

Slow-Moving Common Risk in Small Banks*

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This Version: October 5, 2026
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Abstract

We show that U.S. banks exhibit considerable comovement in balance sheet risk. Estimating dynamic factor models on quarterly Call Report data from 1983Q1 to 2020Q1, we find that common factors explain about three-fifths of the variation in solvency risk and loan quality for small banks, and more than four-fifths for large banks. Macroeconomic conditions account for only part of this comovement. Among small banks, most of the remaining comovement is slow. Fluctuations longer than eight years make up 76% of the variation in their median macro-adjusted common path for solvency risk and 85% for loan quality, compared with 38% and 55% for large banks. The slow fluctuations in small-bank risk also track credit and house prices, with risk lower when both are high, suggesting a link to financial cycles.

JEL Codes: C32; C38; E32; G21

Keywords: small banks; common risk; financial cycle; macroeconomic conditions; dynamic factor models

*We thank John Kandrach, Jeremy Piger, David Evans, George Evans, Jose Carreno, and participants at University of Mississippi, the 2025 Liberal Arts Macroeconomics Conference, the 2024 Southern Economic Association Annual Meeting, Triad Applied Macro Group Seminar Series, and University of Oregon Macro Group Seminar Series for feedback. Computations were performed using the Wake Forest University High Performance Computing Facility ([Information Systems and Wake Forest University, 2021](#)). All errors are our own.

1 Introduction

Many small banks specialize in relationship lending to firms that larger banks find difficult to evaluate (Berger et al., 2005). A rise in a small bank’s balance sheet risk can constrain its lending (Peek and Rosengren, 1995), and a loss of bank lending can in turn reduce local economic activity (Ashcraft, 2005). An individual small bank’s idiosyncratic shocks are unlikely to have aggregate effects, unlike those of a large bank (Amiti and Weinstein, 2018; Buch and Neugebauer, 2011), but small banks can still matter in aggregate through comovement. When risk rises at many small banks simultaneously, these local disruptions may have aggregate consequences, particularly if the rise in risk is persistent (Bernanke, 1983). Yet little is known about how strongly balance sheet risk comoves across small banks or how persistent that comovement is.

We study this comovement using quarterly Call Report data for small U.S. commercial banks from 1983Q1 to 2020Q1. Our two measures of balance sheet risk are the Z-score for solvency risk and the nonperforming loan (NPL) ratio for loan quality. Dynamic factor models quantify the comovement in each measure. After controlling for current and lagged macroeconomic conditions, we assess how much comovement remains and whether it is concentrated at short or long horizons. We also examine its historical association with the financial cycle. A parallel analysis of large banks provides a benchmark.

Our central finding is that comovement in small-bank balance sheet risk is substantial and predominantly slow. On average, common factors explain about three-fifths of the bank-level variation in both Z-scores and NPL ratios. After controlling for macroeconomic conditions, they still explain roughly one-third. Fluctuations longer than eight years account for 76% of the variation in the macro-adjusted median common path for Z-scores and 85% for NPL ratios. The corresponding shares for large banks are 38% and 55%, so comovement is substantially more concentrated at long horizons among small banks. The predominance of slow fluctuations also holds for a fixed set of

continuously reporting small banks, so changing sample composition does not explain it. Finally, the macro-adjusted common paths have historically tracked a financial-cycle proxy based on credit and house prices. When the proxy is high, Z-scores tend to be higher and NPL ratios lower.

We contribute to the literature on comovement in bank risk by showing that its persistence differs by bank size. [Guerrieri and Harkrader \(2021\)](#) separate bank performance into macroeconomic, common banking, and bank-specific variation. [Kapinos et al. \(2022\)](#) develop measures of dynamic banking comovement and relate them to economic activity. [Acharya and Yorulmazer \(2007\)](#) show theoretically that small banks have stronger incentives than large banks to herd. Evidence on bank size and systemic risk centers on large institutions: systemic risk grows with bank size ([Laeven et al., 2016](#)), and the empirical implementations of prominent systemic risk measures use market data for publicly traded financial institutions ([Adrian and Brunnermeier, 2016](#); [Acharya et al., 2017](#)). Most small banks are not publicly traded, however, so we measure risk from balance sheets. Doing so allows us to study more than 7,500 small banks. We show that, net of macroeconomic conditions, their balance sheet risk comoves mainly at horizons longer than eight years. This concentration at long horizons is substantially greater than among large banks.

2 Methodology

Data. Our data are quarterly U.S. Call Reports from 1983Q1 to 2020Q1. We divide commercial banks into small and large using the asset threshold that the Community Reinvestment Act regulations set for large institutions. The threshold was \$1 billion in 2005 and has since been adjusted annually with the CPI-W; we use the same index to extend it back to 1983. Banks below the threshold form our small-bank group, which combines the regulations' small and intermediate small categories. Measuring slow

fluctuations requires long histories. We therefore keep a bank only if it reports in one size group for a single uninterrupted spell of at least 64 quarters (16 years), and we use only its observations from that group.¹ This leaves 7,595 small banks for the Z-score, 7,655 for the NPL ratio, and 270 large banks for each measure.

We measure solvency risk with the Z-score,

$$Z_{it} = \frac{\text{ROA}_{it} + \text{equity}_{it}/\text{assets}_{it}}{\sigma_{\text{ROA},it}}, \quad (1)$$

where ROA is annualized quarterly return on assets and $\sigma_{\text{ROA},it}$ is its standard deviation over a rolling window of up to twelve reports, computed when at least two are available. A higher Z-score means that a larger fall in earnings is needed to exhaust equity, so solvency risk is lower. We measure loan quality with the NPL ratio: nonaccrual loans and leases plus those at least 90 days past due and still accruing, divided by total loans and leases. A higher ratio means poorer loan quality. We standardize each bank's series to zero mean and unit variance over its observed entries.

Dynamic factor model. For each risk measure and size group, we estimate a dynamic factor model that separates common from bank-specific variation:

$$x_{it} = \lambda_i' F_t + e_{it}, \quad F_t = A_1 F_{t-1} + \dots + A_p F_{t-p} + u_t, \quad (2)$$

where x_{it} is the standardized risk measure of bank i in quarter t , F_t is a vector of r common factors, and the loadings λ_i allow banks to differ in their exposure to them. The factors follow a VAR of order p with innovations u_t . The common component, $\chi_{it} = \lambda_i' F_t$, is the part of bank i 's risk that the factors explain, and e_{it} is the bank-specific remainder.

We select an initial factor count, r_{IC} , with the IC_{p2} criterion of [Bai and Ng \(2002\)](#). For each candidate r , BIC selects the lag order p , and the D_1 procedure of [Bai and Ng \(2007\)](#)

¹The 64-quarter minimum trades longer estimation histories against sample coverage. The main qualitative results are unchanged with a minimum as low as 32 quarters.

estimates the number of distinct innovations driving the factors, $\hat{q}(r)$. To keep the model parsimonious, we retain the smallest r that yields the same number of innovations as r_{IC} : $r_{par} = \min\{r : \hat{q}(r) = \hat{q}(r_{IC})\}$. We then estimate the common components with the two-step Kalman smoother of [Doz et al. \(2011\)](#), which accommodates missing observations.

Macroeconomic adjustment. Part of the comovement in bank risk reflects shared macroeconomic conditions (e.g., [Buch et al., 2014](#)). To account for it, we summarize those conditions with four factors, selected by IC_{p2} , from 123 FRED-QD series transformed as in [McCracken and Ng \(2021\)](#). We regress each bank’s risk measure on a constant and lags 0–4 of these factors, which allows responses delayed by up to one year. A contemporaneous-only specification provides a comparison. We then estimate the dynamic factor model on the residuals and interpret the resulting common components as macro-adjusted.

Measuring comovement. We measure comovement as the share of each bank’s variance explained by common factors. Specifically, we divide the variance of a bank’s common component in original units by the variance of its original risk measure, both computed on its observed dates. Because this denominator does not change with macroeconomic adjustment, the shares in [Table 1](#) are comparable across adjustments. For the same reason, the table holds the banks and dates fixed within the common 1984Q1–2020Q1 window. Factor counts and VAR lag orders are fixed at the values selected for the unadjusted model, while loadings and factor dynamics are re-estimated.

We also measure the time horizons of comovement, described below, and repeat the analysis for small banks that report in every quarter. For both, we select factor counts and VAR lag orders separately for each panel, so that each model reflects that panel’s own dynamics. Adjusted panels use only observations with the required macroeconomic lags. In these analyses, we measure comovement with the model-based common share,

$$R_i^2 = \frac{\lambda_i' \Sigma_F \lambda_i}{\lambda_i' \Sigma_F \lambda_i + \psi_i}, \quad (3)$$

where Σ_F is the covariance of the smoothed factors and ψ_i is the estimated idiosyncratic variance. After adjustment, its denominator is the total fitted variance of the residual panel, which differs from the original variance used in Table 1. We report both measures as equally weighted means across banks.

Measuring persistence. We next ask whether comovement is fast or slow. In each quarter, we take the median across banks of the estimated common components in original units. We call this series the median common path. We apply an ideal Fourier filter to isolate its fluctuations with periods longer than 32 quarters (eight years). The cutoff is the one Drehmann et al. (2012) use to separate business cycles from longer financial fluctuations. The long-horizon share is the variance of the filtered path divided by the variance of the unfiltered path. The paths are not detrended, so this share can include secular drift as well as cyclical fluctuations. It describes how comovement is distributed across horizons. The variance shares above measure its amount.

3 Results

Comovement strength. Comovement in small-bank risk is substantial (Table 1). On average, common factors explain 60% of the variation in a small bank’s Z-score and 57% of the variation in its NPL ratio. Macroeconomic conditions account for part of this comovement. After the adjustment with lags 0–4, the shares fall to 36% and 31%. Common factors therefore still explain about one-third of the variation in both measures. For large banks, the shares are 81% and 85% before adjustment and 42% and 29% after. For Z-scores and NPL ratios respectively, the selected models have 6 and 7 factors for small banks and 15 and 13 for large banks. All of our findings are qualitatively unchanged when the large-bank models use the small-bank factor counts.

Table 1: Share of bank-level variation explained by common factors

Banks	Small banks		Large banks	
	Z-score 7,595	NPL 7,655	Z-score 270	NPL 270
<i>Share explained by common factors (%)</i>				
No macro controls	60.3	56.7	80.9	85.4
Contemporaneous controls	47.3	39.4	57.9	45.0
Joint controls at lags 0–4	35.7	30.9	42.1	28.9

Each entry is the mean across banks of the common-component variance divided by the variance of the original risk measure. The sample is 1984Q1–2020Q1. Within each column, the banks, dates, factor count and VAR lag order are the same in every row. The factor count and lag order are those selected for the unadjusted model. Loadings and factor dynamics are re-estimated in each row.

Comovement persistence. After macroeconomic adjustment, comovement among small banks is predominantly slow. Fluctuations longer than eight years account for 76% of the variation in the macro-adjusted median common path for Z-scores and 85% for NPL ratios. The corresponding shares for large banks are 38% and 55%. Comovement is therefore substantially more concentrated at long horizons among small banks. Figure 1 shows the observed medians and the median common paths for small banks. Both findings hold with 24- and 40-quarter cutoffs and across the other robustness checks.²

Changes in the set of small banks over time do not explain the predominance of slow fluctuations. We repeat the analysis for the roughly 3,000 small banks that report in every quarter from 1983Q2 to 2020Q1. Their long-horizon shares are 77% for Z-scores and 89% for NPL ratios, close to the 76% and 85% for the full sample. Comovement is also strong in this sample. The common shares from equation (3) are 75% and 57% before adjustment. After adjustment, they are 70% and 56% of residual variation. Note that these adjusted shares use residual variance in the denominator, so they are not directly comparable with the adjusted shares in Table 1.

²The findings are qualitatively unchanged when we re-estimate the models with alternative factor counts and VAR lag orders. They also hold with a Hodrick–Prescott filter calibrated to 32 quarters and with modest endpoint trimming. The exact shares and the size of the small–large gap vary across specifications.

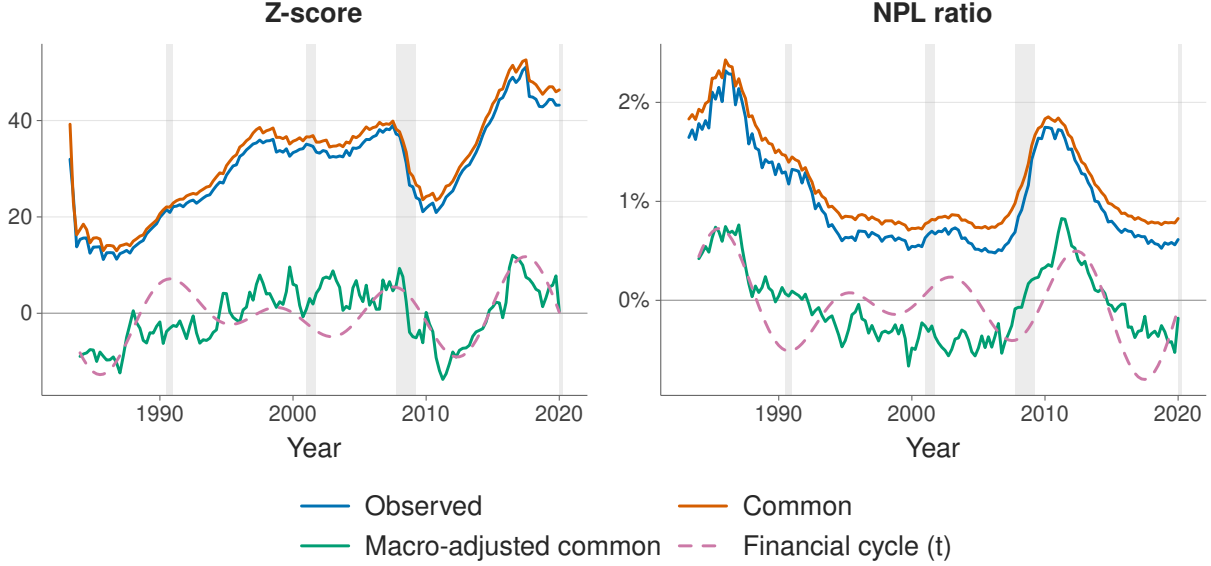


Figure 1: Comovement in small-bank risk, 1983Q1–2020Q1. Bank risk lines are cross-sectional medians in original units: the observed data and the common paths before and after macroeconomic adjustment. Higher Z-scores indicate lower solvency risk. The adjustment uses lags 0–4. The financial-cycle proxy, FC_t , is rescaled to the mean and standard deviation of the macro-adjusted path. Its sign is reversed for the NPL ratio. Shading marks recessions.

Financial-cycle association. Small banks’ macro-adjusted median common paths have historically tracked the financial cycle. Following [Drehmann et al. \(2012\)](#), we build a financial cycle proxy from real credit, the credit-to-GDP ratio, and house prices.³ Over the full sample, its contemporaneous correlation with the median common path is 0.59 for Z-scores and -0.56 for NPL ratios. Both signs mean that small-bank risk is lower when credit and house prices are high. Figure 1 overlays the proxy on both paths. The signs are stable across nearby leads and lags and under a 40–120-quarter band. The magnitudes are more sensitive to the band, especially for the Z-score.

³Credit is the sum of the FRED-QD series `REALLNx` and `BUSLOANSx`, which are real estate loans and commercial and industrial loans deflated by core PCE. Real GDP is `GDPC1` and house prices are `USSTHPI`. All series are from the June 2026 vintage. We take the 32–120-quarter Fourier components of log credit, credit-to-GDP and log house prices. We standardize each to zero mean and unit variance over the full sample and average them.

4 Conclusion

Comovement in bank balance sheet risk differs by bank size not only in strength but also in persistence. After controlling for macroeconomic conditions, comovement among small banks is substantially more concentrated at long horizons than comovement among large banks. For small banks, slow fluctuations are the dominant component of this comovement. Their historical association with credit and house prices links them to the financial cycle. These findings provide an empirical benchmark for understanding why the persistence of comovement differs by bank size and how it relates to broader financial conditions.

Our findings raise several questions for future research. First, the precise sources of slow comovement remain to be identified. For instance, structural changes such as regulation, consolidation, and technological change may contribute in addition to financial cycles. Second, the share of variation explained by common factors differs across banks, which raises the question of which bank characteristics are associated with greater exposure. Finally, future work could test whether slow comovement in small-bank risk affects lending and economic activity, which is the channel that motivates this paper.

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