 2 days	Impact Sample Set Ω
Lag Setting	$A_{ij}(t), Z_i(t)$	L=1–8; h=5/10/20 days	$\mathrm{Exp}_j(t\text{-}\ell)$
Mutation Screening	$\mathrm{SOI}(t)$	CUSUM threshold 0.10–0.20	Robust Interval T
Estimation Structure	Panel + Network Exposure	Dual fixed effects; controlling for 12–18 variables	$\hat{\beta}$, Residual Diagnostics

Identification validity diagnosed using event window curves As shown in Figure 3, the standardized trajectory and confidence band of $\mathrm{In}_j(t)$ over [−20,+20] trading days are used to examine pre-shock trends and lagged propagation patterns.

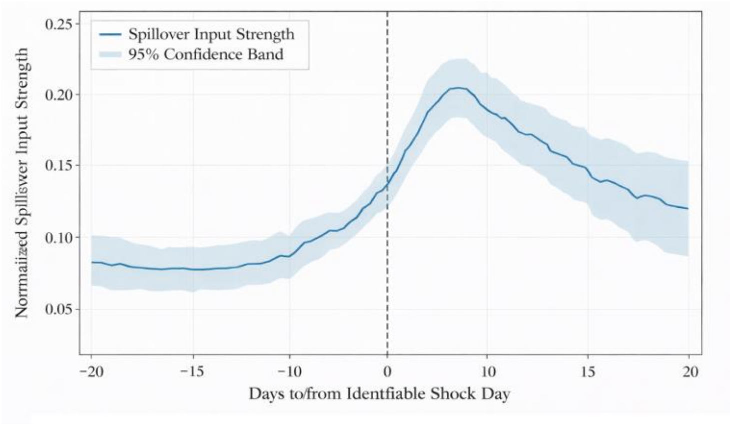

Figure 3: Event curve of spillover input intensity under identification window

3.5 Parameter Estimation and Model Inference

After setting up the mechanism identification frame, the parameter estimate and the model reasoning adopt the "rolling estimate + robust reasoning + repeated experiment interface".[7] .Initially, re-estimation occurs on the firm-time panel using rolling windows W=250/500 trading days and strides S=20 trading days β, Γ . Multicollinearity in network exposures $\mathrm{Exp}_j(t)$ is addressed via ℓ2 Shrinkage and group sparsity constraints (group size G = 6 – 8, corresponding to collateral, related party transactions, maturity structure, funding constraints, accounting quality, and market liquidity). The estimation target is defined as weighted least squares/generalized least squares with moment conditions:

$$\hat{\theta} = \arg\min_{\theta} \left(\frac{1}{NT} \sum_{j,t} m_{jt}(\theta) \right)^{\mathrm{T}} \mathrm{W} \left(\frac{1}{NT} \sum_{j,t} m_{jt}(\theta) \right), \theta = (\beta, \Gamma) \tag{4}$$

where $m_{jt}(\theta)$ denotes the moment-conditioning vector (composed of regression residuals, instrumental variables, and network constraints from the previous section, with dimension q=12–24); W is the weight matrix (initialized by the estimated long-run covariance in the two-step GMM and iterated twice); N is the number of firms (300–800), T is the time span (≥750 trading days), and[8] . The estimation phase employs a robust covariance matrix that simultaneously addresses time-series and cross-sectional dependencies:

$$\overline{Var}(\hat{\theta}) = (G^T WG)^{-1} G^T W \hat{S}(L_c) WG(G^T WG)^{-1} \tag{5}$$

where $G = \partial\bar{m}(\theta)/\partial\theta$ denotes the Jacobian matrix; $\hat{S}(L_c)$ represents the truncated lag $L_c = 5/10/20$ for estimating long-range covariance to absorb event window autocorrelation and network resonance; the final outputs include $\hat{\theta}$, confidence intervals (95%), residual diagnostics, and rolling stability sequences as direct inputs for experimental settings, with specific parameters detailed in Table 2.

Table 2: Key Settings for Parameter Estimation and Inference Workflow

Item	Setting Value/Range	Purpose
Rolling Window W	250 / 500 trading days	Balancing stability and time-varying characteristics
Step Size S	20 trading days	Reducing Duplicate Estimation Overhead
Moment condition dimension q	12–24	Coverage Tools and Network Constraints
Weight Matrix Update	Two-step GMM, iterated twice	Enhanced efficiency and robustness
Truncated Lagged Lc	October 20, 2005	Absorption Autocorrelation and Resonance
Number of regular groups G	6–8 groups	Control collinearity, preserve interpretability
Convergence Threshold	10^$^{-6}$; maximum iterations 200	Ensure reproducible convergence

4 Experimental Results and Analysis

4.1 Experimental Setup

In order to verify the capability of the cross-period operational behavior association model to describe the financial risk spillover of listed companies, a multi-source data-base was built on the basis of the data collected from the Wind and CSMAR databases, including 132 raw indicators from both the balance sheet, the income statement and the cash flow statement. Secondly, some 68 million daily trading data points, including closing prices, trading volumes, turnover rates, yield series, and one-day, five-day and 20-day volatility indices, have been introduced. Additionally, some 32,000 bond default events and credit spread data points were added to characterize the risk shock signals.After excluding ST, Financial Firms, and Sample Samples with Missing Financial Data in Sample Selection, the final Balanced Panel Dataset includes 3,274 Listed Companies with 56 Quarters and 3, 370 Trading Days.Data Preprocessing Uniformly Applied Industry Standardization and 1% - 99% Quantile Trimming. According to the model specification, the intertemporal behavior matrix and the risk status sequence are constructed, which provides a uniform data input environment for the measurement of spillover effects and mechanism recognition[9].

4.2 Analysis of Spillover Effect Identification Results

In order to test the model's ability to recognize the impact of financial risk, we first performed a statistical analysis on the features and distributions of key variables in time series. Based on the balanced panel data of 3,274 sample companies across 56 quarters (2010Q1 – 2023Q4), we constructed a panel dataset linking spillover input intensity and core intertemporal operational behavior exposure. Descriptive statistics are shown in Table 3.

Table 3: Descriptive Statistics of Key Variables

Variable	Number of Observations (N×T)	Mean	Standard Deviation	p25	Median	p75
Spillover Input Intensity (bp)	183,344	15.73	28.41	2.15	6.88	18.26
Intertemporal Behavioral Correlation Exposure	Calculated Based on Adjacency Matrix	0.082	0.174	0.011	0.029	0.078
Short-term debt maturity ratio (%)	183,344	24.61	18.33	8.75	21.03	36.47
Guarantee Balance/Net Assets (%)	183,344	18.95	29.72	0	5.21	24.88
Commitment Maturity Density (times/quarter)	183,344	1.32	2.15	0	1	2

The average spillover intensity is 15.73 bps, with a standard deviation of 28.41, as shown in Table 3. In addition, the 75th percentile (18.26 bp) is significantly higher than the median (6.88 bp), suggesting a significant right-to-left bias in the cross section — meaning that a few firms are subject to extremely high spillover shocks. The average intertemporal behavioral correlation exposure is 0.082, but the 75th percentile (0.078) approaches the average, indicating that the transmission intensity is relatively concentrated in the correlation network, with the majority of transmission path weights clustered around 0.08.

For the sample companies, the average LDR was 24.61%, but with a standard deviation of 18,33, which reflects significant inter-temporal differences in the corporate debt structure. The 75th percentile (24,88%) of the RWA/NAV ratio is well above the average (5,21%), which suggests that the foreign reinsurance activity is concentrated in a subset of enterprises.A further analysis of the time series shows that the average spillover intensity surged to 28.4bp and 31.2bp respectively during the 2015 and 2018 credit-tightening cycles — 80.7% and 98.5% higher than the overall average. At the same time, the IFT of both the LCI and the FCD increased by about 15 to 22% over the same period. This preliminary observation indicates that exogenous shocks amplify the dispersion of inter-temporal trading behaviour, thus exacerbating the network spillover effects of risk [10].

4.3 Heterogeneity and Mechanism Analysis

Based on the analysis of the average effect of intertemporal business behavior on the spillover intensity, we analyzed the heterogeneity of the transmission characteristics from two dimensions, namely, the ownership structure of the company and the location of the supply chain net.On the basis of the grouping of 1,328 state-owned enterprises and 1,946 private enterprises in the sample, and constructing the upstream-downstream association masks from the top five clients/suppliers of listed companies, we used the data of the top 5 clients/suppliers of listed companies to carry out a cluster of statistical and mean difference tests for the intensity of the spillover input and the core explanatory variables. The results are presented in Table 4.

Table 4: Descriptive Statistics and Inter-Group Difference Tests for Heterogeneous Subsamples

Grouping Variable	Subsample	Observed Count	Mean Spillover Input Intensity (bp)	Standard Deviation of Spillover Input Intensity	Mean of behavioral association exposure	Standard Deviation of Behavioral Association Exposure	Intergroup Mean Difference t-Statistic
Ownership Structure	State-Owned Enterprise	74,368	12.84	22.67	0.069	0.141	18.63***
	Private Enterprises	108,976	17.69	31.58	0.091	0.193	
Network Location	Supply Chain Upstream	89,612	19.23	34.85	0.114	0.226	24.71***
	Non-Core Supply Chain	93,732	12.38	21.06	0.053	0.118	

Note: *** indicates significance at the 1% level

The statistics shown in Table 4 show that the average PSI of private firms (17,69 bp) is much higher than that of SOEs (12,84 bp), with a difference of 1% statistically significant. In addition, the average (0.091) and the standard deviation (0.193) of behavioural exposure in the private sector were higher than the SOE sub-sample (0.069, 0.141). This shows that not only are private firms carrying on average higher risk inputs, but they are also exposed to greater heterogeneity in transport pathways. In the supply chain network dimension, firms defined as supply chain related entities — those in the top five in terms of customer or supplier relationships among the sample firms — have an average spillover input intensity of 19.23 bps and a standard deviation of 34.85, significantly higher than that of the non-core supply chain (12.38 bps, 21.06). This demonstrates that the strong coupling in the industry chain greatly increases the transmission intensity and volatility of inter-temporal operational links. These grouping features provide important data support for the introduction of interaction terms in fixed-effects models.

4.4 Robustness and Sensitivity Analysis

In order to guarantee the reliability of core identification results, sensitivity tests were carried out on key model parameters and sample intervals to examine the variation in the statistical properties of the core variables. Table 5 shows a description of the comparison between the intensity of spillover and the exposure of behavior after adjustment of the delay order L, the prediction cycle h, the network sparsity threshold τ, and the exclusion of the samples from the extreme years.

Table 5: Comparison of Core Variable Statistics Under Different Parameter Settings

Parameter Setting	Number of Observations	Mean Spillover Input Intensity (bp)	Standard Deviation	Mean of Behavioral Association Exposure	Behavioral Association Exposure Standard Deviation
Baseline (L=4, h=5, τ=0.15)	183,344	15.73	28.41	0.082	0.174
Lag order L=8	183,344	16.52	30.12	0.097	0.201
Forecast period h=20 days	183,344	17.21	31.46	0.082	0.174
Threshold τ=0.25	183,344	14.89	26.73	0.071	0.153
Excluding 2015 samples	168,224	14.96	26.18	0.079	0.166

As illustrated in Table 5, when the delay sequence is extended from 4 cycles to 8 cycles, the average behavior correlation exposure is increased from 0.082 to 0.097 (+ 18.3%), and the RSD is increased by 15.5%. This suggests that a longer delay window captures more transmission pathways between periods. Extending the forecast period from 5 to 20 days raised the average spillover intensity by 9.4% to 17,21 bps, with a corresponding increase in the standard deviation of 10.7 per cent, reflecting the increased risk accumulation effect as the window lengthened. The average behavioral correlation exposure fell 13.4% to 0.071 after raising the sparsification threshold from 0.15 to 0.25, and the average spillover intensity decreased by 5.3%, reflecting that more stringent network pruning weakened weak-link transmissions.The average spillover intensity fell to 14.96 bps (-4.9%) and the SD decreased by 7.8%, suggesting that the effect of extreme events on the dispersion of risk distribution was more pronounced. The magnitude and direction of these changes are in line with the theory's expectations, and the relative order of the variables is stable, which provides a reliable statistical basis for the testing of the mechanism.

5 Conclusions

The intertemporal operational behavior correlation is defined as a time-variant constraint sequence spanning the "behavioral and financial statements-market", which is combined with the high frequency risk signals from stocks and bonds to create a traceable, alignable, and interpretable network spillover measurement system.The weighted spillover index, which is based on the strength of the LTI and the DVA, differentiates the risk transfer between the ISR and the SC. Reliability is enhanced by event timing constraints, structural break screening, and rolling robust inference.Innovations include an engineering-based encoding of intertemporal constraint variables, a unified interface for asynchronous alignment and sparse noise suppression, as well as edge-level and system-level indicators. Constraints arise from the incomplete disclosure of related transactions and commitments, the reliance on sample coverage in the supply chain, and the variability of network settings that remain sensitive to thresholds and windows.Future work can incorporate fine-grained features from text and contract maturity structures, introduce a hierarchical tool for exogenous macroeconomic shocks, and expand the dynamic test of crossasset spillovers in the context of multi-market linkages.

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