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DETECTING SYSTEMIC LIQUIDITY RISK FROM SHARED COLLATERAL ACROSS NONBANK INSTITUTIONS

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Abstract:

This analysis examines whether collateral composition and dealer concentration distinguish persistent financing differences from subsequent deterioration, informing international debates on secured market surveillance. Public U.S. repo statistics covering May 2010 to December 2020 provide 126 monthly observations and 1,959 collateral class observations across 17 categories. Ordinary least squares models incorporate current growth or class and month effects, with inference robust to temporal and cross-sectional dependence. A ten-percentage point increase in dealer concentration is associated with a 1.10 percentage point wider subsequent margin spread, with a 95 percent confidence interval from 0.55 to 1.65. Collateral composition has no statistically supported association with subsequent aggregate growth. The concentration association survives alternative covariance bandwidths and class coverage restrictions but does not extend to exploratory monthly changes. The evidence identifies conditional financing dispersion without establishing its causal transmission. These findings refine collateralized intermediation frameworks by separating relationships in levels from deterioration signals. Supervisory systems should assess market structure alongside financing distributions and validate warning indicators separately before using them to guide intervention.

Key Words: Repurchase Agreements; Collateral Composition; Dealer Concentration; Margin Dispersion; Panel Regression.

1. Introduction:

Collateralized financing can transmit financial pressure even when lending remains secured. The value of pledged securities, the concentration of financing among dealers and the terms imposed by lenders jointly shape access to liquidity. Adrian and Shin (2010) connect repo activity to adjustments in intermediary balance sheets, while Allen et al. (2012) show theoretically how common asset exposures and funding maturity can generate systemic vulnerability. These relationships make collateral markets relevant to financial stability, but they also create a measurement problem: collateral composition, financing contraction and differences in margin requirements describe distinct aspects of market conditions. Treating them as interchangeable indicators can obscure what an observed market characteristic reveals about subsequent financing outcomes.

Evidence from repo markets demonstrates why these distinctions matter. Gorton and Metrick (2012) associate disruption in securitized financing with deteriorating collateral conditions and rising haircuts. Copeland et al. (2014), however, document relatively stable margins and funding for most borrowers in the U.S. tri party repo market alongside a sharp funding decline for Lehman Brothers. Krishnamurthy et al. (2014) further show that contraction in repo backed by private securities disproportionately affected particular dealers despite its limited aggregate size. Together, these findings establish that financing stress can differ across market segments, collateral categories and borrowers. They also indicate that aggregate quantities and financing terms need separate analysis rather than interpretation through a single measure of liquidity risk.

Two explanatory dimensions follow from this evidence. Collateral composition describes the securities supporting financing, whereas dealer concentration describes how financing within a collateral category is distributed among dominant participants. A larger share of securities with narrower financing alternatives may be associated with weaker subsequent collateral growth. Greater dealer concentration may instead be associated with wider differences in financing terms when dominant borrowers face unequal constraints. Gârleanu and Pedersen (2011) establish the economic importance of margin constraints for asset pricing, while Martin et al. (2014) show that the stability of collateralized borrowing depends on funding market structure. These arguments motivate separate tests of composition and concentration. They do not establish that either variable necessarily predicts monthly deterioration.

International evidence further qualifies any universal relationship between secured financing and instability. Mancini et al. (2016) find that the centrally cleared euro interbank repo market remained resilient during crisis episodes and could absorb shocks. Boissel et al. (2017), by contrast, identify sensitivity to sovereign risk within European cleared repo financing. These findings concern different outcomes and institutional conditions, but their contrast shows why market design matters when interpreting collateral indicators. The relevant international question is therefore not whether collateralized markets are uniformly

stable or fragile. It is which observable characteristics relate to particular financing outcomes, and whether those relationships describe persistent differences or changes over time.

The reviewed evidence does not establish whether collateral composition and dealer concentration provide equivalent information about subsequent aggregate collateral growth and margin dispersion within the monthly U.S. reporting framework examined here. Nor does an association between concentration levels and subsequent financing terms necessarily establish a relationship between their monthly changes. This study aims to distinguish these relationships using observed collateral values, dealer concentration and margin distributions.

The central research question is whether collateral composition and dealer concentration provide distinct information about subsequent financing conditions. The analysis tests whether the non-Fedwire collateral share is associated with subsequent total collateral growth and whether concentration among the three largest dealers within a collateral class is associated with subsequent margin dispersion.

The empirical setting comprises public U.S. tri party repo statistics covering May 2010 to December 2020. The aggregate model uses 126 matched monthly observations and relates the current non Fedwire collateral share to subsequent collateral growth while accounting for current growth. The collateral class model uses 1,959 matched observations across 17 classes and relates current dealer concentration to the following month's margin spread. Dispersion is measured as the difference between the reported 90th and 10th percentile margins. Collateral class and month effects separate persistent category differences from conditions shared across classes. Dependence robust inference, alternative covariance bandwidths, class exclusions and an exploratory specification in monthly changes assess the sensitivity of the estimated relationships. The design estimates subsequent associations rather than causal effects.

The findings identify a distinction between financing levels and monthly deterioration. The non Fedwire collateral share has a negative but imprecisely estimated association with subsequent aggregate collateral growth. Dealer concentration has a positive association with subsequent margin dispersion in the level specification: a ten percentage point increase in concentration corresponds to approximately 1.10 percentage points of additional spread. This association retains its direction across bandwidth and class coverage checks, but it does not extend to the exploratory relationship between monthly changes. The contribution is therefore a qualified interpretation of concentration as information about differences in financing terms, rather than a validated signal of their monthly deterioration. For market monitoring, this distinction supports examining concentration alongside margin distributions while evaluating warning signals separately. Its relevance beyond the U.S. setting lies in the separation of composition, concentration and temporal behaviour, with transferability depending on comparable reporting definitions and institutional arrangements.

2. Theory, Conceptual Framework and Hypotheses Development:

2.1 Theory and Mechanisms:

This analysis draws on collateralized intermediation theory to explain how collateral composition and dealer concentration relate to funding conditions. Repo financing connects securities holdings to cash availability because lenders advance funds against collateral whose acceptability and required margins can change. Adrian and Shin (2010) show how intermediary balance sheet adjustments link repo activity to aggregate liquidity. This mechanism motivates examining collateral values, funding growth and margin dispersion without assuming that larger secured markets necessarily provide greater resilience.

Collateral composition describes the distribution of financing across security classes. The focal predictor is the reported share of collateral that is ineligible for Fedwire settlement. This measure identifies a collateral category rather than directly measuring credit quality or trading liquidity. Its theoretical relevance follows from differences in collateral acceptability. Financing backed by securities with narrower funding alternatives may become harder to replace when lenders reduce exposure.

A larger non Fedwire collateral share may therefore precede weaker growth in total collateral financing. Lenders facing uncertainty can reduce financing against less readily accepted securities, while borrowers may struggle to substitute other collateral. Gorton and Metrick (2012) associate repo market disruption with deteriorating collateral conditions. Shleifer and Vishny (2011) explain how constrained buyers can amplify financing pressure when institutions need to sell similar assets. Together, these arguments support an expected negative association between the focal collateral share and subsequent funding growth.

The expected relationship depends on market structure. Krishnamurthy et al. (2014) find that contraction in repo backed by private securities disproportionately affected particular dealers despite its limited aggregate size. Their evidence indicates that collateral categories can experience different funding responses. Accordingly, the proposed relationship concerns monthly market financing and does not assume that every security within the non Fedwire category carries equal risk.

H1: A higher non Fedwire collateral share is associated with lower total collateral growth in the following month.

Dealer concentration captures the proportion of collateral financing accounted for by the three largest dealers within an asset class. Concentration can expose funding conditions to adjustments by a small number of

borrowers. When these dealers face different financing constraints, their responses may widen the distribution of collateral margins within the class.

The competing mechanism is relationship stability. Large dealers may maintain financing relationships that absorb temporary disturbances and limit changes in contractual terms. Concentration therefore does not mechanically imply tighter funding conditions. Copeland et al. (2014) report relatively stable margins and funding for most borrowers in the tri party repo market alongside a sharp funding decline for Lehman Brothers. Their findings show why funding quantities and margin distributions require separate interpretation.

This analysis evaluates the concentration mechanism through the reported difference between the 90th and 10th percentile margins. A wider spread indicates greater dispersion in financing terms, although it does not establish that all borrowers face higher margins. The theoretical expectation is that concentrated classes exhibit wider subsequent dispersion when dominant dealers differ in their funding needs or lenders reassess their exposures unevenly.

H2: Higher concentration among the three largest dealers within a collateral class is associated with a wider collateral margin spread in that class in the following month.

2.2 Conceptual Framework:

The framework connects observed collateral composition to subsequent financing growth and observed dealer concentration to subsequent margin dispersion. Allen et al. (2012) show theoretically that common assets and debt maturity can jointly shape systemic vulnerability. Greenwood et al. (2015) demonstrate how asset sales by institutions with common exposures can transmit balance sheet pressure. These contributions establish the economic rationale for examining collateral structure, while the empirical relationships remain defined by the available market and collateral class measures.

The first relationship uses monthly observations. The predictor is the non Fedwire collateral share, and the outcome is total collateral growth in the following month. The second relationship uses collateral class observations. The predictor is the reported concentration of the three largest dealers, and the outcome is the margin spread in the following month. Both relationships use reported fields or calculations present in the dataset. The framework treats these variables as observed measures rather than indicators of an unobserved composite construct.

Financial structure can support resilience under some conditions and amplify stress under others. Acemoglu et al. (2015) establish this conditional relationship in a financial network model. Caballero and Simsek (2013) explain how uncertainty about exposures can discourage asset purchases during distress. These theoretical results motivate competing interpretations of the estimated associations rather than a presumption that concentration always destabilizes financing.

Funding scale provides context through total collateral value; repo counts and gross GCF securities volume. These measures describe market activity but do not measure leverage or funding capacity relative to capital. Adrian and Shin (2014) link deleveraging to intermediary risk constraints, indicating why funding quantities alone cannot establish vulnerability. Consequently, scale does not receive a separate directional hypothesis. The framework concentrates on two relationships whose predictors and outcomes have distinct economic meanings. Temporal ordering supports tests of subsequent association, while the observational design does not establish causality.

3. Data:

This analysis establishes data provenance, constructs the analytical samples and defines the measures used to test the proposed relationships. The preparation process preserves reported values and documents every exclusion, transformation and timing decision.

3.1 Data Sources, Population, and Sample Construction:

The analysis uses the Federal Reserve Bank of New York's Tri Party/GCF Repo Statistics. The provider consolidates information supplied by clearing banks on collateral values, collateral composition, dealer concentration and margin distributions. The original workbook and accompanying reproduction record identify the downloaded release, retrieval date and source URL. The analysis uses revised historical observations rather than a sequence of releases preserved at their original publication dates. The source is publicly accessible, although the workbook does not specify a redistribution licence.

The accessible population comprises transactions represented in the published U.S. tri party repo aggregates. It includes financing involving bank affiliated dealers, nonbank participants and the Federal Reserve during the observation period. Bilateral repo transactions are outside this reporting frame. Accordingly, the analytical units are market months and collateral class months, rather than individual nonbank institutions. This distinction matters because financing arrangements and responses differ across repo segments, as documented by Gorton and Metrick (2012), Copeland et al. (2014), and Krishnamurthy et al. (2014).

The analytical window extends from 11 May 2010 to 9 December 2020 and contains 128 monthly snapshots. Observations generally represent activity on the seventh business day of each month, subject to the provider's exceptions. Collateral values are market value stocks on the observation date. They are neither monthly transaction flows nor monthly averages. This interpretation follows the provider's reporting definitions

and preserves the distinction between financing quantities, collateral valuation and funding arrangements emphasized by Adrian and Shin (2010) and Martin et al. (2014).

All available observations within the specified window enter the initial frame. The collateral worksheet contains 2,840 rows, including 640 aggregate and count rows. Removing these summary rows leaves 2,200 observations across 18 collateral classes. The panel is unbalanced because some classes do not appear in every month. Sixteen classes have 128 source records, collateralized debt obligations have 95, and the other category has 57.

The H1 sample matches each month's non Fedwire collateral share and current collateral growth to the following calendar month's total collateral growth. The resulting sample contains 126 observations. Predictor dates extend from June 2010 to November 2020, while outcome dates extend from July 2010 to December 2020. The H2 sample matches current dealer concentration to the following calendar month's margin spread within the same collateral class. It contains 1,959 observations across 17 classes and 127 predictor months. Fifteen classes contribute 127 observations each, collateralized debt obligations contribute 43, and whole loans contribute 11. The Other category contributes no complete observations.

Table 1: Sample construction

Stage	Units Represented	Observations Retained	Inclusion or Exclusion Rule
Published collateral worksheet	18 classes and five summary series	2,840	Retain observations within the analytical window
Collateral class frame	18 classes	2,200	Remove 640 aggregate and count rows
H1 monthly frame	One aggregate market series	128	Use published monthly totals and constructed shares
H1 observations with a subsequent outcome	One aggregate market series	127	Remove the terminal month
H1 estimation sample	One aggregate market series	126	Remove the initial observation without current growth
H2 observations before subsequent month matching	18 classes	2,184	Remove 16 records in the terminal month
H2 records with an adjacent class observation	18 classes	2,163	Remove 21 records without a matching class in the next calendar month
H2 records with current concentration	17 classes	1,963	Remove 200 records without reported concentration
H2 estimation sample	17 classes	1,959	Remove four records without a subsequent margin spread

3.2 Data Integration, Cleaning, and Quality Assurance:

Integration uses the snapshot date for market aggregates and the combination of asset identifier and calendar month for collateral class observations. The audit found no duplicate monthly dates and no duplicate class and date keys. Subsequent observations are matched only when their calendar months are adjacent. The procedure therefore does not treat a later available record as the next month when an intervening observation is absent. These checks address the alignment and definition problems associated with repurposed operational data discussed by Hand (2018).

Source labels indicating unavailable or unreported values remain missing in the analytical calculations. The procedure applies no interpolation, imputation or replacement with zero. Complete records are selected separately for each model, allowing the sample losses to remain visible. This approach documents the missingness mechanism without assuming that disclosure related omissions occur randomly, consistent with the distinctions developed by Little and Rubin (2019).

The monthly total collateral value and non-Fedwire collateral value contain no missing observations. Current monthly growth is unavailable for the initial snapshot because its preceding observation lies outside the analytical sequence. In the collateral class frame, dealer concentration and margin spread each contain 219 missing values. These omissions comprise 46 observations for collateralized debt obligations, 116 for whole loans and 57 for Other. Matching current predictors to subsequent outcomes produces the model specific exclusions reported in Table 1.

The audit checks positive total collateral values, concentration values between zero and 100, nonnegative margin spreads and agreement between reported components and constructed measures. It found no violations of these restrictions. Recalculating the non-Fedwire share, total collateral growth and margin spread reproduced the workbook values to machine precision.

Valid extreme observations remain unchanged. No winsorization, trimming or discretionary outlier deletion is applied. Adams et al. (2019) show why outlier treatment requires attention to the underlying data structure rather than automatic adjustment. Here, retaining the original observations preserves potentially informative changes in collateral values and financing terms.

Monetary values remain in nominal U.S. dollars, expressed in billions where used as collateral stocks. No exchange rate conversion or inflation adjustment is required for the implemented specifications because their focal variables are shares, monthly growth rates, concentration percentages and margin spreads. The reproduction files preserve the input checksum, construction code, retained observations and numerical outputs. These records implement the computational traceability advocated by Peng (2011) and Sandve et al. (2013).

3.3 Variable Measurement, Construction, and Validation:

The measurement framework distinguishes collateral composition, dealer concentration and financing conditions. Asset commonality, exposure distribution and network structure represent different economic mechanisms in Allen et al. (2012), Greenwood et al. (2015), and Acemoglu et al. (2015). Accordingly, the analysis retains the available predictors as separate observed variables rather than combining them into a systemic risk index.

The non Fedwire collateral share measures collateral composition. Dealer concentration measures the share held by the three largest dealers within a reported collateral class. Total collateral growth measures changes in collateral market value, while the margin spread measures dispersion in financing terms. Neither outcome is a direct measure of institutional default or realized liquidity losses. This interpretation preserves the distinction between observable financing conditions and the underlying uncertainty and intermediary constraints examined by Caballero and Simsek (2013) and Adrian and Shin (2014). Equation 1 defines total collateral growth:

$$g_t = \frac{V_t}{V_{t-1}} - 1$$

Here, g_t is monthly collateral growth, and $V_t$is total collateral market value at snapshot t. Growth is stored as a decimal fraction and multiplied by 100 for percentage reporting. Equation 2 defines the non-Fedwire collateral share:

$$s_t = \frac{N_t}{V_t}$$

Here, s_t is the non Fedwire share, and $N_t$is reported non Fedwire collateral market value. Both monetary components use the same currency, scale and snapshot date. Equation 3 defines collateral margin dispersion:

$$d_{it} = p90_{it} - p10_{it}$$

Here, d_{it} is the margin spread for collateral class i in month t. The terms $p90_{it}$and $p10_{it}$denote the reported 90th and 10th percentile margins. The resulting spread is measured in percentage points. The provider defines the margin as collateral value divided by the loan amount, minus one, expressed as a percentage. The analysis preserves this definition. It does not substitute the alternative haircut convention that divides the collateral discount by collateral value.

Table 2: Variable dictionary

Variable	Analytical Role	Definition and Construction	Source Identifier	Unit and Frequency	Transformation And Direction	Missing Value Rule	Coverage and Limitation
Total collateral value, V_t	Construction input	Reported total collateral market value	Source collateral, group_id 0, collateral_value	USD billions; monthly snapshot	Original value retained	Require a positive numeric denominator	128 observations; combines quantity and price changes
Non Fedwire collateral value, N_t	Construction input	Reported value of collateral outside the Fedwire eligible category	Source collateral, group_id 20, collateral_value	USD billions; monthly snapshot	Original value retained	Require a numeric value	128 observations; eligibility does not directly measure trading liquidity
Non Fedwire share, s_t	H1 predictor	Non Fedwire value divided by total value	Monthly analysis, Non Fedwire share	Decimal fraction; monthly	Higher values indicate greater category exposure	Require both monetary components	126 observations in H1
Total collateral growth, g_t	H1 current control and subsequent outcome	Current total value divided by preceding total value, minus one	Monthly analysis, Collateral growth MoM	Decimal growth rate; monthly	Positive values indicate expansion; negative values indicate contraction	Require adjacent months and positive preceding value	127 source growth observations; 126 matched model observations

Variable	Analytical Role	Definition and Construction	Source Identifier	Unit and Frequency	Transformation And Direction	Missing Value Rule	Coverage and Limitation
Dealer concentration, c_{it}	H2 predictor	Reported share held by the three largest dealers within a collateral class	Source collateral, top_3_concentration	Percent; monthly class snapshot	Original scale from zero to 100	Require a numeric current value	1,959 matched observations across 17 classes
Margin spread, d_{it}	H2 subsequent outcome	Reported p90 minus p10 margin	Source collateral, p90 and p10	Percentage points; monthly class snapshot	Higher values indicate wider financing term dispersion	Require both percentiles in the next calendar month	1,959 matched observations; dispersion does not establish a uniform increase in margins

Validation focuses on arithmetic consistency, admissible ranges, identifier uniqueness and calendar matching. The measures are reported quantities or transparent transformations, so factor analysis and internal consistency tests are not applied.

Table 3: Descriptive statistics for the estimation samples

Variable	Observations	Mean	SD	Median	Minimum	Maximum
H1 current non Fedwire share, percent	126	17.653	2.961	17.694	12.537	23.582
H1 current collateral growth, percent	126	0.366	4.814	0.442	−21.346	17.837
H1 subsequent collateral growth, percent	126	0.423	4.808	0.469	−21.346	17.837
H2 current dealer concentration, percent	1,959	47.100	14.738	45.700	22.000	100.000
H2 subsequent margin spread, percentage points	1,959	7.337	5.624	7.000	0.000	28.000

Statistics use the observations retained for each baseline model. Panel statistics weight each retained class and month observation equally rather than weighting observations by collateral value.

3.4 Analytical Framework, Identification, and Reproducibility:

The implemented models estimate subsequent associations. H1 examines whether collateral composition is associated with the following month's collateral growth after accounting for current growth. Equation 4 specifies the monthly model:

$$g_{t+1} = \alpha + \beta s_t + \phi g_t + \varepsilon_{t+1}$$

Here, α is the intercept, β measures the association between the current non Fedwire share and subsequent collateral growth, and ϕ captures the association with current growth. The disturbance is ε_{t+1}. H1 predicts a negative value of β.

Ordinary least squares estimation uses 126 observations. Baseline inference applies a Bartlett heteroskedasticity and autocorrelation consistent covariance estimator with four monthly lags. The calculation applies a degree of freedom correction and a student t reference distribution with the number of retained months minus one degree of freedom.

H2 examines whether dealer concentration is associated with subsequent margin dispersion within collateral classes. Equation 5 specifies the panel model:

$$d_{i,t+1} = \alpha_i + \delta_t + \theta c_{it} + u_{i,t+1}$$

Here, $\alpha_i$represents collateral class effects, $\delta_t$represents predictor month effects, and θ measures the association between current dealer concentration and subsequent margin dispersion. The disturbance is $u_{i,t+1}$. H2 predicts a positive value of θ.

The panel model uses 1,959 observations across 17 classes. Class effects absorb persistent differences across collateral categories, while month effects absorb shocks shared across categories. Estimation therefore draws on variation in concentration within classes after accounting for common monthly conditions.

Baseline panel inference uses a Driscoll and Kraay type covariance estimator constructed from monthly aggregated regression scores with four monthly lags. This approach accommodates contemporaneous dependence across classes and serial dependence over the specified bandwidth. Vogelsang (2012) examines the properties of this class of covariance estimators. The choice also recognizes the dependence issues discussed by Thompson (2011) and the limitations of relying on a small number of clusters emphasized by Cameron and Miller (2015). The resulting inference remains an asymptotic approximation rather than a finite sample guarantee.

Sensitivity calculations retain the baseline observations while increasing the covariance bandwidth to six and twelve months. Additional panel checks remove month effects, omit each collateral class in turn and restrict estimation to the fifteen classes with complete matched coverage. The latter sample contains 1,905 observations and excludes the 54 observations contributed by collateralized debt obligations and whole loans. These checks examine dependence assumptions, common shocks and sensitivity to uneven class coverage.

The specifications and sensitivity checks were selected during manuscript preparation after the descriptive dataset was available. They were not preregistered. The reproduction files retain all implemented variants rather than selecting specifications according to statistical significance. This disclosure follows the transparency principles discussed by Christensen and Miguel (2018) and the concern about consequential analytical choices developed by Simonsohn et al. (2020).

Temporal ordering does not remove omitted variable bias, anticipation or reverse adjustment. Revised historical observations also do not establish what information participants possessed at each snapshot date. Moreover, collateral value growth incorporates market revaluation alongside changes in pledged quantities. The estimates therefore describe subsequent relationships in the observed market aggregates and collateral classes rather than causal funding withdrawals.

4. Methods:

4.1 Research Design and Identification Strategy:

This analysis uses an observational design to estimate subsequent associations in U.S. secured financing markets. The research question concerns whether collateral composition and dealer concentration provide distinct information about subsequent collateral growth and margin dispersion. The analytical units are market months for the aggregate model and collateral class months for the panel model. Both specifications use current explanatory information and outcomes observed in the following calendar month.

The aggregate estimand is the linear association between the current non Fedwire collateral share and subsequent total collateral growth, conditional on current growth. Useful variation comes from changes in collateral composition across monthly snapshots. The panel estimand is the association between current dealer concentration and subsequent margin dispersion after accounting for persistent collateral class differences and common monthly conditions. Its identifying variation comprises changes in concentration within classes that remain after removing class and month effects.

The design does not use treatment assignment, an external instrument or an independently determined institutional change. Consequently, the coefficients represent conditional associations rather than causal effects. Temporal ordering distinguishes current explanatory measures from subsequent outcomes but does not eliminate anticipation, common shocks or feedback from expected financing conditions. Fixed effects absorb specified sources of heterogeneity without removing all changing differences across collateral classes.

The models also distinguish subsequent association from forecast validation. They use revised historical observations and do not reconstruct the information available to market participants at each original publication date. The analysis therefore does not interpret statistical significance as evidence of a usable forecasting system or a validated detector of systemic liquidity events.

4.2 Model Specification and Measurement Alignment:

The baseline specifications are defined in Equations 4 and 5. Their measurement inputs follow the variable dictionary in Table 2, while Table 1 documents the construction of the estimation samples. Equation 4 relates subsequent total collateral growth, g_{t+1}, to the current non Fedwire share, s_t, and current collateral growth, g_t. The intercept is α, the focal coefficient is β, the current growth coefficient is ϕ, and the disturbance is ε_{t+1}. H1 predicts a negative value of β. Current growth accounts for short horizon persistence or reversal in collateral values. Because current growth and composition are measured at the same snapshot, this adjustment defines a conditional relationship rather than a total causal effect of composition.

Equation 5 relates the subsequent margin spread, $d_{i,t+1}$, to current dealer concentration, c_{it}. The index i identifies collateral classes, and t identifies predictor months. Collateral class effects, α_i, absorb persistent category differences, while month effects, δ_t, absorb conditions shared across categories. The focal coefficient is θ, and the disturbance is $u_{i,t+1}$. H2 predicts a positive value of θ. Month effects refer to predictor months; each predictor month maps uniquely to its subsequent outcome month. The panel specification includes an intercept and indicator variables for all but one collateral class and month. The resulting design matrix has full column rank, establishing that concentration retains estimable variation after fixed effects are included. The model does not condition on the current margin spread, so its coefficient may reflect persistent financing conditions as well as subsequent differences. The exploratory change specification examines a distinct relationship using monthly movements.

Equation 6 defines that specification:

$$\Delta d_{i,t+1} = \eta_t + \theta_\Delta \Delta c_{it} + v_{i,t+1}$$

Here, $\Delta d_{i,t+1} = d_{i,t+1} - d_{it}$ is the subsequent change in margin dispersion, and $\Delta c_{it} = c_{it} - c_{i,t-1}$ is the current change in concentration. The term η_t represents month effects, $\theta_\Delta$is the change association, and $v_{i,t+1}$is the disturbance. Differencing removes constant class effects. Equation 6 is estimated only where the required observations occur in adjacent calendar months.

Growth rates and collateral shares enter the aggregate calculations as decimal fractions. Dealer concentration enters on its reported scale from zero to 100, and margin dispersion is measured in percentage points. These scales remain unchanged during estimation. A one percentage point increase in the non Fedwire

share corresponds to a change of 0.01 in its stored value. For the aggregate model, rescaling both growth and shares into percentages leaves their reported slope interpretation unchanged.

The aggregate model retains 126 monthly observations. The panel model retains 1,959 observations across 17 classes and 127 predictor months. Its unbalanced structure reflects differences in reported coverage and model specific completeness. The change model retains 1,937 observations across the same 17 classes and 126 predictor months. These samples support inference about the observed reporting frame rather than the population of individual nonbank institutions.

4.3 Estimation and Statistical Inference:

Both baseline models are estimated by ordinary least squares without observation weights. Each retained monthly observation receives equal weight in the aggregate model, and each retained class and month observation receives equal weight in the panel model. The panel estimates therefore do not weight collateral categories by their market value.

Estimation uses Python 3.12.14, NumPy 2.3.5 and SciPy 1.17.0. Regression coefficients are computed through NumPy's linear least squares routine with its default singular value cutoff. The implementation verifies full column rank and stops if a specification is rank deficient. The calculations are deterministic and require neither random initialization nor a random seed.

For the aggregate model, baseline inference uses a Bartlett heteroskedasticity and autocorrelation consistent covariance estimator with four monthly lags. The panel calculation applies the same weighting principle to regression scores aggregated within predictor months, producing a Driscoll and Kraay type covariance estimator. Monthly aggregation permits contemporaneous dependence across collateral classes, while the lagged score products address temporal dependence under weak dependence conditions. Vogelsang (2012) provides the methodological basis for inference using covariance estimators constructed from cross sectional score aggregates.

For replication, the score for month t is the sum of each observation's regressor vector multiplied by its fitted residual. The covariance calculation starts with the sum of the outer products of these monthly scores. For each lag through bandwidth L, it adds the lagged score cross products and their transposes, weighted by one minus the lag divided by $L + 1$. The baseline bandwidth is four. This weighted matrix is premultiplied and postmultiplied by the inverse regressor cross product matrix.

The covariance estimator is multiplied by the observation count divided by the difference between that count and the number of estimated parameters. Parameter counts include the intercept and fixed effect indicators. The aggregate model contains three estimated parameters, while the baseline panel model contains 144. The change specification contains 127 parameters.

Confidence intervals use the student t distribution with the number of retained predictor months minus one degree of freedom. This gives 125 degrees of freedom for the aggregate and change models and 126 for the baseline panel model. Reported p values are two sided. A directional hypothesis receives baseline support only when the estimated coefficient has the expected sign and its two-sided p value is below 0.05.

The panel procedure avoids relying exclusively on an asymptotic approximation based on seventeen independent class clusters. Cameron and Miller (2015) explain why dependence assumptions and limited cluster counts require particular attention. The selected covariance procedure nevertheless remains an asymptotic approximation that requires suitable temporal dependence conditions; it does not accommodate every possible error process.

4.4 Analytical Checks, Sensitivity and Reproducibility:

Processing begins with the cleaned workbook. The scripts verify identifier uniqueness, chronological order, admissible measurement ranges and consistency between source components and calculated shares, growth rates and margin spreads. They then construct adjacent month predictor and outcome pairs, apply model specific completeness requirements and estimate the resulting specifications.

Missing observations are excluded only when required by the relevant model. The procedure applies no interpolation, imputation or replacement with zero. Valid extreme observations remain unchanged. Consequently, comparisons across specifications are interpreted alongside their retained samples rather than assuming that missing observations are random.

Sensitivity analysis addresses four specific concerns. First, covariance bandwidths of six and twelve months assess how longer dependence windows affect uncertainty while preserving baseline coefficients and observations. Second, removing month effects examines sensitivity to adjustment for shared market conditions on the same panel sample. Third, retaining the fifteen classes with complete matched coverage assesses dependence on sparse categories, producing 1,905 observations. Fourth, excluding each class in turn examines whether a particular category drives the direction or magnitude of the concentration coefficient. These class exclusion calculations assess coefficient stability; separate uncertainty estimates are not computed for every exclusion.

The exploratory change specification in Equation 6 assesses whether the level association extends to monthly movements. Its sample differs because differencing requires additional adjacent observations. It

therefore provides a complementary temporal comparison rather than a direct replication of the level estimand. Differencing does not establish stationarity or remove all measurement error and confounding.

The specifications were selected during manuscript preparation after the descriptive workbook was available and were not preregistered. The change specification was added after inspecting the baseline estimates. These decisions and their timing are documented, and all implemented sensitivity results are retained. This disclosure follows the transparency principles discussed by Christensen and Miguel (2018).

Replication materials contain the input workbook, its checksum, construction and estimation scripts, retained samples, numerical results and execution instructions. The documented sequence allows independent reconstruction of the reported estimates, consistent with the computational reproducibility practices described by Sandve et al. (2013). The methodological contribution is the coordinated comparison of composition, concentration and financing outcomes using established estimators, with explicit separation between relationships in levels and relationships in monthly changes.

5. Findings:

This analysis tests whether collateral composition predicts subsequent collateral growth and whether dealer concentration predicts subsequent margin dispersion. The evidence combines monthly market observations with collateral class observations covering 2010 to 2020. Baseline estimates and sensitivity checks distinguish associations in financing conditions from evidence of monthly deterioration.

The monthly model contains 126 observations after matching current collateral composition and growth to the following month’s growth. The panel model contains 1,959 observations across 17 collateral classes and 127 predictor months. Fifteen classes contribute 127 observations each, while collateralized debt obligations and whole loans contribute 43 and 11 observations, respectively. Missing values remain unfilled, and matching requires adjacent calendar months within the same class.

Table 4 presents the distributions used in estimation. The non Fedwire collateral share averages 17.653 percent, while subsequent collateral growth averages 0.423 percent and ranges from −21.346 to 17.837 percent. This variation indicates substantial monthly movements despite modest average growth. Dealer concentration averages 47.100 percent, and the subsequent margin spread averages 7.337 percentage points. The margin spread, denoted \(d_{it}\), measures the difference between the 90th and 10th percentile collateral margins.

Table 4: Descriptive statistics for the analytical samples

Variable	Observations	Mean	SD	Median	Minimum	Maximum
Current non Fedwire collateral share, percent	126	17.653	2.961	17.694	12.537	23.582
Current collateral growth, percent	126	0.366	4.814	0.442	−21.346	17.837
Subsequent collateral growth, percent	126	0.423	4.808	0.469	−21.346	17.837
Current dealer concentration, percent	1,959	47.100	14.738	45.700	22.000	100.000
Subsequent margin spread, percentage points	1,959	7.337	5.624	7.000	0.000	28.000

Source: Authors’ calculations from the supplied New York Fed dataset. Statistics use the observations retained for each model. Panel observations receive equal weight.

The estimated association between the non-Fedwire collateral share and subsequent collateral growth is negative but imprecise. A one percentage point increase in the share is associated with a 0.077 percentage point reduction in the following month’s growth. The 95 percent confidence interval extends from −0.322 to 0.168 percentage points, and the p value is 0.535. H1 is therefore not supported at the 5 percent level. The interval accommodates both a negative association and a modest positive association, so the result does not establish that collateral composition has no relationship with growth.

Current collateral growth exhibits a clearer association with subsequent growth. A one percentage point increase in current growth is associated with a 0.422 percentage point reduction in the following month’s growth. The confidence interval extends from −0.678 to −0.167, with a p value of 0.0014. This result indicates partial reversal in monthly collateral value movements. Adrian and Shin (2010) connect repo activity to intermediary balance sheet adjustments, but the present coefficient does not identify that mechanism because collateral values reflect both pledged quantities and market prices.

Table 5: Baseline estimates of subsequent collateral growth and margin dispersion

Outcome and Predictor	Coefficient	Robust Standard Error	95 Percent Confidence Interval	p Value	Observations
Subsequent collateral growth: current non Fedwire share	−0.0771	0.1240	−0.3224 to 0.1682	0.5350	126
Subsequent collateral growth: current growth	−0.4223	0.1290	−0.6776 to −0.1669	0.0014	126
Subsequent margin spread: current dealer concentration	0.1100	0.0280	0.0546 to 0.1654	0.0001	1,959

Source: Authors' calculations. The growth model includes an intercept and current collateral growth. The margin dispersion model includes collateral class and month effects. Growth model coefficients express percentage point changes in subsequent growth for a one percentage point increase in the predictor. The panel coefficient expresses percentage point changes in margin spread for a one percentage point increase in concentration. Baseline covariance estimators use four monthly lags.

Dealer concentration has a positive association with subsequent margin dispersion after accounting for collateral class and month effects. A one percentage point increase in concentration is associated with a 0.110 percentage point wider margin spread in the following month. The 95 percent confidence interval ranges from 0.055 to 0.165, with a p value below 0.001. The baseline estimate therefore supports H2.

The magnitude is economically relevant within the observed sample. A ten-percentage point increase in concentration corresponds to a 1.100 percentage point wider subsequent margin spread, with a confidence interval from 0.546 to 1.654 percentage points. This difference equals approximately 15 percent of the sample mean spread. It represents greater dispersion in financing terms rather than a uniform increase in margins. Copeland et al. (2014) document why financing quantities and margin behaviour can differ across borrowers, reinforcing the need to interpret dispersion separately from market wide funding withdrawal.

Inference accounts for temporal dependence and contemporaneous dependence across collateral classes. Increasing the covariance bandwidth changes estimated uncertainty without changing the regression coefficients. This distinction follows the dependence robust inference framework examined by Vogelsang (2012). The sensitivity results in Table 6 show that the positive level association remains statistically distinguishable from zero with six- and twelve-monthly lags, although the longer bandwidth widens its confidence interval.

Table 6: Sensitivity of the concentration and margin dispersion relationship

Specification	Observations	Coefficient	Robust Standard Error	95 Percent Confidence Interval	p Value
Class and month effects, four monthly lags	1,959	0.1100	0.0280	0.0546 to 0.1654	0.0001
Class and month effects, six monthly lags	1,959	0.1100	0.0317	0.0472 to 0.1728	0.0007
Class and month effects, twelve monthly lags	1,959	0.1100	0.0389	0.0329 to 0.1870	0.0055
Fifteen classes with complete matched coverage	1,905	0.1010	0.0292	0.0433 to 0.1587	0.0007
Class effects without month effects	1,959	0.0438	0.0125	0.0190 to 0.0685	0.0006
Monthly changes with month effects, exploratory	1,937	−0.0065	0.0138	−0.0339 to 0.0209	0.6416

Source: Authors' calculations. The first five rows relate current concentration levels to subsequent margin spread levels. The final row relates current changes in concentration to subsequent changes in margin spread. Except where specified, covariance calculations use four monthly lags. The balanced sample excludes the 54 observations contributed by collateralized debt obligations and whole loans.

Restricting estimation to the fifteen classes with complete matched coverage produces a coefficient of 0.101, close to the baseline estimate of 0.110. The positive association therefore does not depend on the two sparsely represented classes. Omitting each collateral class in turn also preserves a positive coefficient, with estimates ranging from 0.092 to 0.139. These calculations establish stability of direction across class exclusions, although uncertainty was not estimated separately for every exclusion.

Removing month effects reduces the coefficient from 0.110 to 0.044. The association remains positive, but its magnitude depends on accounting for common monthly conditions. This sensitivity indicates that pooled financing conditions and changes within collateral classes contribute differently to the estimated relationship. Krishnamurthy et al. (2014) similarly demonstrate the importance of distinguishing aggregate repo movements from exposures concentrated in particular market segments.

An additional exploratory specification assesses whether the level relationship extends to monthly changes. After differencing adjacent observations, the coefficient becomes −0.0065, with a confidence interval from −0.0339 to 0.0209 and a p value of 0.642. The sample contains 1,937 observations across 17 classes. This result does not support an association between current concentration changes and subsequent changes in margin dispersion.

The contrast between levels and changes limits the interpretation of H2. Concentration is associated with wider subsequent margin spreads in the level specification, but the evidence does not establish that monthly increases in concentration precede monthly widening. Differencing also changes the identifying variation and

can amplify measurement noise, so the exploratory result does not prove that the level association is absent. It does, however, prevent interpreting the baseline estimate as a reliable signal of monthly deterioration.

The change specification was introduced after inspecting the baseline estimates and is reported as exploratory. Retaining this result alongside the supportive level estimates follows the transparency principles discussed by Christensen and Miguel (2018). The baseline models and sensitivity calculations estimate associations rather than causal effects.

6. Discussion:

Wider differences in financing terms do not necessarily signal faster monthly deterioration. Table 5 and Equation 5 show that greater dealer concentration is associated with wider subsequent collateral margin spreads, while Table 6 shows no corresponding association between monthly changes. A ten-percentage point increase in concentration corresponds to approximately 1.10 percentage points of additional margin dispersion in the level specification. The contribution of this analysis is the distinction between a conditional relationship in financing levels and a signal of subsequent deterioration. Gârleanu and Pedersen (2011) establish how margin constraints can generate differences in asset pricing. The present evidence adds a temporal qualification: concentration relates to the distribution of financing terms, but that relationship does not translate into a supported monthly change signal.

The specification comparison reveals that common market conditions materially affect the estimated concentration relationship. In Table 6, introducing month effects increases the coefficient from approximately 0.044 to 0.110. Equation 5 therefore separates shared monthly conditions from the association observed within collateral classes. This increase shows that omitting common conditions understates the conditional relationship in this sample; it does not identify a transmission mechanism. Gorton and Ordoñez (2014) explain how changing incentives to acquire collateral information can alter secured financing conditions. Their framework provides an economic interpretation for differentiated financing terms, while the present estimates establish the narrower empirical result that concentration and subsequent margin dispersion remain associated after accounting for common monthly conditions. The analytical advance lies in separating these sources of variation rather than treating concentration as an isolated market characteristic.

The contrast between the two hypotheses challenges the use of collateral composition and dealer concentration as interchangeable indicators. Table 5 and Equation 4 provide no precise evidence that a larger non Fedwire collateral share precedes lower aggregate collateral growth. Equation 5, by contrast, identifies a positive association between concentration and subsequent margin dispersion. These coefficients concern different outcomes and cannot be interpreted as shares of a common total effect. Their significance is conceptual: the composition of collateral financing and the distribution of financing terms contain different information. Acharya et al. (2011) show theoretically that collateral debt capacity depends on rollover conditions and liquidation opportunities rather than collateral quality alone. The present findings accordingly narrow the empirical usefulness of a simple collateral category share without rejecting the broader relevance of collateral constraints. They direct attention toward the particular financing outcome being measured.

The strongest structural insight concerns the boundary between persistent financing differences and short horizon warning signals. In Table 6, the positive level association survives longer covariance bandwidths, complete class coverage and individual class exclusions. Its disappearance in the exploratory change specification nevertheless prevents interpreting concentration increases as reliable precursors of margin spread widening. Together, Tables 4 and 6 show why substantial variation and stable coefficient signs are insufficient to establish predictive usefulness. The practical implication is to examine dealer concentration alongside the distribution of margins when reviewing collateral classes, while requiring separate evidence before using concentration changes to trigger intervention. This interpretation also preserves the distinction between a wider margin distribution and a general tightening of financing: Equation 3 measures dispersion, not the direction of every borrower's financing terms.

International evidence reinforces the importance of market design when interpreting these relationships. Mancini et al. (2016) find resilience in the centrally cleared euro interbank repo market, whereas Boissel et al. (2017) identify sensitivity to sovereign risk within European cleared repo financing. These findings differ in their measured outcomes and institutional conditions, so the U.S. concentration estimate should not be treated as a universal instability parameter. The transferable contribution is an analytical distinction: market structure, financing dispersion and monthly deterioration require separate measurement. Tables 5 and 6 support monitoring concentration as contextual information about financing differences, rather than treating it as a validated crisis indicator. Comparative research can extend Equation 5 across clearing arrangements using harmonized margin definitions and observation frequencies to determine whether the level association persists and whether its failure to translate into monthly changes depends on institutional design.

7. Conclusion and Implications:

Financial stability depends on distinguishing persistent financing differences from signals of approaching deterioration. This analysis shows that the distribution of secured financing contains information about subsequent differences in borrowing terms, while monthly movements do not provide the same evidence.

Its core contribution is an empirical distinction between structural association and deterioration over time. This distinction refines collateralized intermediation frameworks by showing that relationships observed in levels cannot automatically support claims about adjustment mechanisms or impending stress. The evidence supports interpreting market structure alongside contractual financing conditions, with attention to common market circumstances. For managers, this means reviewing the distribution of financing terms across collateral categories rather than relying exclusively on aggregate growth or average conditions. Operational monitoring should maintain separate assessments of structural exposure and monthly change, supported by consistent definitions and traceable records. For policymakers, the findings support combining market structure information with financing distributions while requiring additional validation before adopting intervention thresholds. This approach can improve the interpretation of supervisory information and reduce unwarranted responses to ambiguous movements. Its international relevance lies in a transferable analytical principle: structural differences and warning signals require distinct evaluation. Better separation of these functions can support decisions intended to protect financing continuity, market participation and economic activity.

The available market aggregates create opportunities for more detailed investigation. Transaction records linking borrowers, lenders and individual securities would permit direct examination of shared exposures and contractual adjustment. More frequent observations could distinguish abrupt financing withdrawals from valuation changes and gradual portfolio reallocation. Comparable datasets across clearing arrangements would establish whether the observed level relationship depends on institutional design. Designs exploiting independently determined institutional changes could strengthen causal identification. Subsequent research should also evaluate predictive performance on observations excluded from model development. These extensions would establish where the findings generalize and when structural information becomes useful for anticipating financing deterioration.

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