**Article:**

Tolikas, K. (2026) The two clocks of systemic importance. Economics Letters, 268. 113151. ISSN: 0165-1765

https://doi.org/10.1016/j.econlet.2026.113151

# The Two Clocks of Systemic Importance

Forthcoming in *Economics Letters*

Konstantinos Tolikas*
Sheffield University Management School, University of Sheffield

**Abstract**

Systemic importance has two dimensions, a bank's contribution to system-wide tail risk ($\Delta$CoVaR) and its exposure to it (marginal expected shortfall, MES). Using daily $\Delta$CoVaR and MES for 24 publicly traded Global Systemically Important Banks over 2012–2025, we show the two rankings move on different clocks. Contribution rankings reorder at the same rate in calm times, the pandemic, and after. Exposure rankings survive the pandemic but re-anchor sharply at the 2022–2023 interest-rate regime change, as euro-area banks fall and US and Japanese banks rise. Shocks rotate which banks contribute to systemic risk; only regime changes move which are exposed.

**Keywords:** Systemic risk; G-SIBs; $\Delta$CoVaR; MES; Interest-rate regime.
**JEL classification:** C58; E43; G01; G21; G28.

* Konstantinos Tolikas, Sheffield University Management School, University of Sheffield, Conduit Road, Sheffield S10 1FL, United Kingdom. Tel./fax: +44 114 222 3224. *E-mail address:* k.tolikas@sheffield.ac.uk.

## 1. Introduction

Market-based systemic risk measurement distinguishes a bank's contribution to system-wide tail risk, measured by ΔCoVaR (Adrian and Brunnermeier, 2016), from its exposure to system-wide distress, measured by marginal expected shortfall (Acharya et al., 2017). The cross-sectional rankings of these measures load heavily on persistent institutional characteristics (Benoit et al., 2017), and the regulatory designations meant to capture systemic importance are built from slow-moving structural indicators (Basel Committee on Banking Supervision, 2013). One response to movements in the rankings has been to extract their common information rather than interpret each movement separately (Nucera et al., 2016). This paper asks instead what it takes to move the rankings of systemic importance, and whether the two dimensions move together. The answer is that exposure rankings are not simply stable, as a decade of evidence suggests; they are stable only within a macro-financial regime. The 2022–2023 interest-rate regime change, a major global tightening cycle, sharply reordered them, while contribution rankings rotated at the same pace as in every other state of the world. The reordering follows the monetary regime. As policy rates normalised after a decade near zero, euro-area banks—long the most exposed, because negative rates had compressed their margins—fell in relative exposure, while US and Japanese banks rose.

We establish this by ranking Global Systemically Important Banks (G-SIBs) on each of the two measures, period by period, and comparing the rankings across three economically distinct intervals of 2012–2025, namely a split of the tranquil 2010s, the Covid-19 pandemic, and the post-tightening years. Throughout we study relative standing rather than the level of systemic risk, with rank one the most exposed bank. Absolute exposure rose for every bank in the more volatile post-2023 window, so the finding concerns who is most exposed relative to peers, not the overall level. Contribution to systemic risk reorders continuously, with a cross-period rank correlation near 0.5 in all three comparisons. Exposure to it ignores the pandemic, the largest exogenous shock of the post-reform era (rank correlation 0.83), and then re-anchors at the regime change (rank correlation −0.01 with the pre-pandemic ordering). The re-anchoring has a perfect regional structure: every euro-area bank falls, by a median of eleven ranks in exposure, and every US and Japanese bank rises. The pre-period contains its own corroborating variation, since the only two-year windows of the 2010s in which the exposure ordering bent are the ones spanning the 2017–2018 US tightening. Neither fact is anticipated, since exposure rankings inherit the stability of the slow-moving characteristics they load on (Benoit et al., 2017), so much so that exposure measured before the global financial crisis forecast banks' losses in it (Acharya et al., 2017), yet the flip occurs within two years in the very dimension that had just passed through the pandemic largely unchanged.

Two lessons follow. For measurement, the celebrated stability of exposure-type rankings is regime-conditional, not absolute: exposure is invariant to shocks but not to changes in the regime that defines banks' sensitivities to common stress. For policy, designations and stress-testing priorities calibrated to the low-rate-era exposure ranking were, by 2024, calibrated to a ranking that no longer described the cross-section, even after excluding the 2023 banking-stress episode from the estimation window. Surveillance of systemic importance therefore needs two clocks, a fast one for the shock-driven rotation of which banks contribute to systemic risk, and a slow one, re-read at regime changes, for which banks are exposed to it.

The remainder of the paper proceeds as follows. Section 2 describes the data and the ranking design, Section 3 presents the results, and Section 4 interprets them and concludes.

## 2. Data and design

The sample comprises the 24 publicly traded G-SIBs with continuous listings over 2012–2025; Credit Suisse, resolved in June 2023, is excluded throughout so that every comparison uses an identical cross-section. Daily US-dollar total-return and market-capitalisation data are from Refinitiv; the daily return panel extends through December 2025. Because dollar returns embed exchange-rate movements, all results are also computed from local-currency returns, an exercise used purely as a no-FX robustness check rather than as an investable system portfolio (Table 1, Panel C).

Because the question concerns rankings across well-separated periods, each measure is estimated once per period from that period's daily returns, so consecutive periods share no observations and no mechanical smoothing links them. Let $r_{i,t}$ denote the daily return of bank $i$, $r_{s,t}$ that of the system portfolio, and $\hat{q}_{i,\alpha}$ the within-period $\alpha$-quantile of $r_{i,t}$. Within each period we estimate, at $q = 5\%$,

$$\Delta\mathrm{CoVaR}_i = \hat{\beta}_i\Big(\hat{q}_{i,0.50} - \hat{q}_{i,q}\Big), \qquad \mathrm{MES}_i = -\frac{1}{|\mathcal{T}|}\sum_{t\in\mathcal{T}} r_{i,t}, \qquad \mathcal{T} = \Big\{t : r_{s,t} \le \hat{q}_{s,q}\Big\}, \tag{1}$$

where $\hat{\beta}_i$ is the slope of the $q$-quantile regression of $r_{s,t}$ on $r_{i,t}$ (Adrian and Brunnermeier, 2016; Koenker and Bassett, 1978; Acharya et al., 2017). Both measures follow a positive-loss convention, so that a higher ΔCoVaR indicates a larger contribution to system tail risk and a higher MES a larger average loss on system tail days. Because the analysis compares rankings rather than levels, a higher rank denotes a more systemically important bank on the dimension in question. The system portfolio is value-weighted, with weights frozen at end-2022 for post-2022 periods so that they carry no post-period information. We compare four periods: the two halves of the tranquil pre-pandemic decade (2012–2015, 2016–2019), the pre-pandemic period as a whole (2012–2019), the pandemic (2020–2022), and the post-regime-change period (2024–2025). We exclude 2023, which contains the March 2023 banking stress, an endogenous shock distinct from the regime change studied here.[1] Excluding it gives

[1]In March 2023 the failures of Silicon Valley Bank and Signature Bank triggered a run on US regional-bank deposits, and an acute loss of confidence in Credit Suisse ended in its takeover by UBS, arranged by

Table 1: Rank persistence of the two dimensions across three comparisons

| | Contribution ($\Delta$CoVaR) | Exposure (MES) |
|---|---|---|
| *Panel A: Baseline (value-weighted system, $q = 5\%$, Spearman)* | | |
| Tranquil split (2012–2015 vs 2016–2019) | 0.45 | 0.76 |
| Pandemic (pre-Covid vs 2020–2022) | 0.53 | 0.83 |
| Regime change (pre-Covid vs 2024–2025) | 0.48 | −0.01 |
| *Panel B: Bootstrap test, regime-change persistence vs tranquil benchmark* | | |
| Difference (tranquil − post) | −0.04 [−0.46, 0.39] | 0.75 [0.36, 1.12] |
| $p$-value | 0.57 | <0.001 |
| *Panel C: Regime-change comparison, alternative designs* | | |
| Tail threshold $q = 10\%$ | 0.59 | 0.31 |
| Equal-weighted system | 0.69 | 0.23 |
| Leave-one-out system | 0.52 | 0.23 |
| Kendall's tau | 0.37 | 0.01 |
| Excluding the Japanese banks | 0.28 | 0.12 |
| Local-currency returns | 0.53 | 0.25 |
| Including 2023 in the post-period | 0.64 | 0.36 |
| 2024 and 2025 separately | 0.31, 0.54 | −0.22, 0.24 |

*Notes:* Rank correlations of per-period rankings of $\Delta$CoVaR and MES across the stated periods, for the 24 G-SIBs with continuous listings over 2012–2025. Each measure is estimated once per period from daily returns (quantile-regression $\Delta$CoVaR and non-parametric MES, $q = 5\%$ unless stated), with a value-weighted system portfolio (weights frozen at end-2022 for post-2022 periods). Panel B reports a pairs bootstrap (10,000 draws over banks) of the difference between the tranquil-split persistence and the regime-change persistence, with the 95% confidence interval and the one-sided probability that the difference is non-positive. In Panel C the tranquil and pandemic benchmarks move with the design, and in every case they remain far above the post-regime-change value; for the two most important checks they are 0.71 and 0.80 (leave-one-out) and 0.74 and 0.75 (local currency, with the system portfolio and every per-period estimate rebuilt from local-currency returns throughout). The 2023-inclusive row retains the baseline design and its Panel A benchmarks; its attenuation reflects a window that straddles the regime transition, and the regional separation of Section 3 remains exact.

the cleanest measurement window, since the post-period then lies entirely within the new rate regime, free of both the transition itself and an unrelated endogenous shock. Panel C of Table 1 shows that including 2023 leaves the results intact. Each entry of Table 1 is the Spearman rank correlation between the cross-sectional rankings of one measure estimated in two disjoint periods, so values near one indicate that the ordering of banks persists and values near zero that it has dissolved. Inference on persistence differences uses a pairs bootstrap over banks (10,000 draws); the regional comparison uses an exact rank-sum test.

## 3. Results

Table 1 contains the central result and Figure 1 visualises it.

Three facts stand out. First, the contribution clock never stops. Its cross-period rank

the Swiss authorities.

correlation is 0.45 across the tranquil split, 0.53 across the pandemic, and 0.48 across the regime change. The three are statistically indistinguishable; the bootstrap cannot reject equality of the post-period and tranquil values ($p$-value = 0.57). Whatever the state of the world, roughly the same substantial reordering takes place in which banks transmit systemic risk, consistent with the state-sensitivity of contribution-type measures documented by Löffler and Raupach (2018).

Second, the exposure clock remains still through events that re-rank contribution, then moves all at once. Post-regime-change exposure rankings are uncorrelated with their pre-pandemic counterparts. The persistence shortfall relative to the tranquil benchmark is 0.75, with a 95% confidence interval of $[0.36, 1.12]$, and Panel C shows the collapse in every design, including a leave-one-out system portfolio that removes any mechanical role for the focal bank's own weight. Nor is the two-year length of the post-period window driving the result. Estimating MES rankings on every two-year window of the pre-Covid decade, five of the seven windows correlate between 0.89 and 0.97 with the full pre-Covid ranking, so short windows by themselves degrade the ordering only mildly; the post-period window, at $-0.01$, lies far outside that range. Tellingly, the only two pre-Covid windows in which the ordering bent, 2017–2018 and 2018–2019 at 0.45 and 0.51, are precisely the windows spanning the previous US tightening cycle, after which the old ordering returned as rates fell back. The exposure ordering, in other words, bends when rates tighten temporarily and re-anchors when the rate regime changes durably.

Third, the re-anchoring is structural rather than statistical. The pre-pandemic top of the exposure ranking was a euro-area phenomenon, and by 2024–2025 every one of the seven euro-area banks had fallen and every one of the eight US and three Japanese banks had risen, with median rank changes of $-11$ for the euro area, $+8$ for the United States, $+13$ for Japan, and $-2$ elsewhere, and with JPMorgan moving from rank 16 to 2, Citigroup from 10 to 1, and Mizuho from 24 to 9 (Figure 1(b)).

The regional ordering itself inverted: the median euro-area bank was the fourth most exposed of the 24 before the pandemic and the fifteenth after the regime change, the median US bank moved from fourteenth to fifth, and the median Japanese bank from twenty-third to tenth, while the regional structure of contribution barely moved, with the median US bank ranked fifth or sixth on $\Delta$CoVaR in both periods. The separation is exact, and an exact rank-sum test rejects equal distributions with a $p$-value of 0.0005, while the same test on contribution rank changes finds no regional structure ($p$-value = 0.16), so the regional signature belongs specifically to the dimension that re-anchored.

Most starkly, none of the five most exposed banks of the 2010s, namely UniCredit, Deutsche Bank, Société Générale, ING, and Crédit Agricole, remains in the post-period top five, which consists entirely of US banks. A reshuffling this coherent is not estimation noise on twenty-five tail days, and it is not a currency artifact, since with all returns and the system portfolio measured in local currencies the regime-change exposure correlation is 0.25 against within-regime benchmarks of 0.74 and 0.75 (Table 1, Panel C) and the regional separation remains exact. The pattern is the footprint of the monetary-regime change introduced in Section 1 and developed in Section 4, under which rate normalisation restored euro-area bank profitability after a decade of negative rates, the end of yield-curve control re-rated the Japanese banks, and the large dollar franchises were left carrying the marginal sensitivity to global financial stress, inverting the European tilt in global systemic risk documented for the previous decade by Bostandzic and Weiß (2018).

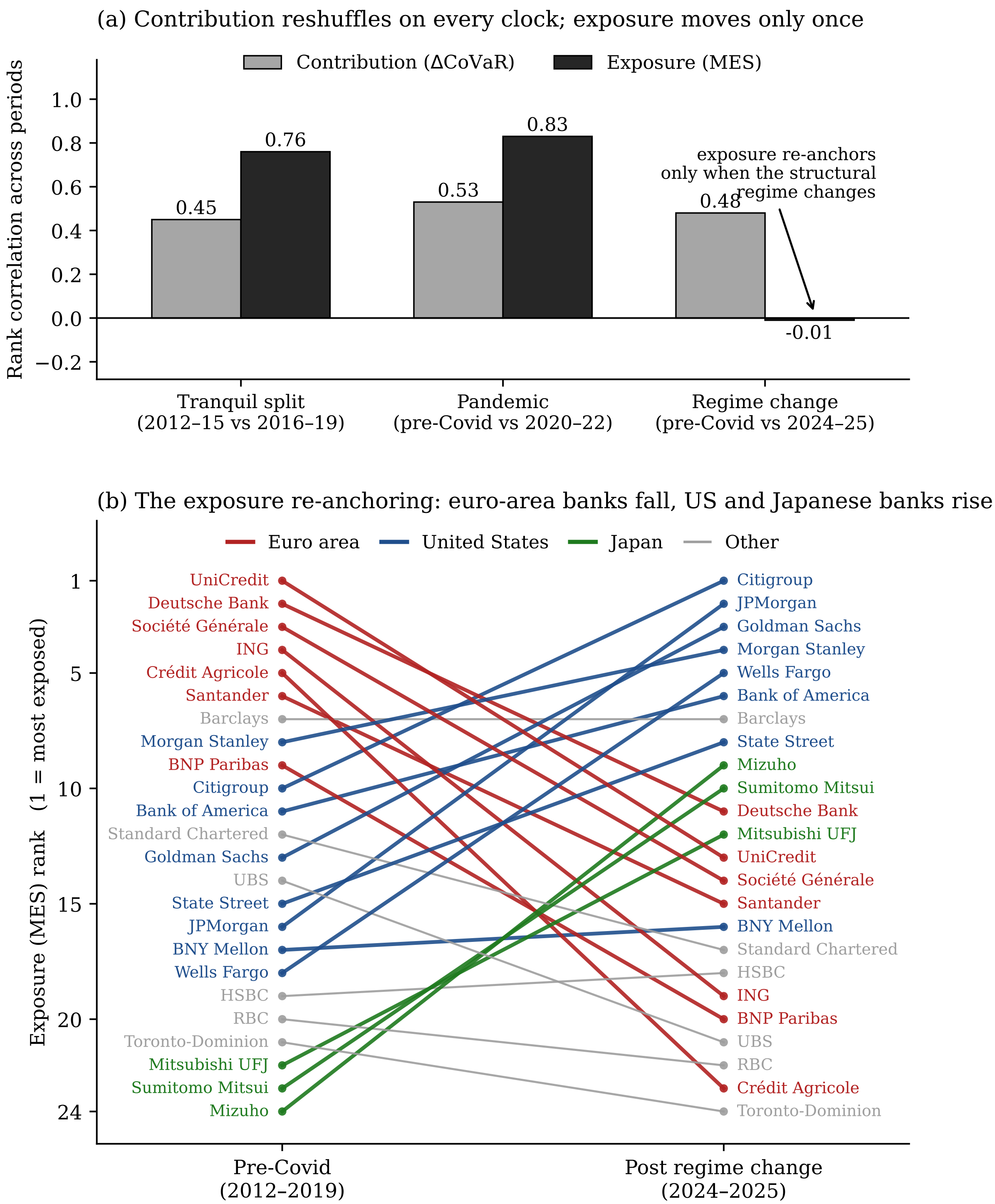


Figure 1: The two clocks of systemic importance. *Notes:* Panel (a) reports Spearman rank correlations of per-period rankings across the three comparisons of Table 1, Panel A. Panel (b) traces each bank's exposure (MES) rank from the pre-Covid period (2012–2019) to the post-regime-change period (2024–2025); 1 is the most exposed rank, and colours mark euro-area, US, and Japanese banks.

## 4. Interpretation and conclusion

A factor view organises the evidence. Bank returns load on a persistent common banking factor, with loadings set by institutional structure and the macro-financial regime, and on shock-specific factors, with loadings set by the incidence of the active shock on each business model. Contribution conditions on a bank's own distress, inherits the state dependence of whatever shock is active, and reorders continuously. Exposure conditions on system-wide distress, is anchored in the persistent loadings, and ignores shocks. The post-2023 evidence isolates the complement of that invariance: when the regime defining the persistent loadings itself changes, the exposure ordering re-anchors, even after excluding the 2023 banking-stress episode from the estimation window.

The regime in question is the monetary one. Regulatory and macroprudential change are implausible candidates on timing alone, because the Basel and G-SIB frameworks apply near-uniformly across the three regions and did not change differentially over 2022–2024, whereas the monetary regime shifted sharply and with a clear regional incidence. The euro area's exit from negative policy rates ended a decade of compressed lending margins (Heider et al., 2019) that had made euro-area banks the marginal casualties of common stress, interest-rate risk became a salient systemic factor that crystallised first among US banks in March 2023, and the Bank of Japan's exit from yield-curve control re-linked the bond-heavy Japanese banks to global rates. Each region's move in Figure 1(b) matches its place in this reconfiguration, and the regional inversion, present in exposure and absent in contribution, together with the bending of the ordering during the previous tightening cycle, points to the rate regime rather than to bank-specific events. Pinning the channel down bank by bank, through the pass-through of the rate regime to lending margins, bond-book duration, and deposit franchises, is a natural next step on a broader cross-section, and we read the rate-regime account as an interpretation consistent with the evidence rather than a formally identified mechanism.

What we learn is that the stability which makes exposure rankings and structural designations attractive for annual regulatory exercises is borrowed from the regime, not intrinsic to the banks. Within two years of the tightening, the market-implied stress-test priority list was headed by the largest US banks rather than the euro-area banks that had headed it for a decade. Systemic-risk surveillance needs two clocks, a fast one for who transmits systemic risk and a slow one for who is exposed to it, and the slow clock must be re-read whenever the macro-financial regime turns.

## Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author used AI-assisted tools in order to improve the proofreading and presentation of the manuscript. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the

published article.

# References


Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson, 2017, Measuring Systemic Risk, *Review of Financial Studies* 30, 2–47.

Adrian, T., and M. K. Brunnermeier, 2016, CoVaR, *American Economic Review* 106, 1705–1741.

Basel Committee on Banking Supervision, 2013, Global Systemically Important Banks: Updated Assessment Methodology and the Higher Loss Absorbency Requirement, Technical report, Bank for International Settlements.

Benoit, S., J. Colliard, C. Hurlin, and C. Pérignon, 2017, Where the Risks Lie: A Survey on Systemic Risk, *Review of Finance* 21, 109–152.

Bostandzic, D., and G. N. F. Weiß, 2018, Why Do Some Banks Contribute More to Global Systemic Risk?, *Journal of Financial Intermediation* 35, 17–40.

Heider, F., F. Saidi, and G. Schepens, 2019, Life below Zero: Bank Lending under Negative Policy Rates, *Review of Financial Studies* 32, 3728–3761.

Koenker, R., and G. Bassett, 1978, Regression Quantiles, *Econometrica* 46, 33–50.

Löffler, G., and P. Raupach, 2018, Pitfalls in the Use of Systemic Risk Measures, *Journal of Financial and Quantitative Analysis* 53, 269–298.

Nucera, F., B. Schwaab, S. J. Koopman, and A. Lucas, 2016, The Information in Systemic Risk Rankings, *Journal of Empirical Finance* 38, 461–475.