








Modelling Financial Markets

Chapter 18: Systemic Risk and Networks



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When Does One Bank's Distress Become the System's Problem?



Tobias Adrian. Photo: Chianoo Adrian (2021); CC BY-SA 3.0; Wikimedia Commons

"We propose a measure of systemic risk, ΔCoVaR, defined as the change in the value at risk of the financial system conditional on an institution being under distress relative to its median state."

— *Adrian & Brunnermeier (2016)*

- Thirteen banks from the US (United States), Europe and Romania, January 2010–September 2026
  - their declines are simultaneous: the euro-area crisis, COVID-19, the 2023 bank failures
- Risk of each bank in isolation: VaR 1% (Value-at-Risk), the daily loss exceeded with probability 1%
  - contribution to the system: ΔCoVaR 1% (CoVaR: the VaR of the system when an institution is in distress), the additional loss of the system when the bank moves from its median to its VaR
- The two rankings hardly agree: the Spearman rank correlation between VaR and ΔCoVaR is 0.13, across eleven banks
  - Deutsche Bank and ING (the Dutch ING Groep) have the largest VaR (7.19% and 7.16%), but only an average ΔCoVaR
  - JPMorgan has one of the smallest VaR (4.83%), but one of the largest ΔCoVaR
- The systemic measures do not give a single ranking either
  - MES 5% (Marginal Expected Shortfall): the average loss of the bank on the worst 5% of market days
  - the rank correlation between MES 5% and ΔCoVaR 1% is −0.04

Central chart: VaR and ΔCoVaR Measure Different Things

The Idea of the Chapter

From one bank to the system

- **Systemic risk**: the risk that the distress of one or several institutions impairs the financial system as a whole
  - and, through it, the real economy
- An **externality**: a bank does not pay for the losses its failure imposes on others
- Three families of measures (survey: Benoit, Colliard, Hurlin & Pérignon (2017))
  - **Exposure**: what does the bank lose when the market crashes?
  - MES: its average loss on crash days; SRISK (systemic risk): its capital shortfall in a crisis
  - **Contribution**: how much worse is the system when the bank is in distress?
  - ΔCoVaR, with CoVaR the VaR of the system conditional on the bank
  - **Connectedness**: through which links do shocks travel?
  - Spillover networks (how shocks pass between banks) and tail networks

The Plan of the Chapter: Tail Losses and Financial Networks

Two parts

- Part I: from the data to bank-level measures of systemic risk
  - data and conventions
  - exposure: MES, LRMES (the MES of a crisis lasting months), SRISK
  - contribution: CoVaR, ΔCoVaR, and how far rankings can be trusted
- Part II: networks, stress tests and a research case
  - spillover networks and the Financial Risk Meter
  - stress tests and climate risk
  - a case study on quantile connectedness
  - one pass of the discovery loop with AI (artificial intelligence)

What you should be able to do

- compute the MES, LRMES and SRISK of a bank and the break-even leverage Λ^*
- derive ΔCoVaR from the quantile regression and test the differences between banks
- compute the connectedness table of a VAR (Vector AutoRegression) and interpret the net spillover network
- interpret the Financial Risk Meter, stress tests and quantile connectedness
- Further Topics and Appendix: reading for familiarity

- Textbooks: Franke, Härdle & Hafner (2019), Härdle, Chen & Overbeck (2017)
- Detailed examples and advanced topics are in Further Topics, after the Conclusions
  - the footer button leads there; the Back button returns to the starting slide

Bank Runs: Northern Rock 2007 and Silicon Valley Bank 2023



Depositors queue outside a Northern Rock branch, Brighton, 14 September 2007

Photo: Dominic Alves (2007); CC BY 2.0; Wikimedia Commons

- Northern Rock (2007): a British mortgage lender
  - hit by the freeze in funding markets after the US subprime losses
  - depositors queued to withdraw their savings
- SVB (2023): a digital run
  - the FDIC (Federal Deposit Insurance Corporation) took the bank over on 10 March FDIC (2023)
  - two days later all depositors of SVB and Signature Bank were protected on **systemic** risk grounds Federal Reserve Board (2023)

Through Which Channels Does Contagion Travel?

- One bank's distress becomes systemic through three channels
  - **Funding runs**: depositors and lenders withdraw from any bank that looks similar
  - **Common exposures** and **fire sales**: forced selling lowers prices for every holder
  - **Counterparty links**: one bank's liability is another bank's asset, so a default passes losses to its creditors

Thirteen Banks, Three Markets: Prices and Log Returns

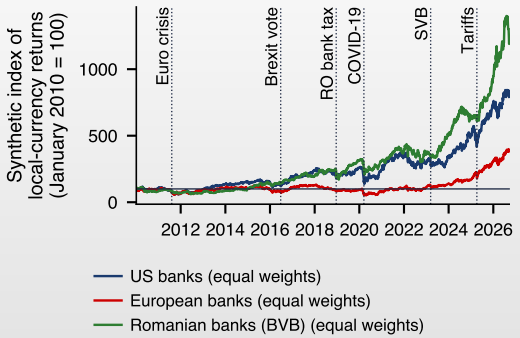
Group	Banks (ticker, used in some charts)	Market index
US banks	JPMorgan (JPM), Bank of America (BAC), Citigroup (C), Goldman Sachs (GS), Morgan Stanley (MS), Wells Fargo (WFC)	S&P 500
European banks	Deutsche Bank (DBK), BNP Paribas (BNP), Santander (SAN), ING (INGA), HSBC (HSBA)	Euro Stoxx 50
Romanian banks	Banca Transilvania (TLV), BRD-Groupe Société Générale (BRD; "BRD-Groupe SG" in charts)	BET
Volatility	the VIX index (implied volatility of the S&P 500)	

- Daily prices, January 2010 to 18 September 2026, adjusted for dividends and splits
  - Aligned on 3 962 common trading dates first, then 3 961 log returns between consecutive common dates, $r_t = 100(\ln P_t - \ln P_{t-\mathbf{1}})$, in %
  - A return can span several sessions: 177 intervals cover more than one session of the S&P 500 (Standard & Poor's 500), up to 6
  - On each region's own calendar, MES 5% changes by at most 0.17 points and ΔCoVaR 1% by at most 0.32 points
- Special cases
  - Romanian banks, traded on the Bucharest Stock Exchange (BVB, index BET): days without trades removed
  - Historical stress scenarios for the international banks start in 2007

Losses as Positive Numbers and the System Portfolio

- Return X, loss $L = -X$
  - the level α is a **tail probability** (Chapter 7)
  - $\mathrm{VaR}_\alpha(X) = -q_\alpha(X)$, with q_α the α-quantile of X
  - We write VaR 1%, CoVaR 1%, MES 5%, all positive when they are losses
- **System** return X^{sys}: the equal-weighted portfolio of the other banks of the same region
  - $X^{sys} = \frac{1}{n}\sum_j X_j$, a first-order approximation of the log return of the daily rebalanced portfolio
  - CoVaR is stated for this aggregate, while MES conditions on the regional market index

Three Banking Systems, 2010–2026



- Equal-weighted portfolios of the banks of each region, rebalanced daily
  - Vertical lines mark the episodes used in this chapter
  - No currency conversion: European banks in euro (EUR), HSBC (originally the Hongkong and Shanghai Banking Corporation) in pounds sterling (GBP)
  - Banks listed today: survivors selected with hindsight
- Synthetic indices of local-currency returns (January 2010 = 100): 791 (US), 384 (Europe), 1 233 (Romania)
  - Maximum drawdown: US 51% (2011-11-23), Europe 61% (2020-04-21), Romania 47% (2012-06-06)
  - Annualised volatility: 29%, 30%, 23% (market indices: 18%, 21%, 18%)
- The falls are **simultaneous**: euro crisis, COVID-19, 2023 bank failures
  - Romanian banks also have their own shock: the bank-tax announcement of December 2018 (label "RO bank tax")

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How Much Does a Bank Lose When the Market Crashes?

- **Exposure**: the loss of the bank given a market crisis, not its stand-alone VaR
  - What matters are the banks that run out of capital exactly when the system needs it
- Three steps, from one crash day to a crisis
  - MES: the average loss of the bank on the worst 5% of market days, the level used by Acharya, Pedersen, Philippon & Richardson (2017)
  - LRMES: the loss of the bank in a crisis lasting weeks or months
  - SRISK: the capital the bank would lack after that loss

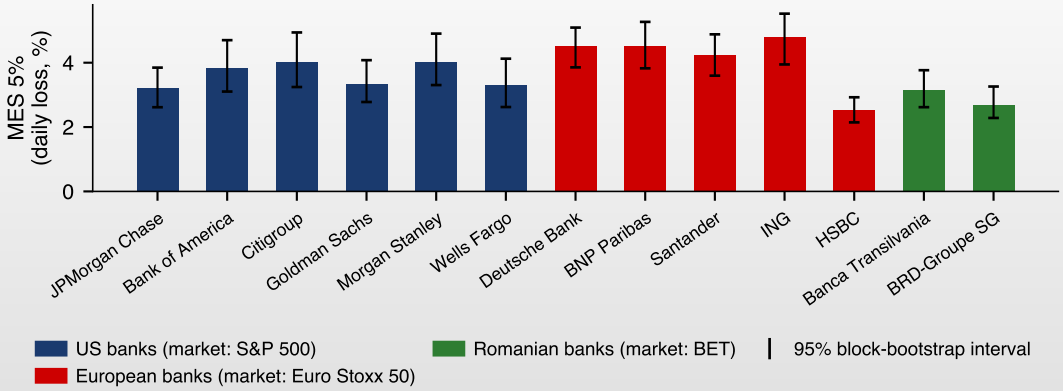
MES, Intuitively

- The question: how much does a bank lose on average on the days when the market has a very bad day?
- The computation: pick the worst 5% days of the market index (about 200 days out of 3 961) and average the bank's losses on those same days
- Compare with the market: on these days the S&P 500 lost 2.72% on average, JPMorgan 3.21%, Morgan Stanley 4.03%
  - the banks lose more than the market precisely on the market's bad days
- The difference from VaR: VaR looks at the bank's bad days; MES looks at the market's bad days, when the other banks suffer too
- Why "marginal": if the market were itself a portfolio of these banks, its average loss on the bad days would split exactly across the banks by MES, weighted by their weights
  - our indices are not such portfolios, so here MES measures the bank's exposure
- The next step, LRMES, goes from one bad day to a six-month crisis

Marginal Expected Shortfall and the Euler Property

- **MES** (Marginal Expected Shortfall) of bank i at level α Acharya, Pedersen, Philippon & Richardson (2017)
  - $\mathrm{MES}_{i,\alpha} = -\mathbb{E}[X_i \mid X_m \leq q_\alpha(X_m)]$: the average loss of the bank on the worst α share of days for the market m
- Why "marginal": **if** $m = \sum_i w_i X_i$ is the portfolio itself, then $\mathrm{ES}_\alpha(X_m) = \sum_i w_i \,\mathrm{MES}_{i,\alpha}$
  - this is the Euler allocation (proof in the Appendix)
  - Our market indices are **not** portfolios of these 13 banks
  - Here MES measures **exposure**, not a share of the index ES (Expected Shortfall)
- Historical estimate: average $-X_i$ over the days with $X_m \leq \hat{q}_\alpha(X_m)$
  - With $\alpha = 5\%$ and 3 961 days, about 200 days

MES 5% of Thirteen Banks (1/2)



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MES 5% of Thirteen Banks (2/2)

- Average daily loss of each bank on the worst 5% of days for its market index, 2010–2026
  - 95% intervals: moving-block bootstrap, blocks of 20 days
  - MES exists if the bank's loss is integrable on the market's tail days
  - The Normal interval needs a finite long-run variance of the influence function and weak dependence, not in general a fourth moment
- US banks: 3.21% (JPMorgan) to 4.03% (Morgan Stanley)
  - Europe up to 4.79% (ING)
  - Same days, market: 2.72% (S&P 500), 3.16% (Euro Stoxx 50): banks lose more
- HSBC is the exception in Europe (2.53%, below the index)
  - A London listing with business concentrated in Asia
- Banca Transilvania 3.14%, BRD (BRD–Groupe Société Générale) 2.69%
  - BET itself 2.69%
- Type of evidence: description (it shows what happened in the data, without testing a cause)

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LRMES, Intuitively

- MES looks at a single bad day; a real crisis lasts months, for example a market fall of 40% in six months
- **LRMES**: how much the bank's shares lose, on average, if the market goes through such a crisis
- The simple version, without simulation: start from the bank's loss on a day when the market falls by more than 2% ($\mathrm{MES}^{2\%}$) and extend it to a long crisis
  - the factor 18 makes the step from one day to six months, with a constant beta: $\mathrm{LRMES} \approx 1 - e^{-18\,\mathrm{MES}^{2\%}}$
  - example: $\mathrm{MES}^{2\%} = 3\%$ gives 41.7%
- For our banks: from 37% (HSBC) to 58% (ING); JPMorgan 48%, Banca Transilvania 52%
  - several banks would lose more than the market itself
- The version in Further Topics: simulate many six-month paths and average the bank's loss over those in which the market falls by more than 40%
- Why it matters: LRMES enters SRISK directly; the more the shares fall, the less capital remains

From MES to a Crisis: LRMES

- **LRMES** (Long-Run MES): the expected fall of the bank's market equity in a crisis
  - $\mathrm{LRMES}_{i,t} = -\mathbb{E}_t\left[R_{i,t+\mathbf{1}:t+h} \mid R_{m,t+\mathbf{1}:t+h} < C\right]$, with R the h-day arithmetic returns of bank and market
  - Crisis: the market falls below $C = -40\%$ over six months Acharya, Engle & Richardson (2012), or below $C = -10\%$ over $h = 22$ days Brownlees & Engle (2017)
- Shortcut of Acharya, Engle & Richardson (2012), without simulation: $\mathrm{LRMES}_i \approx 1 - \exp(-18 \times \mathrm{MES}_i^{\mathbf{2\%}})$
  - $\mathrm{MES}_i^{\mathbf{2\%}}$: average daily loss of the bank on days when the market falls by more than 2%
  - The 18 scales it to the six-month crisis, with a constant beta
  - Example: $\mathrm{MES}^{\mathbf{2\%}} = 3\%$ gives $1 - e^{-\mathbf{0.54}} = 41.7\%$
- On our banks: 37% (HSBC) to 58% (ING)
  - JPMorgan 48%, Banca Transilvania 52%

SRISK, Intuitively

- The question: if the market falls by 40% in six months, how much new money would the bank need to stay adequately capitalised?
- Three ingredients: how much the bank owes (D), what its shares are worth today (W) and how much the shares would fall in the crisis (LRMES)
- The computation on the chapter's example: $D = 900$, $W = 100$, LRMES $= 41.7\%$
  - after the crisis, the shares are worth $(1 - 0.417) \times 100 = 58.3$
  - the prudential rule requires capital of at least $k = 8\%$ of quasi-assets: $0.08 \times (900 + 58.3) = 76.7$
  - $76.7 - 58.3 = 18.4$ is missing: this is SRISK
- A positive SRISK: a capital hole that, in a crisis, someone would have to fill (new shareholders or the state); the sum over banks is the SRISK of the system
- What makes it large: large debt relative to capital and a large fall of the shares in the crisis
  - for our banks LRMES runs from 37% (HSBC) to 58% (ING)

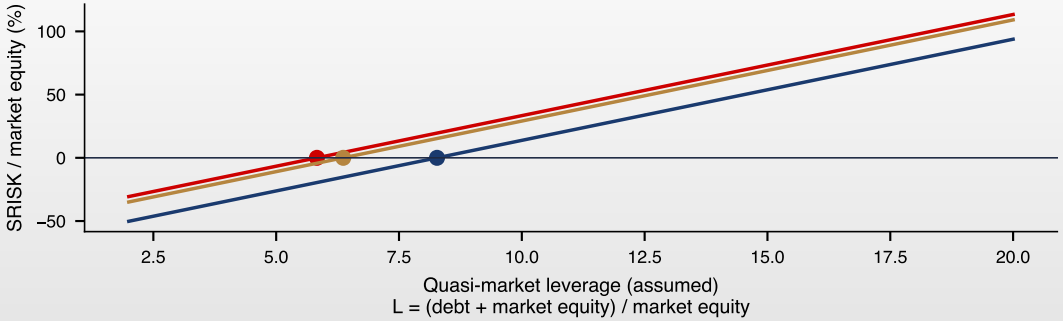
SRISK and the Break-Even Leverage (1/2)

- **SRISK** (systemic risk): the capital a bank would lack in a severe market crisis
- Equity must be at least a share k of quasi-assets, book debt D plus market equity W Brownlees & Engle (2017)
  - $\mathrm{SRISK}_i = k\,D_i - (1-k)(1-\mathrm{LRMES}_i)\,W_i$, assuming debt is not renegotiated in the crisis
  - Equivalently, $k[D_i + (1-\mathrm{LRMES}_i)W_i] - (1-\mathrm{LRMES}_i)W_i$
  - That is, the capital required after the crisis minus the capital left
- $k = 8\%$ for US firms Brownlees & Engle (2017) and $k = 5.5\%$ for European firms Engle, Jondeau & Rockinger (2015)
  - IFRS (International Financial Reporting Standards) balance sheets allow less **netting** of derivatives than US GAAP (Generally Accepted Accounting Principles)
  - So they report larger assets
- Positive SRISK is a capital shortfall
  - the system SRISK, the sum of the positive values, is published by V-Lab, New York University Stern School of Business

SRISK and the Break-Even Leverage (2/2)

- Divide by W, with quasi-market leverage $\Lambda = (D + W)/W$: $\dfrac{\mathrm{SRISK}}{W} = k(\Lambda - 1) - (1 - k)(1 - \mathrm{LRMES})$
- SRISK is positive once Λ exceeds the **break-even leverage** $\Lambda^* = 1 + \dfrac{(1 - k)(1 - \mathrm{LRMES})}{k}$
- Example: $D = 900$, $W = 100$ (so $\Lambda = 10$), $\mathrm{LRMES} = 41.7\%$
  - $\mathrm{SRISK} = 0.08 \times 900 - 0.92 \times (1 - 41.7\%) \times 100 = 72 - 53.6 = 18.4$
  - $\Lambda^* = 7.7 < \Lambda = 10$: a shortfall
- Our data contain prices, not balance sheets
  - we report Λ^* from the estimated LRMES
  - we treat leverage as an **assumption**

SRISK as a Function of Leverage (1/2)



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SRISK as a Function of Leverage (2/2)

- Banks with the highest, median and lowest LRMES
  - dots mark Λ^*
  - Leverage on the horizontal axis is assumed, not observed
- Curves in the chart, with $k = 8\%$ and the shortcut LRMES: $\Lambda^* = 5.8$ (ING), 6.4 (Santander), 8.3 (HSBC)
  - Other banks: JPMorgan 7.0, Morgan Stanley 6.0, Banca Transilvania 6.5, BRD 7.1
- Above Λ^* the bank needs new capital in a 40% market crash
  - i.e. with debt above 4.8–7.3 times market equity
- With $k = 5.5\%$ the thresholds rise (ING 8.2, HSBC 11.9)
  - SRISK depends on the chosen prudential ratio
- Limits of the calculation
  - LRMES extrapolates daily data
  - market equity itself falls in a crisis
  - LRMES simulated with an asymmetric GARCH (GJR) and dynamic conditional correlations (DCC) is 0.43 to 0.92 of the shortcut (Further Topics): Λ^* depends on the model
- Type of evidence: description
  - a threshold computed for an assumed leverage, not an observed capital shortfall

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▸ Further Topics: LRMES by simulation

How Much Worse Is the System When a Bank Is in Distress?

- MES looks from the market to the bank
  - **contribution** looks the other way, from the bank to the system
- We need a quantile in the tail of the system, not its mean
  - Quantile regression estimates the conditional quantile directly Koenker & Bassett (1978)
- Levels: $\alpha = 1\%$ and $\alpha = 5\%$, those reported by Adrian & Brunnermeier (2016)
  - we compare the rankings at the two levels
- Questions of this section
  - How much does each bank add to the tail loss of the system?
  - Are the differences between banks statistically significant?

CoVaR, Intuitively

- The VaR of a bank answers the question: how much can the bank lose on one of its worst 1% days?
- The regulator has another question: how much does the rest of the banking system lose on a day when this bank is in distress?
- **CoVaR**: the VaR of the system, computed for the days on which the bank is at its own VaR
- **ΔCoVaR**: how much this loss of the system rises compared with an ordinary day for the bank (median return)
  - it is the bank's contribution to the tail risk of the system, not its own risk
- The two can differ a lot: a bank with small losses of its own can drag the system down with it
  - JPMorgan has one of the smallest VaR (4.83%), but one of the largest ΔCoVaR
  - Deutsche Bank has the largest VaR (7.19%), but only an average ΔCoVaR
- The estimation in words: draw the line that follows the worst 1% days of the system as a function of the bank's return (quantile regression); its slope shows how much the bank adds

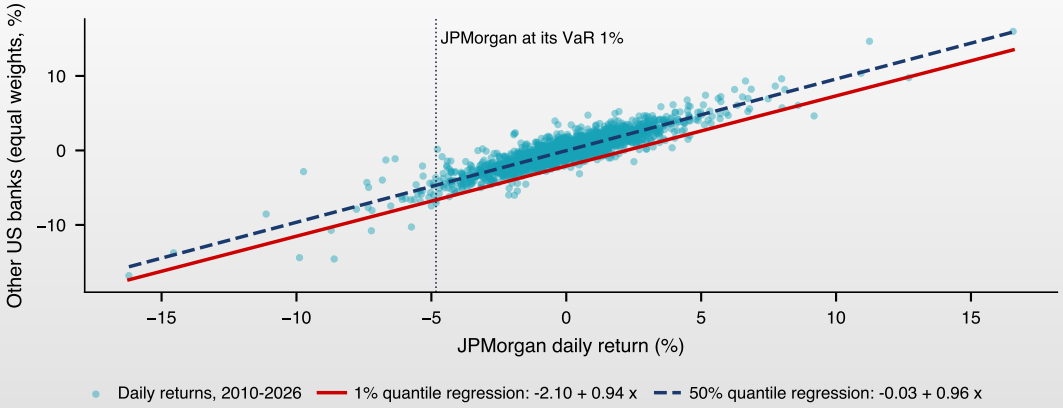
CoVaR: the VaR of the System Given a Bank in Distress

- **CoVaR** of the system conditional on bank i at its VaR Adrian & Brunnermeier (2016)
  - $P\left(X^{sys} \leq -\mathrm{CoVaR}_{\alpha}^{sys|i} \;\middle|\; X_i = -\mathrm{VaR}_{i,\alpha}\right) = \alpha$
  - The loss of the system that is exceeded with probability α on a day when bank i is at its own VaR
- **ΔCoVaR**: the change from the median state of the bank, a normal day, to its distress state
  - $\Delta\mathrm{CoVaR}_{\alpha}^{sys|i} = \mathrm{CoVaR}_{\alpha}^{sys|X_i=q_\alpha} - \mathrm{CoVaR}_{\alpha}^{sys|X_i=q_{50\%}}$, with the bank return fixed at the quantile shown
- ΔCoVaR measures the **contribution** of bank i to the tail risk of the system
- Reversing the roles gives the **exposure CoVaR**
  - the VaR of bank i when the system is in distress

Estimating CoVaR by Quantile Regression

- Quantile regression Koenker & Bassett (1978): $q_\alpha(Y \mid x) = a_\alpha + b_\alpha x$
  - $(\hat{a}_\alpha, \hat{b}_\alpha) = \arg\min_{a,b} \sum_t \rho_\alpha(y_t - a - bx_t)$
  - The **check function** $\rho_\alpha(u) = u\,(\alpha - 1\{u < 0\})$ weights negative residuals by $1 - \alpha$ and positive ones by α
- 1. Regress the system on the bank: $\hat{q}_\alpha(X^{sys} \mid X_i) = \hat{a}_\alpha + \hat{b}_\alpha X_i$
- 2. Plug in the bank's distress quantile: $\mathrm{CoVaR}_\alpha^{sys|i} = -\left(\hat{a}_\alpha + \hat{b}_\alpha \hat{q}_\alpha(X_i)\right)$
- 3. $\Delta\mathrm{CoVaR}_\alpha^{sys|i} = \hat{b}_\alpha\,(\hat{q}_{\mathbf{50\%}}(X_i) - \hat{q}_\alpha(X_i))$
  - the intercept cancels
- Uncertainty: moving-block bootstrap with 999 resamples
  - it keeps volatility clustering
  - The block length grows like $n^{\mathbf{1/3}}$ Hall, Horowitz & Jing (1995): $3\,961^{\mathbf{1/3}} \approx 16$, raised to 20 observations, about one trading month

Quantile Regression: JPMorgan and the Other US Banks (1/2)



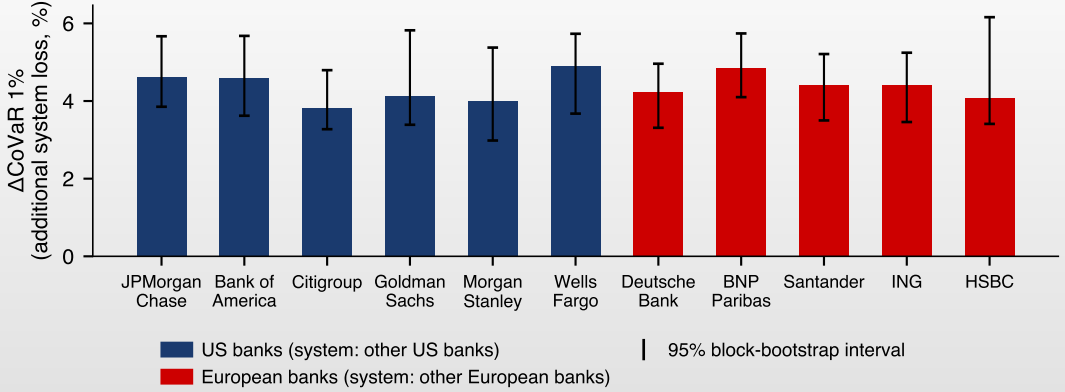
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Quantile Regression: JPMorgan and the Other US Banks (2/2)

- Daily returns 2010–2026, 1% and 50% quantile regression lines
  - dotted line: JPMorgan at its VaR 1%
- 1% line: $\hat{q}_{1\%} = -2.10 + 0.94\, X_i$
  - median line: $-0.03 + 0.96\, X_i$
  - Similar slopes: the 1% line is shifted down, not steeper
- With JPMorgan at its VaR 1% (4.83%), the other US banks have CoVaR 1% = 6.64%
  - Against the system VaR 1% of 5.07% and the CoVaR 1% of 2.03% with JPMorgan at its median
- $\Delta\mathrm{CoVaR}_{1\%} = 4.62\%$
  - JPMorgan in distress adds about 4.62 points to the tail loss of the system
  - Association, not causation: a common shock hits all banks on the same day

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ΔCoVaR 1% of Eleven Banks (1/2)



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ΔCoVaR 1% of Eleven Banks (2/2)

- Bars: ΔCoVaR, the **extra** system loss when the bank moves from its median to its VaR
  - with 95% bootstrap intervals
  - No Romanian banks: with only two, the "system" of the other bank would be one single bank
- From 3.81% (Citigroup) to 4.89% (Wells Fargo)
  - intervals 1.5–2.8 points wide
  - The marginal intervals overlap, e.g. Citigroup $[3.27, 4.79]$ and Wells Fargo $[3.68, 5.73]$
- Overlap is **not** a test
  - estimates from the same days are strongly correlated
  - so the interval for the difference can be narrower
- At $\alpha = 5\%$ the values are smaller (JPMorgan 2.63%) and the ranking changes
  - Spearman correlation of the 1% and 5% rankings: also 0.13 (by coincidence, as for VaR vs ΔCoVaR), a fragile basis for regulation
- Type of evidence: association (the variables move together; this does not prove causation)

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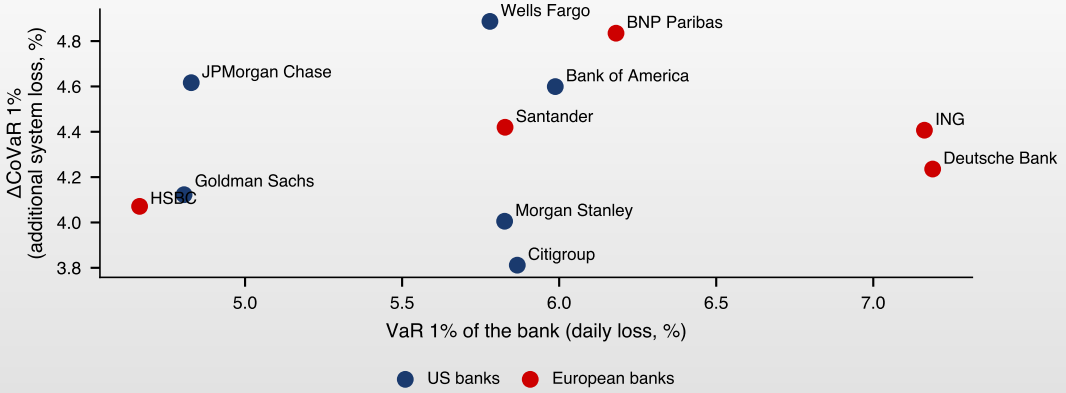
Testing ΔCoVaR 1%

- All tests use the same 999 block-bootstrap draws for every bank
  - so the estimates keep their dependence (details: Appendix)
- (1) No contribution, H_0: $b_\alpha = 0$
  - Standard error of the slope $\hat{b}_{1\%}$ from the same bootstrap draws, Holm (1979) correction over the 11 banks
  - z-ratios from 8.7 (HSBC) to 22.6 (Citigroup): the slope is positive for all 11 banks, also after Holm (Quantile Regression: Asymptotics)
  - With the kernel sandwich standard error Hendricks & Koenker (1992), valid only for serially uncorrelated scores: t from 4.0 to 6.9
- (2) Tail slope equal to the median slope, H_0: $b_\alpha = b_{50\%}$: rejected for 2 of 11 banks (Citigroup, ING, also after Holm)
  - not rejecting for the other 9 does not prove equality
- (3) Equal contributions, H_0: $\Delta\mathrm{CoVaR}_i = \Delta\mathrm{CoVaR}_j$
  - dominance tests: Castro & Ferrari (2014); results by bank: Appendix
  - At $\alpha = 1\%$: 4 of 25 within-region pairs differ at 5% (0 after Holm); joint Wald $p = 0.011$ (US), 0.28 (Europe)
  - At $\alpha = 5\%$: 3 of 25 pairs differ (0 after Holm); joint Wald $p = 0.017$ (US), 0.038 (Europe)

Reading the Tests: Holm and the Joint Wald Test

- **Many pairs, one family**: 25 pairs tested at 5%
  - more than one false "difference" is expected even with equal contributions
  - Holm (1979): sort $p_{(1)} \leq \cdots \leq p_{(m)}$ and reject while $p_{(k)} \leq 0.05/(m-k+1)$
  - The family-wise error stays below 5% for any dependence
  - Toy check, $p = 0.010, 0.030, 0.040$: $0.010 \leq 0.05/3$ (reject), $0.030 > 0.05/2$ (stop): one rejection instead of three
- **Joint Wald test** of equal contributions within a region
  - $W = \hat{d}^\top \hat{V}^{-1} \hat{d} \sim \chi^2$ with the number of banks minus 1 degrees of freedom
  - $\hat{d}$: differences from one reference bank (any choice gives the same W)
  - $\hat{V}$: their bootstrap covariance
- US: the joint test rejects ($p = 0.011$) while 0 of 25 pairs survive Holm
  - The joint test pools moderate differences; Holm needs one very strong pair ($p_{(1)} \leq 0.05/25$)
  - So the contributions are not all equal, but we do not know which pair differs

VaR and ΔCoVaR Measure Different Things (1/2)



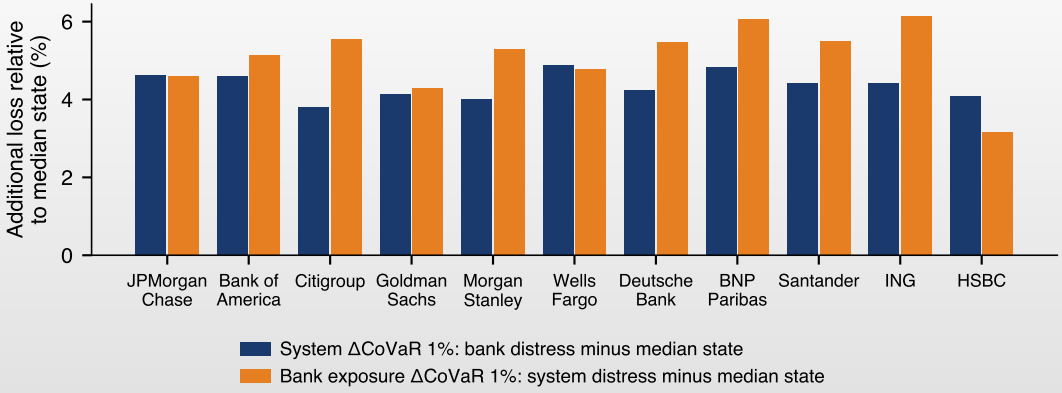
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VaR and ΔCoVaR Measure Different Things (2/2)

- Horizontal axis: VaR 1% of the bank, vertical axis: its ΔCoVaR 1%
  - eleven banks, 2010–2026
- Spearman rank correlation between VaR and ΔCoVaR: 0.13
  - Deutsche Bank and ING: the largest VaR (7.19%, 7.16%), only average ΔCoVaR
  - JPMorgan: one of the smallest VaR (4.83%), one of the largest ΔCoVaR
- Central message of Adrian & Brunnermeier (2016)
  - Regulating each bank by its own VaR ignores its contribution to the system
- Caveat: with eleven banks and overlapping intervals the correlation is very uncertain

MFM_ch18_covar

Contribution versus Exposure (1/2)



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Contribution versus Exposure (2/2)

- Blue, contribution: loss of the system when the bank is in distress
- Orange, exposure: loss of the bank when the system is in distress
  - X_i regressed on X^{sys}, quantiles of X^{sys} plugged in
- The direction matters: ING has contribution 4.41% and exposure 6.14%
  - BNP Paribas (BNP: Banque Nationale de Paris): 4.83% and 6.07%
- HSBC: contribution 4.07%, exposure only 3.17%
- Exposure exceeds contribution for most European banks
- Both are associations, not causal effects
- Exposure matters for the bank's own capital
  - contribution matters for the regulator

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How Much Can We Trust a Ranking?

- Rankings by different systemic measures disagree and carry wide uncertainty Nucera, Schwaab, Koopman & Lucas (2016)
  - combine measures and report rank uncertainty
- Model risk Danielsson, James, Valenzuela & Zer (2016)
  - simulated vs shortcut LRMES
  - Girardi–Ergün vs quantile-regression CoVaR
  - $\alpha = 1\%$ vs 5%
- Effective tail sample αn: 40 days at 1%, 198 at 5%
  - At 1% the kernel and block-bootstrap standard errors disagree (Appendix)
- Out-of-sample backtests of the Girardi–Ergün CoVaR 5% reject for no bank (Appendix)
  - With about 7.4 expected joint hits their power is low
- What survives are large, tested differences
  - across regions and in the tail slope of some banks
  - not the order of eleven close point estimates

Through Which Links Do Shocks Travel between Banks?

- MES and CoVaR look at one bank and one aggregate
  - a crisis, however, travels between many banks at once
- A network answers three questions
  - Who transmits shocks and who receives them?
  - How connected is the system as a whole?
  - Does connectedness rise in crises?
- The approach: the forecast-error variance decomposition of a VAR Diebold & Yilmaz (2014)
  - on the daily volatilities of the banks

From Pairs to Networks: the Variance Decomposition (1/2)

- A **network** looks at all pairs of banks at once
  - Nodes: banks; directed edges: how much of the future uncertainty of bank i comes from shocks to bank j
- Vector autoregression (VAR) of order p for N series y_t
  - $y_t = c + \sum_{l=1}^{p} A_l\, y_{t-l} + \varepsilon_t$, $\mathrm{Cov}(\varepsilon_t) = \Sigma$
  - Each series is regressed on p lags of all series
  - c: constants; A_l: $N \times N$ coefficient matrices
  - ε_t: shocks; Σ: their covariance matrix (assumptions: Appendix)
- Variance-decomposition networks Diebold & Yilmaz (2009), Diebold & Yilmaz (2012), Diebold & Yilmaz (2014): the approach of this section
- Other networks
  - Granger causality Billio, Getmansky, Lo & Pelizzon (2012) (Appendix)
  - tail networks TENET (Tail-Event driven NETwork risk) Härdle, Wang & Yu (2016)
  - the Financial Risk Meter (next section)

From Pairs to Networks: the Variance Decomposition (2/2)

- The H-day forecast error of y_i is a sum of shocks to all series
  - so its variance can be split by source
  - Moving-average form $y_t = \mu + \sum_{h \geq \mathbf{0}} \Phi_h \varepsilon_{t-h}$: Φ_h is the response of y after h days to a shock today, $\Phi_{\mathbf{0}} = I$
- Orthogonal (Cholesky) shocks depend on the ordering of the series
  - the **generalized** decomposition does not Koop, Pesaran & Potter (1996), Pesaran & Shin (1998)
  - $\theta_{ij}(H) = \frac{\sigma_{jj}^{-\mathbf{1}} \sum_{h=\mathbf{0}}^{H-\mathbf{1}} (e_i^\top \Phi_h \Sigma e_j)^{\mathbf{2}}}{\sum_{h=\mathbf{0}}^{H-\mathbf{1}} e_i^\top \Phi_h \Sigma \Phi_h^\top e_i}$, normalised: $\tilde{\theta}_{ij} = \theta_{ij} / \sum_j \theta_{ij}$
  - Numerator: the part of the forecast error variance of i due to a shock in j
  - Denominator: the total forecast error variance of i
  - e_i: the i-th unit vector (it picks series i)
  - σ_{jj}: the variance of shock j, the j-th diagonal element of Σ

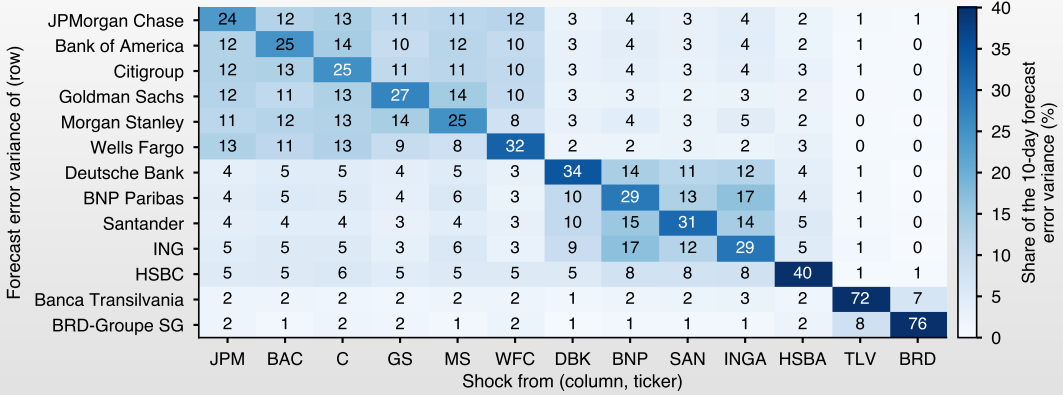
The Connectedness Table

- $\tilde{\theta}_{ij}$ (in %): the share of the H-day forecast error variance of i due to shocks in j Diebold & Yilmaz (2014)
  - Each row sums to 100; before normalisation it does not, because generalized shocks are correlated
- **From** others: $F_i = \sum_{j \neq i} \tilde{\theta}_{ij}$
- **To** others: $T_j = \sum_{i \neq j} \tilde{\theta}_{ij}$
- **Net**: $T_i - F_i$, positive for a net transmitter
- **Pairwise net**: $\tilde{\theta}_{ji} - \tilde{\theta}_{ij} > 0$ means i transmits net to j
  - drawn as an arrow $i \to j$
- **Total connectedness**: $C = \frac{1}{N} \sum_{i \neq j} \tilde{\theta}_{ij}$
  - the average share of variance that comes from the others

Parkinson Range Volatility and the VAR of the Thirteen Banks

- **Parkinson volatility** from the daily high price $P_t^{\max}$ and low price $P_t^{\min}$ Parkinson (1980)
  - $\hat{\sigma}_t^2 = \dfrac{(\ln P_t^{\max} - \ln P_t^{\min})^2}{4 \ln 2}$, annualised $100\sqrt{252\,\hat{\sigma}_t^2}$, used in logs
  - Unbiased for the variance of a Brownian motion without drift and more efficient than the squared return
  - 8 days with high equal to low, all with positive volume (Banca Transilvania 3, BRD 5): imputed with the smallest positive variance so far, not Parkinson estimates
  - Without these days total connectedness is 63.94%, against 63.93%
- Our model: VAR on the log volatility of the 13 banks, a range-based volatility as in Demirer et al. (2018)
  - Volatility, not returns: it jumps in crises, so its network shows where stress travels
  - Order by the Bayesian information criterion (BIC): $p = 2$
  - Horizon $H = 10$ days, as in Diebold & Yilmaz (2012)
  - US banks close after European ones; the VAR lags capture next-day transmission

The Connectedness Table of Thirteen Banks (1/2)



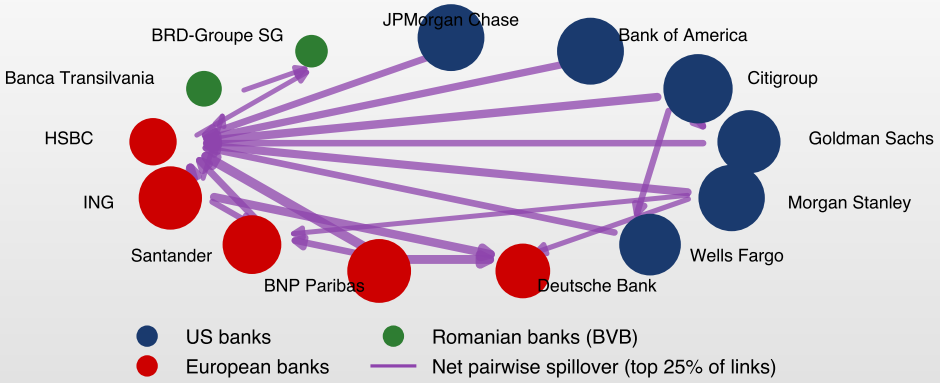
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The Connectedness Table of Thirteen Banks (2/2)

- Row i, column j: share (%) of the 10-day forecast error variance of bank i due to shocks in bank j
  - full sample (tickers of the data table)
- Total connectedness $C = 63.9\%$
  - on average two thirds of a bank's volatility risk comes from the other banks
  - On returns instead of volatility: $C = 75.4\%$
- Two regional blocks
  - a US bank receives 84.0% from US shocks
  - a European bank 72.7% from European shocks
  - Across the Atlantic: 26.2% from US to a European bank, 15.0% the other way
- Romanian banks: mostly their own shocks
  - 72.3% (Banca Transilvania) and 76.1% (BRD)
  - From US banks 10.3%, from European banks 8.0%
- Type of evidence: description
  - an edge is a share of forecast error variance, not a causal exposure
  - The VAR(2) residuals remain serially correlated (Appendix); with 22 lags, $C = 59.6\%$

MFM_ch18_spillover

The Net Spillover Network (1/2)



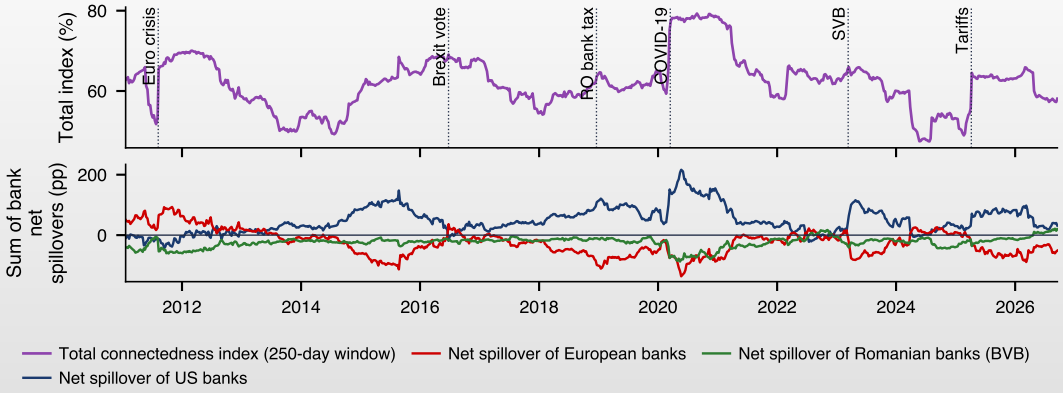
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The Net Spillover Network (2/2)

- Arrow $j \to i$ when j transmits net to i (largest 25% of pairwise net spillovers)
- Node size grows with the spillover to others
- Net transmitters: Citigroup (+19.0), Bank of America (+10.9), Morgan Stanley (+9.9), JPMorgan (+9.8)
- Net receivers: HSBC (−23.6), BRD (−13.0), Deutsche Bank (−12.6), Banca Transilvania (−12.2)
  - HSBC receives from almost every bank: it trades in London, between Asia and New York
- Within Europe, BNP Paribas and ING transmit to Deutsche Bank and Santander
- Only 8 of the 13 net positions have marginal 95% bootstrap intervals that exclude zero (Further Topics)
- A full-sample network averages quiet and crisis years

MFM_ch18_spillover

Connectedness over Time (1/2)



MFM_ch18_spillover_rolling ▶ Interactive

Connectedness over Time (2/2)

- Top: total connectedness on rolling 250-day windows
  - VAR(2), $H = 10$, every 5 days
- Bottom: net spillover summed by region
- The total index ranges from 47.4% (2024-07-24) to 79.3% (2020-08-27)
  - mean 62.0%
  - COVID-19: from 61.8% in 2019 to 78.4% in spring 2020
  - After the 2023 bank failures 66.0%, in the calm year 2024 53.5%
  - The index rises within days
  - Its fall about 250 days later partly reflects the crisis leaving the window
  - Levels depend on the window, estimator and VAR order, the changes over time do not (elastic net, Further Topics)
- US banks are net transmitters in 89% of the windows
  - sum of their net spillovers, on average +48.4 points
- European banks were net transmitters during the euro crisis of 2011–2012
  - and mostly net receivers afterwards
- Romanian banks are net receivers on average (−24.1 points on average)

MFM_ch18_spillover_rolling

How Tight Are the Links between Banks in the Tail?

- The spillover network describes an average shock, while systemic risk sits in the tail
- Financial Risk Meter (FRM) Mihoci, Althof, Chen & Härdle (2020): one quantile regression at $\tau = 5\%$ for each firm j
  - its return on **all** other firms and on lagged macro variables
  - With 100 firms and 63 days there are more regressors than days
  - The LASSO (Least Absolute Shrinkage and Selection Operator) penalty keeps only the strong links
  - The FRM is the average selected penalty, an indicator of tail interdependence and systemic stress
- The question of this section: does this indicator track systemic stress on our 13 banks too?

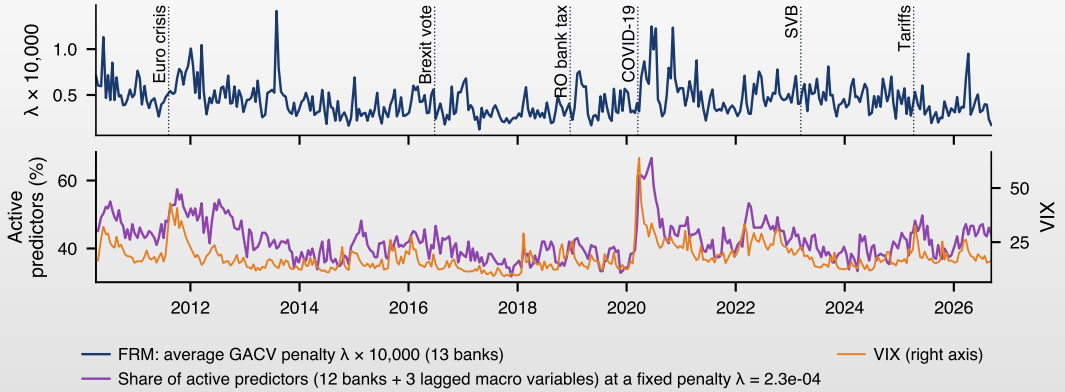
The Financial Risk Meter and the GACV Penalty (1/2)

- **LASSO** (Least Absolute Shrinkage and Selection Operator) quantile regression Belloni & Chernozhukov (2011)
  - $\hat{\beta}_j(\lambda) = \arg\min_\beta \frac{1}{n} \sum_t \rho_\tau \left(X_{j,t} - \beta_{\mathbf{0}} - \beta^\top Z_{-j,t} \right) + \lambda \|\beta\|_{\mathbf{1}}$, over the n days of the window
  - $X_{j,t}$: return of firm j
  - $Z_{-j,t}$: returns of the other firms and the lagged macro variables (S&P 500 and Euro Stoxx 50 returns, log change of the VIX)
  - A larger λ leaves fewer active coefficients
- **GACV** (Generalized Approximate Cross-Validation) trades fit against the number of active coefficients
  - $\mathrm{GACV}(\lambda) = \frac{\sum_t \rho_\tau \left(X_{j,t} - \hat{X}_{j,t}(\lambda) \right)}{n - \mathrm{df}(\lambda)}$, $\hat{X}_{j,t}(\lambda)$: fitted quantile; df: number of interpolated observations, equal to 1 + the number of nonzero slopes (intercept included)
  - The selected λ_j minimises GACV
  - The FRM is the average of the λ_j

The Financial Risk Meter and the GACV Penalty (2/2)

- The FRM was built for US financial firms Mihoci, Althof, Chen & Härdle (2020)
  - and for emerging markets Ben Amor, Althof & Härdle (2022) and China Wang, Althof & Härdle (2023)
  - Extensions: FRM based on expectiles Ren, Lu, Li & Härdle (2022), for cryptocurrencies Ren, Althof & Härdle (2025) and for the EU (European Union) energy sector Toma, Dima, Grecu, Pele & Lessmann (2026)
- Our version: 13 banks
  - macro variables S&P 500, Euro Stoxx 50 and VIX at $t-1$
  - 63-day windows every 10 days
  - $\tau = 5\%$ and 63-day windows, about one trading quarter, are those of Mihoci, Althof, Chen & Härdle (2020)
  - 15 regressors for 63 days: far fewer than in the published FRM

The Financial Risk Meter of Thirteen Banks (1/2)



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The Financial Risk Meter of Thirteen Banks (2/2)

- Top: average GACV penalty over 13 banks
  - 390 windows of 63 days
  - Bottom: share of active predictors at a fixed λ, with the VIX
- The average GACV penalty is noisy: correlation with the VIX only 0.34
- At a fixed $\lambda = 2.3 \times 10^{-4}$ the share of active predictors follows the VIX more closely (0.65)
  - From 32% (2017-11-20) to 67% (2020-06-16); average 42%
- Lesson: on this small panel, neither measure is shown to be a reliable systemic-risk indicator
  - The fixed-penalty count is only an exploratory sensitivity check
- Type of evidence: description

MFM_ch18_frm

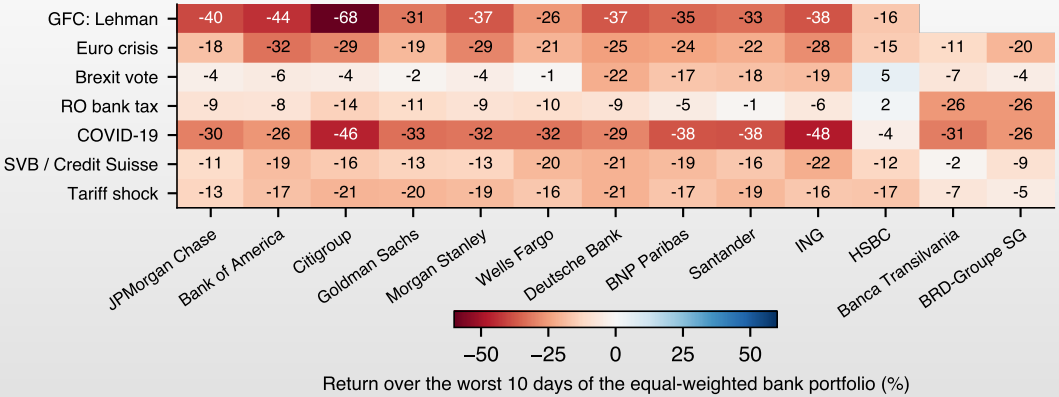
How Much Would We Lose in a Severe but Plausible Scenario? (1/2)

- A **stress test** applies a severe but plausible scenario to the banks and measures the loss
  - **Historical**: replay a past crisis
  - **Hypothetical**: shock chosen factors
  - **Reverse**: find the most plausible scenario behind a given loss (e.g. one that would make the bank non-viable)
  - Supervisory tests: Federal Reserve stress tests (US), European Banking Authority (EU)
  - Global systemically important banks: a regulatory list, scored by the Basel Committee
  - Score: size, interconnectedness, substitutability, complexity and cross-border activity
  - These banks hold extra capital Basel Committee (2018)

How Much Would We Lose in a Severe but Plausible Scenario? (2/2)

- Seven episodes, each a window of a few weeks around a known shock
  - Lehman (autumn 2008; "GFC" in the chart: global financial crisis), euro crisis (summer 2011), Brexit vote (June 2016), Romanian bank tax (December 2018)
  - COVID-19 (March 2020), SVB and Credit Suisse (March 2023), the tariff shock (April 2025)
- In each window: the **10 consecutive trading days with the lowest cumulative return**
  - cumulative return of the equal-weighted bank portfolio
  - We report every bank's return over that interval
  - Ten days match the market-risk horizon (Chapter 7)
  - 2008 uses the 11 international banks only: the Romanian series start in 2010

Seven Historical Stress Scenarios (1/2)



MFM_ch18_stress ▶ Interactive

Seven Historical Stress Scenarios (2/2)

- Simple return (%) of each bank over the worst 10 consecutive days of the bank portfolio in each episode
  - $100(e^{\sum_t r_t/100} - 1)$; blank: no data
- Portfolio loss: Lehman 37.6% (2008-11-10 – 2008-11-21)
  - COVID-19 31.9%, euro crisis 22.3%
  - Tariffs 16.0%, SVB 14.8%, Romanian bank tax 10.2%, Brexit 7.9%
- Worst single cells: Citigroup −68% in 2008 (−114% as a cumulative log return)
  - ING −48% in March 2020
- Shocks are local as well as global: Brexit hit mainly European banks
- The Romanian bank tax hit Romanian banks hardest (−26%, −26%)
  - US banks lost between 8% and 14%
- A stress test built only on global crises would miss the domestic political shock
- Type of evidence: description

MFM_ch18_stress

Climate Risk: Physical and Transition Risk



Seat of the European Central Bank, Frankfurt, 2015

Photo: DXR (2015); CC BY-SA 4.0; Wikimedia Commons

- **Physical risk**: losses from floods, droughts, heat and storms
  - these events damage collateral and borrowers
- **Transition risk**: losses from the move to a low-carbon economy
  - carbon prices, regulation, technology
- "Green swan" risks: potentially extremely disruptive events
  - they could be behind the next systemic financial crisis
  - backward-looking risk models cannot anticipate them Bolton et al. (2020)

The ECB Climate Stress Test of 2022: Results

- 104 significant banks took part in the ECB (European Central Bank) test of 2022
  - a bottom-up projection of losses covered 41 of them ECB Banking Supervision (2022)
  - bottom-up: each bank runs the supervisor's scenarios on its own data and models
- About 60% of banks had no climate risk stress-testing framework
- Only 20% considered climate risk when granting loans
- Credit and market losses of around EUR 70 billion for the 41 banks
  - scenarios: a short-term disorderly transition and two physical risk scenarios
  - The ECB states that this significantly understates the risk
  - Reasons: data gaps, rudimentary models, no second-round effects

Limits of Stress Tests

- Scenarios are chosen by people: the crisis that comes is rarely the one that was tested
- Second-round effects are hard to model and usually left out
  - fire sales, funding runs, counterparty losses
  - as the ECB noted for its climate test
- Market-based measures (MES, CoVaR, connectedness) react quickly but only after prices move
  - balance-sheet stress tests look forward but slowly
- Early-warning research combines market measures with balance-sheet data
  - e.g. entropy-based measures of market risk Pele, Lazar & Dufour (2017)

Does the Network Change with the Size of Shocks?

- Ando, Greenwood-Nimmo & Shin (2022): does the topology of a financial network change with the **size** of shocks?
  - Their version of the question of Diebold & Yilmaz (2014): how much of the future uncertainty of i is due to idiosyncratic shocks from j, as the shock size varies?
- Why it matters: the connectedness of this chapter is estimated at the conditional mean
  - OLS (Ordinary Least Squares), LASSO, elastic net Demirer et al. (2018)
  - i.e. it describes how an average shock spreads
  - Systemic shocks are larger than average
  - Reading a rise in rolling connectedness as a crisis signal assumes that mean relations also hold in the tails
- Link to this chapter: the quantile regression of CoVaR Adrian & Brunnermeier (2016), Koenker & Bassett (1978)
  - now inside the VAR and its variance decomposition
  - Giglio, Kelly & Pruitt (2016) showed that systemic risk shifts the lower tail of future output more than its centre
  - Ando, Greenwood-Nimmo & Shin (2022) ask the same tail-versus-centre question of the network itself
- Application: the credit risk loop between sovereigns and their banks
  - bailouts move bank risk onto the state

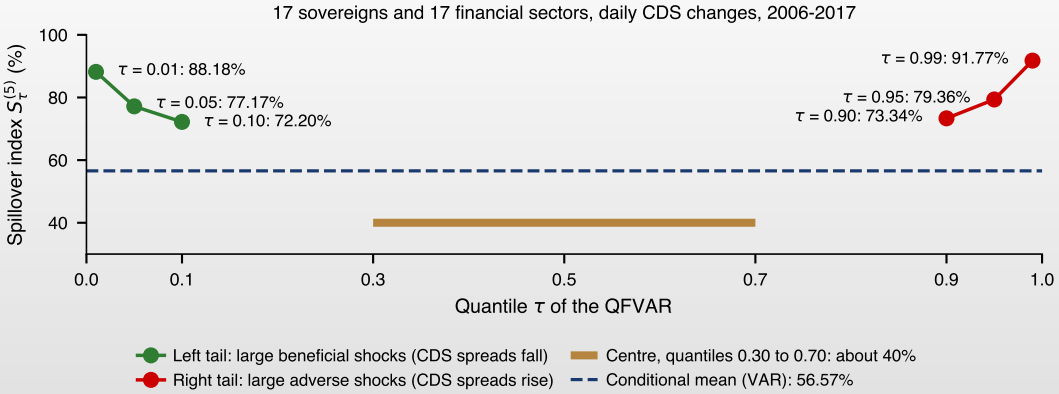
CDS Data and the Factor Quantile VAR

- CDS (credit default swap) spread: the annual premium paid for protection against default
  - default of a sovereign or bank; premium in basis points of the insured amount (1 bp = 0.01%)
  - it rises when default risk rises, so an increase is bad news
- Data: daily first differences of 5-year CDS spreads (basis points)
  - 17 sovereigns and 17 national financial sectors, $m = 34$
  - 3 January 2006 – 29 December 2017, 3 129 days
- Quantile factor VAR (QFVAR): $y_t = \mu + \sum_{j=1}^{p} \Phi_j y_{t-j} + \Gamma f_t + v_t$
  - each equation fitted at quantile τ by minimising the check loss
  - y_t: the m CDS changes; μ: constants; Φ_j: VAR coefficient matrices; Γ: factor loadings
  - Unobserved factors f_t absorb common shocks, so v_t is idiosyncratic
  - Their number by the criterion of Ando & Bai (2020): 10 at the mean

Spillovers and Adverse Credit Shocks

- Generalized forecast error variance decomposition (FEVD) of the idiosyncratic shocks at quantile τ
  - rows normalised to 1
  - spillover index $S_\tau^{(h)} = m^{-1} \sum_i F_{i \leftarrow \bullet, \tau}^{(h)}$
  - $F_{i \leftarrow \bullet, \tau}^{(h)}$: the share of the h-day forecast error variance of i that comes from the others
  - It is the "from" of the connectedness table; $S_\tau^{(h)}$ is its average over the m series
- Rolling windows of $w = 250$ days (2 880 windows)
  - number of factors fixed at its full-sample value (full specification: Appendix)
- Relative tail dependence $\mathrm{RTD} = S_{0.95}^{(5)} - S_{0.05}^{(5)}$
  - For CDS changes the right tail ($\tau = 0.95$) holds large adverse shocks, the left tail ($\tau = 0.05$) large beneficial ones

Spillovers across Quantiles (1/2)



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Spillovers across Quantiles (2/2)

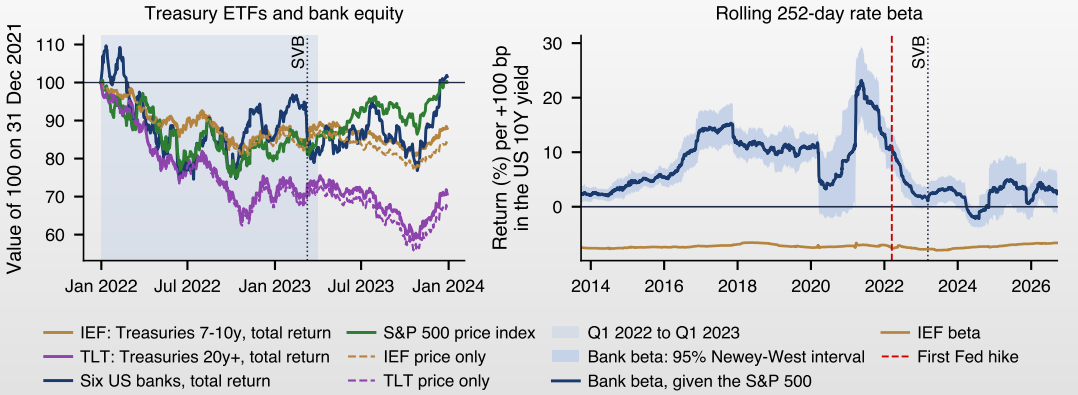
- Full-sample spillover index $S_\tau^{(5)}$ at each quantile τ
  - vs the conditional-mean index (source: Ando, Greenwood-Nimmo & Shin (2022))
- U-shaped profile: about 40% in the centre, 88.18% at $\tau = 0.01$, 91.77% at $\tau = 0.99$
  - The mean index (56.57%) describes neither regime: too high for small shocks, too low for large ones
- Full sample: almost symmetric tails, $\mathrm{RTD} = 79.36 - 77.17 = 2.19$ points
  - in rolling windows the asymmetry is stronger (Further Topics)
- For stress testing: mean connectedness understates spillovers in a crisis
  - it understates how much of a sector's forecast error variance comes from other sectors
- Type of evidence: description
  - the quantile profile shows where connectedness rises, not through which channel it travels

MFM_ch18_quantile_connectedness

Did Higher Rates Make US Banks Fragile?

- Jiang, Matvos, Piskorski & Seru (2024): how much did the market value of US bank assets fall after the rate increases of 2022?
  - and when can such a loss trigger a run of uninsured depositors?
- The mechanism: a higher rate lowers the market value of fixed-rate securities and loans
  - Securities held at amortised cost do not show the loss in reported equity
- The offset: the deposit franchise, the value of deposits paid below the market rate
  - it rises with the rate, but vanishes for the deposits that leave
- The paper's numbers: bank assets fell by about 10% on average from the first quarter of 2022 to the first quarter of 2023
  - the aggregate loss: about 2 trillion dollars in the abstract, 2.2 trillion in the introduction
- The most fragile banks: large losses, little capital and high uninsured leverage
  - uninsured leverage: uninsured deposits relative to assets
  - SVB is the case the paper analyses in detail

Treasuries and Bank Equity, 2022–2023



MFM_ch18_bank_rate_risk ▶ Interactive

Balance Sheets in the Paper, Market Data in the Course

- The paper uses the quarterly balance sheets of US banks (Call Reports)
  - assets are marked to market by remaining maturity, with price indices of bonds of the same maturity
  - a run model: a bank becomes insolvent if its assets at market prices no longer cover insured deposits once the uninsured depositors leave
- The course replication, without balance sheets: (1) the price change of two US Treasury ETFs (exchange-traded funds)
  - IEF: maturities of 7–10 years; TLT (iShares 20+ Year Treasury Bond ETF): maturities above 20 years
  - ETFs are portfolios with changing holdings, not a revaluation of bank balance sheets
- (2) The rate beta of bank equity, on rolling 252-day windows: $r_{B,t} = a + b_M\, r_{M,t} + b_Y\, \Delta y_t + \varepsilon_t$
  - $r_{B,t}$: daily return of the six US banks, equal weights; $r_{M,t}$: return of the S&P 500
  - Δy_t: daily change of the US 10-year Treasury yield; b_Y is reported per $+100$ bp
  - The 95% interval: Newey–West standard errors with 5 lags; finite fourth moments with weak dependence are a convenient sufficient condition, not a necessary one
- $b_Y > 0$: a positive conditional association, consistent with a deposit franchise larger than the loss on assets
  - the contemporaneous regression does not separate the deposit channel from other shocks and does not identify the value of the deposit franchise

The Rate Beta Fell in 2022 (1/2)

- 31 Dec 2021 to 31 Mar 2023: the 10-year yield rose from 1.51% to 3.47%, the 2-year yield from 0.73% to 4.03%
  - The IEF price fell by 13.8%, the TLT price by 28.2%: the same order of magnitude as the average fall of about 10% in the paper
  - Total returns, distributions reinvested: -11.8% (IEF) and -26.2% (TLT)
- The rate beta of the six banks, per $+100$ bp: $+7.7\%$ from Sep 2012 to Dec 2019 ($t = 12.4$)
  - from Jan 2022 to 9 Mar 2023: $+2.0\%$ ($t = 2.0$); the IEF beta: -7.8%
  - the rolling window: $+12.8\%$ at the end of 2021; on 10 Mar 2023: $+1.08\%$, interval $[-0.40, 2.56]$
  - A direct test of the change (interaction with the period, Newey–West): -6.5 points against $+8.4\%$ in Sep 2012 to Dec 2021 ($t = -5.0$)

The Rate Beta Fell in 2022 (2/2)

- The SVB week (closes of 8 and 17 Mar 2023): the six banks -12.5%, the S&P 500 -1.9%
  - the 2-year yield fell by 125 bp and IEF gained 4.5%
- Type of evidence: conditional association; the positive one weakened, in some windows indistinguishable from zero
  - an insignificant coefficient does not prove a zero coefficient; the change is tested directly, by an interaction
- The limits
  - the beta falls from May 2021 (its maximum: $+23.2\%$) and was between $+2.0\%$ and $+6.0\%$ in 2013–2015
  - the data hold neither uninsured deposits nor regional banks like SVB

Does Connectedness Warn of Crises, or Only Track Volatility?

An open research question: systemic risk or only volatility?

- Connectedness indices are monitored as early-warning tools
  - but an index from a VAR on volatilities may co-move with volatility without adding predictive information
  - Live research: regularised VAR networks Demirer et al. (2018); tail connectedness differs from mean connectedness Ando, Greenwood-Nimmo & Shin (2022)
- Formal version: $y_{t+h} = a + \beta_C C_t + \gamma \ln \sigma_t + e_{t+h}$, $H_0 : \beta_C = 0$, $H_1 : \beta_C > 0$
  - y_{t+h}: future bank stress; C_t: total connectedness; σ_t: current volatility
  - Evidence against H_1: the confidence interval (CI) for β_C rules out economically relevant effects, not mere non-significance
- Identification: an edge is a share of forecast error variance, not a causal exposure
  - A common shock raises volatility and connectedness together, with no bank infecting another

The Discovery Loop, Step by Step (1/2)

- **Literature**: map what is known, then verify every reference
  - Resolve each DOI (Digital Object Identifier) on Crossref and check that the paper really controls for volatility
  - Search with Semantic Scholar, Elicit or Google Scholar
- **Hypotheses**: competing readings of a rise in connectedness, each with its own test
  - E.g. a common shock fades with volatility
  - Contagion has a direction: shocks of net transmitters precede those of receivers
- **Data and code**: on the course data, replicating a known number first
  - Replicate first: mean 62.0% and maximum 79.3% (2020-08-27), as in this chapter

The Discovery Loop, Step by Step (2/2)

- **Robustness**, fixed before the predictive regressions are run
  - Every cell of the grid is reported
  - The family is corrected with Holm or controlled with the FDR (false discovery rate)
- **Critique**: ask the assistant to attack the result
  - Expect: add current volatility as a control, then test the increment of R^2 and of the out-of-sample loss
- **Report**: standardised effects with HAC t-statistics, every cell of the grid, what failed
  - HAC: heteroskedasticity- and autocorrelation-consistent
  - The prompts that shaped the design go into `AI_USE.md` (reusable prompts and the researcher's checks: Appendix)

Mini-Case: Is Connectedness More Than Volatility? (1/2)

- Typical assistant proposal: "high total connectedness warns of future bank stress"
  - Tested on 731 weekly dates, 2011–2026
  - y_{t+h}: log mean Parkinson volatility of the 13 banks over the next $h = 63$ days
  - Control: the same over the last 20 days
  - Standardised variables; Newey–West with 13 lags, because the 63-day target overlaps across about 13 weeks
- Connectedness alone: $\hat{\beta}_C = 0.40$ ($t = 4.63$), $R^2 = 0.16$
  - the proposal looks right

Mini-Case: Is Connectedness More Than Volatility? (2/2)

- With current volatility: $\hat{\beta}_C = 0.08$ ($t = 0.75$), $\hat{\gamma} = 0.53$ ($t = 4.13$)
  - With 26, 50 and 100 HAC lags: $t = 0.70, 0.67, 0.68$
  - $R^2 = 0.343$ vs 0.339 with volatility alone
  - Correlation of C_t with volatility 0.59
  - Next 63-day maximum drawdown: $\hat{\beta}_C = -0.10$ ($t = -1.32$) even as the only regressor
- Interpretation: given current volatility, connectedness adds no significant predictive content
  - Not proof of zero: in our sample the persistence of volatility explains most of the predictive content
  - Network information may still matter in the tails Ando, Greenwood-Nimmo & Shin (2022) or for the direction of transmission
- Type of evidence: association
  - predictive, estimated retrospectively: $p = 2$ chosen on the full sample, the regression on all observations
  - given current volatility; it does not rule out a common shock

Your Turn: a Project Seed

- **Question**
  - Does **tail** connectedness predict bank distress beyond volatility, out of sample?
- **Replicate first**
  - Our rolling index: mean 62.0%, maximum 79.3% (2020-08-27)
  - The six-group connectedness table of Demirer et al. (2018) for 2003–2014: directional entries and row/column totals
  - Explain the deviations; the authors publish the replication data (journaldata.zbw.eu)
- **Extend**
  - Quantile connectedness at $\tau = 5\%$ Ando, Greenwood-Nimmo & Shin (2022)
  - Out-of-sample evaluation from 2018
  - MES and SRISK as alternative targets

Which Bank Is Most Systemic? (1/2)

Bank	VaR 1%	MES 5%	ΔCoVaR 1%	Net spillover	Λ^*
JPMorgan	4.83	3.21	4.62	9.8	7.0
Bank of America	5.99	3.84	4.60	10.9	6.2
Citigroup	5.87	4.03	3.81	19.0	6.0
Goldman Sachs	4.81	3.34	4.12	2.4	6.8
Morgan Stanley	5.83	4.03	4.01	9.9	6.0
Wells Fargo	5.78	3.31	4.89	3.6	6.8
Deutsche Bank	7.19	4.53	4.24	−12.6	6.1
BNP Paribas	6.18	4.52	4.83	6.0	6.1
Santander	5.83	4.22	4.42	−5.4	6.4
ING	7.16	4.79	4.41	5.2	5.8
HSBC	4.66	2.53	4.07	−23.6	8.3
Banca Transilvania	5.06	3.14	–	−12.2	6.5
BRD-Groupe SG	4.42	2.69	–	−13.0	7.1

- Daily losses in %
  - net spillover of volatility: to minus from
  - Λ^*: break-even leverage with $k = 8\%$ and the shortcut LRMES (six-month crisis, market -40%)
  - –: no ΔCoVaR for the two Romanian banks, whose "system" would be a single bank

Which Bank Is Most Systemic? (2/2)

- Rank correlations across the eleven international banks
  - MES and ΔCoVaR -0.04
  - MES and net spillover 0.04
  - ΔCoVaR and net spillover -0.04
  - By contrast, VaR and MES: 0.88
- No single ranking
  - supervisors combine several indicators with size and balance-sheet data, as in the Basel Committee (2018) methodology
- Romanian banks have a moderate MES
  - they are net receivers of volatility
  - their break-even leverage is close to that of US banks

Key Takeaways

- Systemic risk lives in the joint tail
  - exposure (MES, SRISK), contribution (ΔCoVaR), connectedness (spillover and tail networks)
- Euro-area banks have the largest MES in our sample (4.2–4.8%)
- US banks are the main net transmitters of volatility
- VaR and ΔCoVaR rank banks differently, and rankings are uncertain
  - test differences, report intervals, state αn
- Market-based measures jump in crises
  - stress tests and balance sheets are needed to see risk building up
- Romanian banks: mostly their own shocks
  - they receive more volatility spillover than they transmit

Common Mistakes

- Reading ΔCoVaR or a spillover edge as causal
  - a common shock creates the same pattern
- Reading overlapping intervals as "equal" and separate ones as "different"
  - Test the difference on joint draws and correct for the number of pairs (Holm and the joint Wald test)
- Including the bank itself in the system portfolio
  - its own return adds a mechanical self-contribution
- Orthogonal variance decompositions whose results depend on the order of the banks
- Reporting SRISK without balance sheets, or the $1 - e^{-18\mathrm{MES}}$ shortcut as the published measure
- Drawing net labels without intervals

The Practical Decision

- **What I choose**
  - for a bank, three measures reported together: MES (exposure), ΔCoVaR (contribution), net spillover (connectedness)
  - not a single ranking: the rank correlations between them lie between -0.04 and 0.04
  - differences between banks tested on joint bootstrap draws, with Holm and the joint Wald test
  - for a crisis, 10-day historical scenarios that include local shocks (the bank tax: -26% for the Romanian banks)
- **Under which conditions**
  - market-based measures react only after prices move: the build-up of risk needs balance sheets and stress tests
  - SRISK only with balance-sheet leverage; without it I report Λ^*, for a stated scenario
- **What result would make me drop it**
  - the ΔCoVaR ranking: a joint Wald test that does not reject equal contributions (Europe, 1%: $p = 0.28$)
  - the transmitter or receiver label: a bootstrap interval of the net position that contains zero (5 of the 13 banks)
  - connectedness as a warning signal: an interval for β_C that rules out relevant effects once volatility is controlled for; here $\hat{\beta}_C = 0.08$ ($t = 0.75$) is only insignificant

LRMES via GJR–GARCH and DCC: the Model

- Model of Brownlees & Engle (2017): zero-mean daily log returns of the bank and of the market
  - estimated by two-step quasi-maximum likelihood (QML)
- Volatility: GJR–GARCH(1,1) Glosten, Jagannathan & Runkle (1993)
  - GARCH: generalized autoregressive conditional heteroskedasticity
  - $\sigma_t^2 = \omega + (\alpha + \gamma\, 1\{r_{t-1} < 0\})\, r_{t-1}^2 + \beta\, \sigma_{t-1}^2$
  - $\gamma > 0$: extra reaction after a fall (leverage effect)
  - Here α is not the tail level
- Correlation: DCC(1,1) (dynamic conditional correlation) Engle (2002)
  - $Q_t = (1 - a - b)\, S + a\, \epsilon_{t-1} \epsilon_{t-1}^\top + b\, Q_{t-1}$, $\rho_t = Q_{12,t} / \sqrt{Q_{11,t} Q_{22,t}}$
  - $\epsilon_t = (r_{it}/\sigma_{it}, r_{mt}/\sigma_{mt})^\top$: standardised returns
  - S: their sample correlation matrix ($\bar{Q}$ in Engle (2002))
  - a: reaction and b: persistence of the correlation
  - ρ_t: today's bank–market correlation

LRMES via GJR–GARCH and DCC: Simulation

- Simulation (details: Appendix)
  - Resample **pairs** $(\xi_{it}, \epsilon_{mt})$: the standardised market shock and the part of the bank shock uncorrelated with the market
  - Pairs keep the tail dependence that the Normal distribution misses
  - Filter the GARCH and DCC recursions h days ahead from today's σ^2 and ρ
  - LRMES: minus the average bank return over the crisis paths, those with $R_{m,t+\mathbf{1}:t+h} < C$
- Per market: 200 000 paths of 22 days ($C = -10\%$) and 400 000 of 126 days ($C = -40\%$)
  - data to 2026-09-18
- Probability of the 22-day crisis: today 1.3% (S&P 500), 4.4% (Euro Stoxx 50), 3.9% (BET)
  - against 12%, 19%, 8% on 31 March 2020

LRMES by Simulation: Thirteen Banks (1/2)

Bank	LRMES today	90% range	LRMES 31.03.2020	ρ_T	Λ^* (22 days)
JPMorgan	10.6	$[-1, 25]$	23.7	0.53	11.3
Bank of America	14.2	$[-4, 36]$	23.1	0.44	10.9
Citigroup	12.9	$[-1, 29]$	32.7	0.53	11.0
Goldman Sachs	16.5	$[1, 34]$	25.0	0.65	10.6
Morgan Stanley	16.3	$[1, 32]$	27.2	0.65	10.6
Wells Fargo	6.8	$[-9, 23]$	22.9	0.32	11.7
Deutsche Bank	14.3	$[2, 28]$	25.9	0.66	10.9
BNP Paribas	15.5	$[2, 32]$	28.7	0.68	10.7
Santander	16.7	$[4, 34]$	26.6	0.76	10.6
ING	12.4	$[1, 27]$	33.2	0.68	11.1
HSBC	8.4	$[-1, 19]$	11.0	0.58	11.5
Banca Transilvania	12.3	$[-2, 33]$	17.3	0.74	11.1
BRD-Groupe SG	11.3	$[-1, 27]$	15.8	0.64	11.2

- LRMES (%): market fall below -10% in 22 days Brownlees & Engle (2017)
  - 90% range: 5% and 95% quantiles of the bank's loss on the crisis paths; ρ_T: last DCC correlation
  - Λ^* with $k = 8\%$ from this 22-day LRMES (not comparable with the shortcut Λ^*)

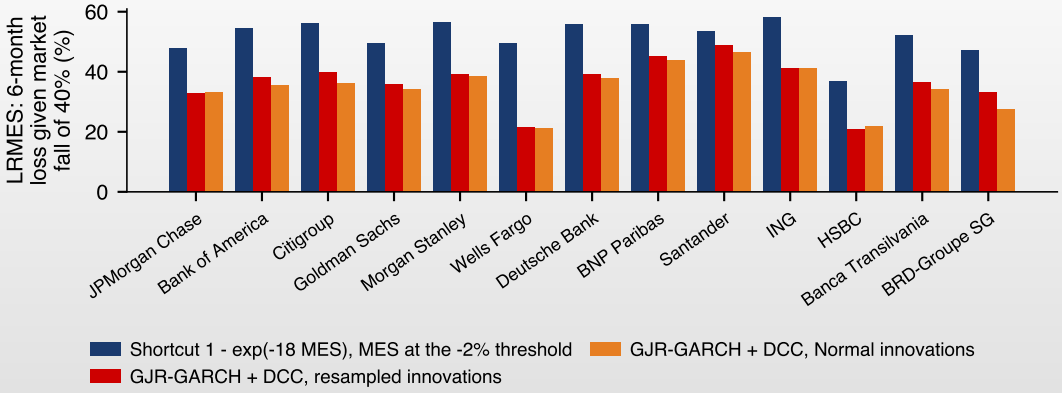
LRMES by Simulation: Thirteen Banks (2/2)

- LRMES is **conditional**: it moves with today's volatility and correlation
  - JPMorgan: 10.6% today, 23.7% with the information of 31 March 2020
  - Deutsche Bank: 14.3% and 25.9%
- The 90% range is wide Brownlees & Engle (2017)
  - LRMES is an average over crisis paths
  - The shortfall in one particular crisis can be much larger
  - The range describes scenario dispersion, not uncertainty about the estimated mean
- The scenario, not only the bank, sets the level
  - One-month, -10% crisis: LRMES about a third of the six-month, -40% numbers of Acharya, Engle & Richardson (2012)

Reading the LRMES Table: Ranges and Scenarios

- A negative lower end of the 90% range is not a sign error
  - A negative path loss is a gain: on at least 5% of the crisis paths the bank's shares rise while the market falls
  - It happens when the bank is weakly correlated with its market today, e.g. Wells Fargo: $\rho_T = 0.32$, range $[-9, 23]$
- Λ^* inherits the crisis scenario through LRMES, so compare it only within one scenario
  - example: JPMorgan, $k = 8\%$
  - Shortcut, six months, market -40%: LRMES 48%, $\Lambda^* = 7.0$
  - Simulation, 126 days, market -40%: LRMES 33%, $\Lambda^* = 8.7$
  - Simulation, 22 days, market -10%: LRMES 10.6%, $\Lambda^* = 11.3$

Model Risk: LRMES under Three Specifications (1/2)



MFM_ch18_srisk_sim

Model Risk: LRMES under Three Specifications (2/2)

- Six-month crisis, market -40% Acharya, Engle & Richardson (2012)
  - shortcut $1 - e^{-18\,\mathrm{MES}^{2\%}}$ vs GJR–GARCH + DCC simulation with resampled or Normal innovations
- Simulated LRMES over the shortcut: 0.43 to 0.92
  - rank correlation 0.79
  - JPMorgan: 48% (shortcut), 33% (resampled), 33% (Normal)
  - ING: 58%, 41%, 41%
  - The shortcut uses the whole history
  - The simulation starts from today's volatility
- Resampled vs Normal innovations: rank correlation 0.97
  - Levels differ most for Citigroup (39.8% vs 36.0%) and BRD (33.1% vs 27.6%)
- Same data, different defensible models, different numbers: model risk Danielsson, James, Valenzuela & Zer (2016)

MFM_ch18_srisk_sim

Losses at Least Equal to VaR: the Girardi–Ergün CoVaR

- Girardi & Ergün (2013) condition on the bank's loss being **at least** its VaR
  - $P\left(X^{sys} \leq -\mathrm{CoVaR}^{\leqq}_{\alpha} \,\middle|\, X_i \leq -\mathrm{VaR}_{i,\alpha}\right) = \alpha \iff P\left(X^{sys} \leq -\mathrm{CoVaR}^{\leqq}_{\alpha}, X_i \leq -\mathrm{VaR}_{i,\alpha}\right) = \alpha^2$
  - Benchmark state of $\Delta\mathrm{CoVaR}^{\leqq}$: $|X_i - \mu_i| \leq \sigma_i$ instead of the median
  - Below we compare levels only
- It rises with the strength of dependence, which the CoVaR given $X_i = -\mathrm{VaR}_{i,\alpha}$ need not do Mainik & Schaanning (2014)
- It can be **backtested**: the joint hit has probability α^2
- Historical estimate at $\alpha = 5\%$, on the 199 days with $X_i \leq \hat{q}_{5\%}(X_i)$
  - JPMorgan 7.69% vs 3.81% by quantile regression
  - eleven banks: 7.3–8.2% vs 3.6–4.8%
  - Under the Normal distribution this change raises CoVaR only modestly
  - The factor of two points to departures from the Normal benchmark, without identifying their cause

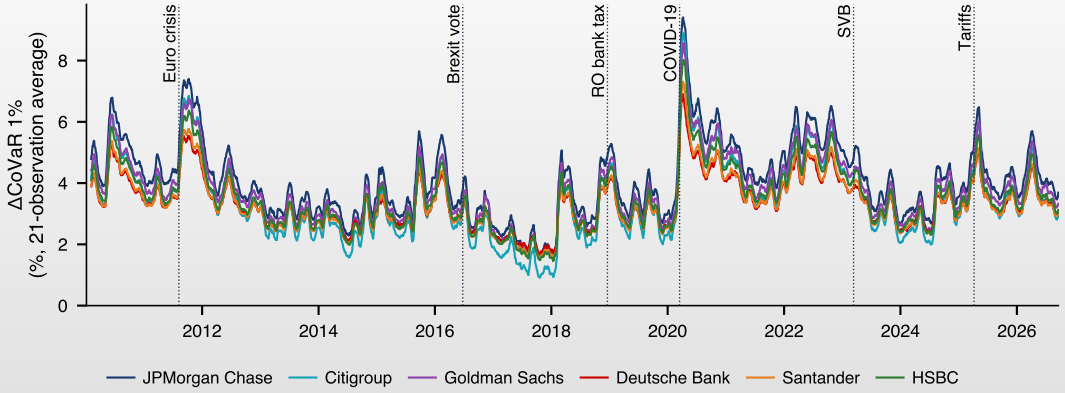
A Normal Check: Which CoVaR Rises with Dependence?

- Bivariate Normal with zero means, $\sigma_{sys} = 1.5$, $\alpha = 1\%$, $z = -2.326$
  - the bank sits at its VaR, $X_i = -\mathrm{VaR}_{i,\alpha}$
  - Given the bank, the system has mean $\rho\,\sigma_{sys} z$ and standard deviation $\sigma_{sys}\sqrt{1-\rho^2}$
  - Hence $\mathrm{CoVaR}_\alpha = \sigma_{sys}|z|\left(\rho + \sqrt{1-\rho^2}\right)$ and, with the median state $X_i = 0$, $\Delta\mathrm{CoVaR}_\alpha = \rho\,\sigma_{sys}|z|$
- From $\rho = 0.6$ to $\rho = 0.9$: $\mathrm{CoVaR}_{1\%}$ falls from 4.89% to 4.66%
  - because $\rho + \sqrt{1-\rho^2}$ peaks at $\rho = 0.71$
  - $\Delta\mathrm{CoVaR}_{1\%}$ rises from 2.09% to 3.14%
- Lesson: a CoVaR level conditioned on $X_i = -\mathrm{VaR}_{i,\alpha}$ can fall when banks become more interdependent
  - while ΔCoVaR and $\mathrm{CoVaR}^{\leq}$ rise with ρ Mainik & Schaanning (2014)

ΔCoVaR 1% over Time: State Variables

- The question: does the contribution of a bank rise in stress periods?
- The quantiles of the bank depend on state variables M_{t-1} Adrian & Brunnermeier (2016)
  - M_{t-1}: log VIX, regional index return and system return, all lagged one day
  - $\Delta\mathrm{CoVaR}_{\alpha,t} = \hat{b}\left(\hat{q}_{50\%,t}(X_i) - \hat{q}_{\alpha,t}(X_i)\right)$, with $\hat{q}_{\cdot,t}$ conditional on M_{t-1} (Appendix)
- The slope $\hat{b}$ stays constant: ΔCoVaR moves with the conditional VaR of the bank

ΔCoVaR 1% over Time (1/2)



MFM_ch18_covar_dynamic

ΔCoVaR 1% over Time (2/2)

- Six banks, moving averages over 21 observations of the daily ΔCoVaR 1%
- JPMorgan: mean 2.16% in 2017, mean 9.06% in March 2020
  - peak 10.99% on 2020-03-18
  - Deutsche Bank: mean 2.04% in 2017, mean 6.65% in March 2020
- Low in calm periods, exactly when risk may build up in balance sheets
  - Hence Adrian & Brunnermeier (2016) propose a forward ΔCoVaR, predicted from leverage, size and maturity mismatch
  - Maturity mismatch: long-term assets funded by short-term debt, which must be rolled over

MFM_ch18_covar_dynamic

Example: the Connectedness Table for Two Banks

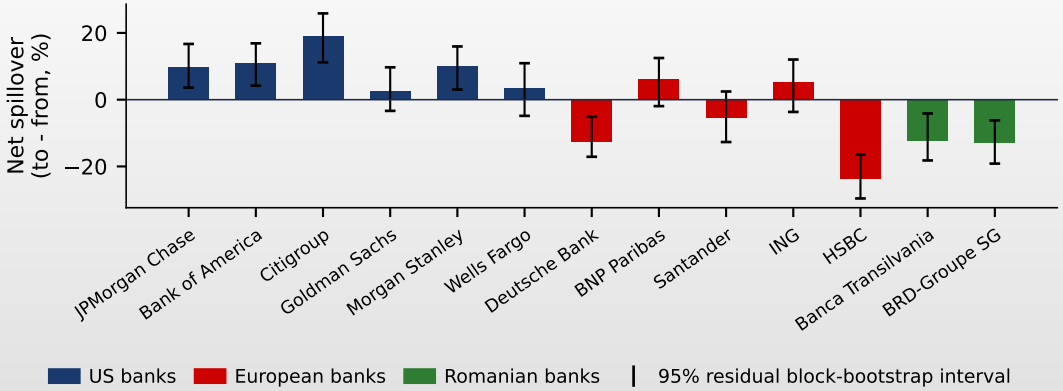
Bank $i \setminus$ shock j	1	2	F_i
1	80	20	20
2	40	60	40
T_j	40	20	

- Toy normalised table $\tilde{\theta}_{ij}$ (%)
  - row i: the bank whose variance is split
  - column j: the source of the shock
  - rows sum to 100
- Off-diagonal cells only
  - From others: $F_1 = 20$, $F_2 = 40$ (row sums)
  - To others: $T_1 = 40$, $T_2 = 20$ (column sums)
- Net: bank 1 $40 - 20 = +20$ (transmitter), bank 2 -20
  - net positions always sum to zero
- Total: $C = (20 + 40)/2 = 30\%$

Estimation Error: How Reliable Is the Network?

- The question: which "transmitter" and "receiver" labels survive estimation error?
- A VAR(1) on 13 series has 169 slope coefficients
  - the VAR(2) used here has $2 \times 169 = 338$
  - A 250-day window: 250 observations per equation for 26 slopes and a constant
  - The table is a nonlinear function of all of them
- Residual block bootstrap, 999 draws
  - Resample 20-day blocks of residual vectors, rebuild the series with the estimated VAR, re-estimate, recompute the table

Estimation Error: Bootstrap Intervals for the Network (1/2)



MFM_ch18_spillover_uncertainty

Estimation Error: Bootstrap Intervals for the Network (2/2)

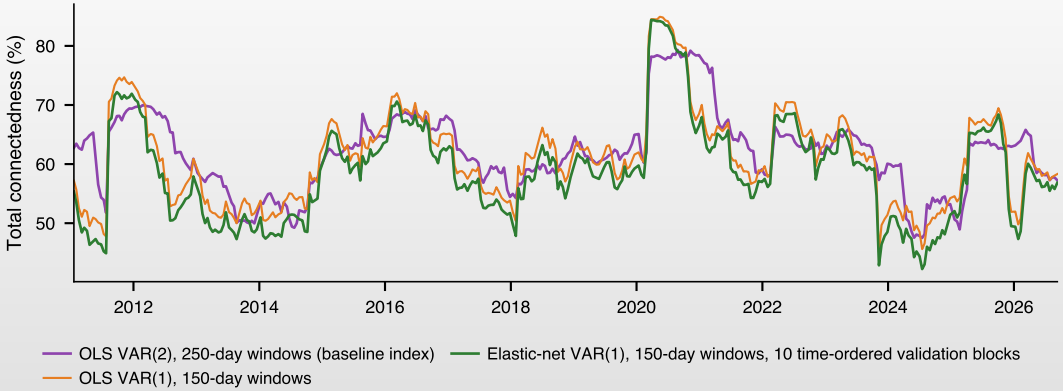
- Full sample, $p = 2$: $C = 63.9\%$, 95% interval $[59.9, 65.8]$
  - Peak window (to 2020-08-27): $C = 79.3\%$, $[65.9, 83.0]$, an interval that ignores the selection of the peak window
  - Bootstrap mean 75.8%: small samples also bias C
- 8 of 13 net positions have marginal intervals that exclude zero, with no multiple-testing correction
  - For the other 5 the sign of the net position is not statistically distinguishable from zero
  - The net spillover network draws the largest 25% of links, some of them not significant
  - Hence the intervals

MFM_ch18_spillover_uncertainty

Elastic-Net Connectedness: Does the Network Depend on the Estimator?

- A VAR(2) on 13 series has 338 slopes: in short windows OLS overfits
- Demirer et al. (2018): each VAR equation by the adaptive elastic net
  - in the 150-day windows, the plain elastic net
  - λ chosen equation by equation by validation on 10 consecutive time blocks (definition in the Appendix)
- We compare, on the same window end dates, the base index with indices on 150-day windows

OLS and Elastic-Net Connectedness in Rolling Windows (1/2)



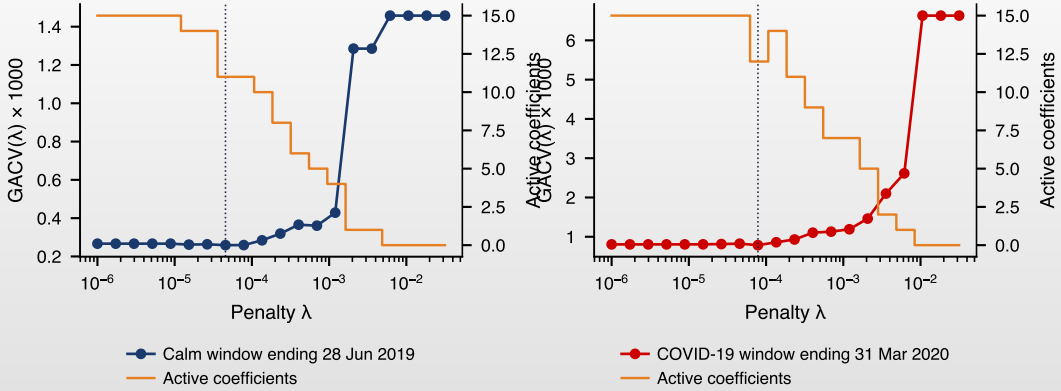
MFM_ch18_spillover_uncertainty

OLS and Elastic-Net Connectedness in Rolling Windows (2/2)

- Full sample: $C = 63.1\%$ (OLS, ordinary least squares: 63.9%)
  - 55% of coefficients non-zero
- Means over 372 common window end dates, moving by 10 trading days
  - baseline recomputed on those same dates
  - Baseline (OLS VAR(2), 250 days) 62.0%
  - OLS VAR(1), 150 days 61.1%; elastic-net VAR(1), 150 days 58.7%
- The dynamics agree: correlation 0.82 between the elastic-net and the base index
  - crisis peaks in the same weeks
  - Levels depend on window, estimator and lag order
  - Changes over time are robust

MFM_ch18_spillover_uncertainty

GACV in a Calm and in a Crisis Window (1/2)



MFM_ch18_frm

GACV in a Calm and in a Crisis Window (2/2)

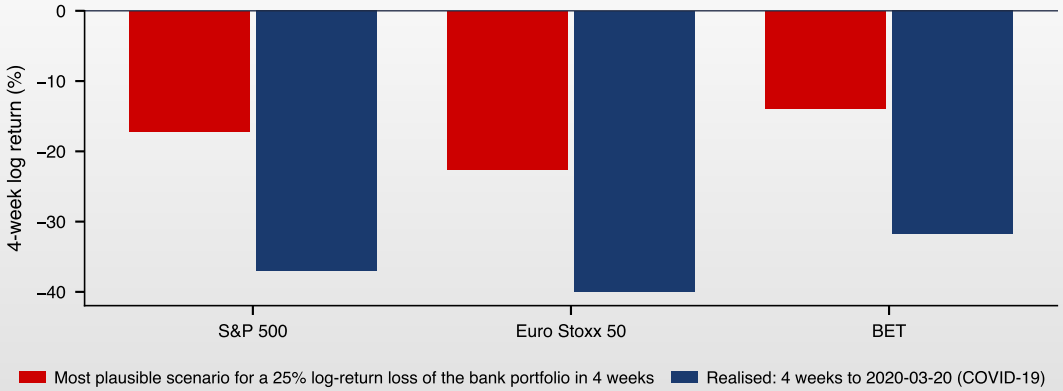
- JPMorgan on the other 12 banks and three lagged macro variables, 63 days
  - Dotted line: selected λ; orange: active coefficients
- Calm window (to 28 June 2019): $\hat{\lambda} = 4.5 \times 10^{-5}$, 11 of 15 coefficients active
  - COVID-19 window (to 31 March 2020): $\hat{\lambda} = 7.8 \times 10^{-5}$, 12 active
- In the crisis the whole GACV curve is about three times higher
  - The check loss is in return units, and crisis returns are larger
- With few regressors the minimum lies at almost no penalty: the selection is noisy

MFM_ch18_frm

Reverse Stress Testing

- Factor model of weekly bank log returns (%): $X_i = \beta_i^\top f + e_i$
  - factors f = (S&P 500, Euro Stoxx 50, BET)
  - Over h weeks $f \sim N(0, h\Sigma)$, Σ: weekly factor covariance, no serial covariance
- Loss of the equal-weighted portfolio of the 13 banks: $L = -b^\top f$ (log loss in %)
  - b: the average of the β_i
  - residual $\sum_i w_i e_i$ set to zero
- Most plausible scenario with loss ℓ^*
  - minimise the squared Mahalanobis distance $f^\top (h\Sigma)^{-\mathbf{1}} f$ subject to $-b^\top f = \ell^*$
  - $f^* = -\ell^* \dfrac{h\Sigma\, b}{b^\top h\Sigma\, b}, \qquad d^* = \dfrac{\ell^*}{\sqrt{b^\top h\Sigma\, b}}$
  - d^*: the target loss in portfolio standard deviations
  - Larger means less plausible (two-factor example: Appendix)

The Most Plausible Scenario for a 25% Log-Return Loss (1/2)



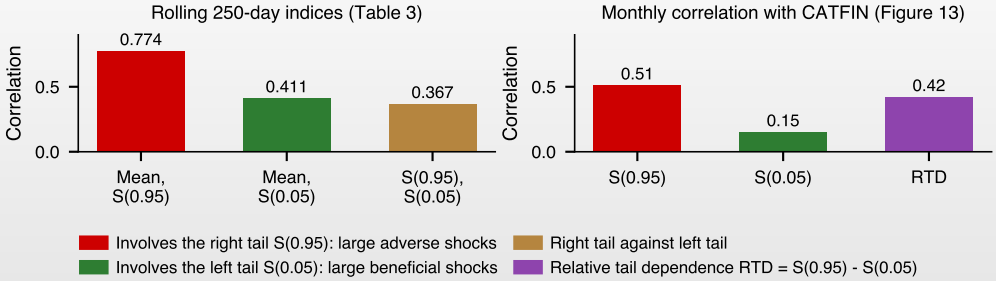
MFM_ch18_stress

The Most Plausible Scenario for a 25% Log-Return Loss (2/2)

- Weekly data 2010–2026 (871 weeks), four-week horizon, the length of the acute phase of March 2020
  - Red: f^* for $\ell^* = 25\%$
  - Blue: factor moves in the worst four weeks of 2020
- $b = (0.45, 0.65, 0.18)$
  - four-week standard deviation of the portfolio 5.79%
  - A 25% log loss (arithmetic 22.1%) needs S&P 500 −17.2%, Euro Stoxx 50 −22.6%, BET −13.9% together
- $d^* = 4.31$: Normal probability 8.0×10^{-6} per four weeks
  - Yet in the four weeks to 2020-03-20 the portfolio had a log loss of 52.0% (factor model: 48.5%)
- The shape of the scenario is informative, its probability is not
  - heavy tails and rising correlations make Normal probabilities far too small

MFM_ch18_stress

The Tails Move Apart (1/2)



- Left: correlations between the rolling indices ($w = 250$ days, $h = 5$)
- Right: monthly correlations with CATFIN (source: Ando, Greenwood-Nimmo & Shin (2022))
- CATFIN: the average of three VaR 1% estimates for financial stocks Allen, Bali & Tang (2012)

MFM_ch18_quantile_connectedness

The Tails Move Apart (2/2)

- The mean index follows the adverse tail far more than the beneficial tail
  - correlation 0.774 with $S_{0.95}$, against 0.411 with $S_{0.05}$
  - A rise in mean connectedness is mainly a rise in bad-news spillovers
- The two tails share little variation (0.367)
  - Two indicators, not one index measured twice
  - Hence RTD (Relative Tail Dependence) is informative: about ± 15 points in rolling windows, against 2.19 on the full sample
- Against CATFIN: 0.51 for $S_{0.95}$, 0.42 for RTD, only 0.15 for $S_{0.05}$
  - CATFIN moves with adverse-shock spillovers more than with beneficial ones (weak bilateral links and the timing of RTD: Appendix)

Extension to Our 13 Banks: Specification and Open Questions

- Course data: daily closes of the 13 banks of this chapter, 2010–2026
  - course dataset; US, euro area and United Kingdom, Romania
  - y_t = daily loss $-r_t$ in %, so that the right tail is the adverse one, as for CDS
  - Data limitations: equity losses instead of CDS spreads
  - 13 banks and no sovereigns ($m = 13$ instead of 34)
  - Different closing times of US, European and Romanian markets
- Limits stated by the authors
  - the lag order of the mean is imposed at every quantile
  - the quantile is held fixed along the horizon (other limits: Appendix)
- Open extension
  - Does the RTD of the 13 banks rise before March 2020 and the March 2023 bank failures?
  - Does it predict bank stress beyond current volatility and the mean-based index of this chapter?
  - For forecasting, select lag order and factors on a training sample only

Your Turn: a Project Seed

- **Deliverables**
  - A grid of specifications fixed in writing before the regressions
  - A notebook that regenerates every number
  - HAC inference and out-of-sample losses for every cell
- **AI log** (templates)
  - `AI_USE.md`: the prompts that shaped the design
  - `AI_ERRORS.md`: each wrong claim (a VAR on price levels, OLS t-statistics on overlapping windows) and the test that caught it

MES as an Euler Contribution: Proof (1/2)

- Portfolio $X_p = \sum_i w_i X_i$ with a continuous distribution
  - $\mathrm{ES}_\alpha(X_p) = -\mathbb{E}[X_p \mid X_p \leq q_\alpha(X_p)]$
  - ES_α is positively homogeneous of degree 1 in w, so by Euler's theorem $\mathrm{ES}_\alpha(X_p) = \sum_i w_i \, \partial \mathrm{ES}_\alpha / \partial w_i$
  - Write $\mathrm{ES}_\alpha = -\frac{1}{\alpha}\mathbb{E}\left[X_p 1\{X_p \leq q_\alpha(w)\}\right]$, with f_p the density of X_p
  - The derivative has an interior and a boundary term:
    $$\frac{\partial}{\partial w_i}\mathbb{E}[X_p 1\{X_p \leq q_\alpha\}] = \mathbb{E}[X_i 1\{X_p \leq q_\alpha\}] + q_\alpha f_p(q_\alpha)\left(\frac{\partial q_\alpha}{\partial w_i} - \mathbb{E}[X_i \mid X_p = q_\alpha]\right)$$
  - The quantile derivative is $\partial q_\alpha / \partial w_i = \mathbb{E}[X_i \mid X_p = q_\alpha]$ Gouriéroux, Laurent & Scaillet (2000), so the boundary term is zero
  - Hence $\partial \mathrm{ES}_\alpha / \partial w_i = -\mathbb{E}[X_i \mid X_p \leq q_\alpha(X_p)] = \mathrm{MES}_{i,\alpha}$ with $m = p$ Gouriéroux, Laurent & Scaillet (2000), Scaillet (2004)

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MES as an Euler Contribution: Proof (2/2)

- Check on our data: equal-weighted portfolio of the six US banks, $\alpha = 5\%$ (199 tail days)
  - $\mathrm{ES}_{5\%}$ of the portfolio $= 4.32\% =$ average of the six MES conditional on the portfolio (4.32%)
  - The identity is exact, also for the historical estimator
  - Conditioning on the S&P 500 instead gives an average MES of 3.63% (JPMorgan: 3.21% vs 3.84%)
  - The identity fails when $m \neq p$
- Under the bivariate Normal distribution with zero means, $\mathrm{MES}_{i,\alpha} = \beta_i \, \mathrm{ES}_\alpha(X_m)$: a beta times a constant

Back

LRMES Simulation: Innovations and Recursions

- Standardised residuals $\epsilon_{it} = r_{it}/\sigma_{it}$, $\epsilon_{mt} = r_{mt}/\sigma_{mt}$
  - S is their sample correlation matrix, the long-run target of Q_t
  - Bank innovation orthogonal to the market: $\xi_{it} = (\epsilon_{it} - \rho_t\,\epsilon_{mt})/\sqrt{1-\rho_t^2}$ Brownlees & Engle (2017)
- Each simulated day s: draw a past date τ and take the pair $(\xi_{i\tau}, \epsilon_{m\tau})$
  - rebuild the bank shock with the **simulated** correlation
  - $\epsilon_{i,t+s} = \rho_{t+s}\,\epsilon_{m\tau} + \sqrt{1-\rho_{t+s}^2}\,\xi_{i\tau}$, then update σ^2 and Q with the new returns
- Restrictions, so that $\sigma_t^2 > 0$ and Q_t is positive definite
  - GJR–GARCH: $\omega > 0$, $\alpha \geq 0$, $\alpha + \gamma \geq 0$, $\beta \geq 0$, $\alpha + \gamma/2 + \beta < 1$ (finite variance for symmetric innovations)
  - in general, finite variance needs $\alpha + \gamma\,\mathbb{E}[\epsilon^2 1\{\epsilon < 0\}] + \beta < 1$
  - DCC: $a, b > 0$, $a + b < 1$
  - Initialisation: $Q_1 = S$ in estimation; the simulation starts from σ_{T+1}^2 and Q_{T+1} filtered to the last date

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Quantile Regression: Asymptotics

- Asymptotics for a fixed α, with $\hat{\theta}_\alpha = (\hat{a}_\alpha, \hat{b}_\alpha)^\top$
  - n days, $x_t = (1, X_{i,t})^\top$, f_t: the conditional density of Y at its α-quantile
  - $\sqrt{n}(\hat{\theta}_\alpha - \theta_\alpha) \Rightarrow N\left(0,\ \alpha(1-\alpha)\, D_{\mathbf{1}}^{-\mathbf{1}} D_{\mathbf{0}} D_{\mathbf{1}}^{-\mathbf{1}}\right)$, $D_{\mathbf{0}} = \mathbb{E}[x_t x_t^\top]$, $D_{\mathbf{1}} = \mathbb{E}[f_t\, x_t x_t^\top]$
  - Assumes independent observations (or scores $x_t(\alpha - 1\{u_t < 0\})$ that are a martingale difference), $f_t > 0$ near the quantile and $D_{\mathbf{0}}$, $D_{\mathbf{1}}$ positive definite
  - With serially dependent scores the variance becomes $D_{\mathbf{1}}^{-\mathbf{1}} \Omega D_{\mathbf{1}}^{-\mathbf{1}}$, with $\Omega = \sum_h \mathrm{Cov}(x_t \psi_t,\ x_{t-h}\psi_{t-h})$ and $\psi_t = \alpha - 1\{u_t < 0\}$: a HAC estimate or a block bootstrap
  - The **sparsity** $1/f_t$ must be estimated (kernel or bandwidth)
  - At $\alpha = 1\%$ few observations lie near the quantile, so this estimate is noisy
- The slope b_α can change with α
  - the bank may matter more for the system in the tail than in the centre

Back

Extremal Quantiles: Why $\alpha = 1\%$ Is Hard

- At $\alpha = 1\%$ only $\alpha n = 40$ days remain in the tail
  - The Normal approximation above assumes $\alpha n \to \infty$ fast; with αn of a few dozen it can be poor
  - Extremal-quantile theory (extreme-value limits, subsampling) is the alternative built for this case Chernozhukov & Fernández-Val (2011)
- For the same slope $\hat{b}_{1\%}$, the block-bootstrap standard error is about 0.3 times the kernel-based one
  - median over banks; the ratio ranges from 0.21 to 0.46
  - the two methods give clearly different uncertainty
  - The kernel-based standard error rests on a sparsity estimate from the few observations near the 1% quantile
  - The bootstrap redraws the same few tail days: the gap shows method uncertainty, not which interval covers correctly
- Practical rule: report $\alpha = 5\%$ and $\alpha = 1\%$ with αn
  - expect the 1% ranking to be the noisier one
  - The low Spearman correlation between the 1% and 5% rankings (0.13) may reflect estimation noise, genuine differences between the two tail levels, or both

Back

Testing ΔCoVaR: Three Hypotheses

- (1) $H_0: b_\alpha = 0$ (no contribution)
  - The joint asymptotics of $(\hat{b}_\alpha, \hat{b}_{50\%})$ Koenker & Bassett (1982) assume serially uncorrelated scores
  - Here: the variance of $\hat{b}_\alpha$ from the same 999 block-bootstrap draws, Holm correction over the 11 banks
- (2) $H_0: b_\alpha = b_{50\%}$ (tail link equal to the central link)
  - We estimate the variance of $\hat{b}_\alpha - \hat{b}_{50\%}$ from 999 moving-block bootstrap draws that keep the pairs of days together
- (3) $H_0: \Delta\mathrm{CoVaR}_i = \Delta\mathrm{CoVaR}_j$ (equal contributions)
  - $z_{ij} = (\Delta\widehat{\mathrm{CoVaR}}_i - \Delta\widehat{\mathrm{CoVaR}}_j)/\widehat{\mathrm{se}}^*$ for each pair, with $\widehat{\mathrm{se}}^*$ the bootstrap standard error of the difference
  - Holm (1979) correction over the pairs; a joint Wald test that all are equal

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Testing ΔCoVaR 1%: Results

Bank	ΔCoVaR	$\hat{b}_{1\%}$	z^*	$\hat{b}_{50\%}$	$\hat{b}_{1\%} - \hat{b}_{50\%}$	p
JPMorgan	4.62	0.94	19.3	0.96	−0.02	0.66
Bank of America	4.60	0.76	14.2	0.78	−0.02	0.73
Citigroup	3.81	0.64	22.6	0.76	−0.11	< 0.001
Goldman Sachs	4.12	0.85	14.3	0.84	0.00	0.99
Morgan Stanley	4.01	0.68	13.0	0.73	−0.05	0.28
Wells Fargo	4.89	0.84	17.8	0.78	0.06	0.16
Deutsche Bank	4.24	0.59	15.3	0.60	−0.01	0.68
BNP Paribas	4.83	0.77	21.8	0.74	0.03	0.37
Santander	4.42	0.75	19.3	0.69	0.07	0.06
ING	4.41	0.61	19.4	0.71	−0.10	0.001
HSBC	4.07	0.87	8.7	0.86	0.01	0.95

- z^*: $\hat{b}_{1\%}$ divided by its block-bootstrap standard error (same 999 draws); all 11 slopes stay positive at 5% after Holm
- With the kernel standard error, valid only for serially uncorrelated scores: t from 4.0 to 6.9
- p: p-value of $b_{1\%} = b_{50\%}$
  - from $z = (\hat{b}_{1\%} - \hat{b}_{50\%})/\widehat{\mathrm{se}}^*$, with the bootstrap standard error $\widehat{\mathrm{se}}^*$ and the Normal approximation
- pair tests and joint Wald tests: main slide

Back

Time-Varying ΔCoVaR with State Variables

- State variables M_{t-1} Adrian & Brunnermeier (2016)
  - log VIX, the return of the regional index and of the system, all lagged one day
  - $q_\alpha(X_{i,t} \mid M_{t-1}) = a_i + c_i^\top M_{t-1}$ at α and at 50% (a_i, c_i: intercept and coefficients of the bank's quantile regression)
  - $q_\alpha(X_t^{sys} \mid X_{i,t}, M_{t-1}) = a + b\,X_{i,t} + c^\top M_{t-1}$
- Then $\Delta\mathrm{CoVaR}_{\alpha,t} = \hat{b}\left(\hat{q}_{50\%,t}(X_i) - \hat{q}_{\alpha,t}(X_i)\right)$
  - It moves with the bank's conditional VaR, which moves with the VIX
- The slope $\hat{b}$ is constant: time variation comes from the state, not from the link

Back

Backtesting CoVaR and MES (1/2)

- Systemic measures are conditional risk measures, so they need **conditional** backtests Banulescu-Radu, Hurlin, Leymarie & Scaillet (2021)
  - For $\mathrm{CoVaR}^{\leq}$: hit $I_t = 1\{X_t^{sys} \leq -\mathrm{CoVaR}_t^{\leq},\ X_{i,t} \leq -\mathrm{VaR}_{i,t}\}$ with $P(I_t = 1) = \alpha^2$ under H_0
  - This holds if both the bank VaR and the conditional quantile are calibrated
  - The Kupiec test checks that the hit frequency is α^2
  - With x hits in n days and $\hat{\pi} = x/n$, $\mathrm{LR}_{\mathrm{POF}} = -2\ln \dfrac{(1-\alpha^2)^{n-x}(\alpha^2)^x}{(1-\hat{\pi})^{n-x}\hat{\pi}^x} \sim \chi_1^2$ under H_0 (Chapter 8)
  - The Christoffersen test also checks that hits are independent: a hit today must not make one tomorrow more likely
  - The bank VaR is checked separately, against its own rate α
  - For MES: the cumulative joint violation process of Banulescu-Radu, Hurlin, Leymarie & Scaillet (2021)

Back

Backtesting CoVaR and MES (2/2)

- Our out-of-sample check: historical $\mathrm{CoVaR}^{\leq}_{5\%}$ on an expanding window
  - from day 1 000, 2 961 forecast days per bank
  - Expected joint hits 7.4; observed 5–9 across the eleven banks (JPMorgan 9)
  - Smallest Kupiec $p = 0.35$: no rejection
  - Power is limited: if the true joint rate were twice α^2, the 5% Kupiec test would reject in 62% of samples of this length with independent hits
  - So even a doubling is missed about one time in three
  - The χ^2_1 threshold is asymptotic: the exact size of the rejection region is 4.1%

Back

VAR Assumptions and the Lag Order of the Rolling Index

- The VAR(p) of From Pairs to Networks
  - Assumptions: stable VAR (roots of $\det(I - \sum_l A_l z^l)$ outside the unit circle), ε_t serially uncorrelated with finite, positive definite Σ
  - Moving-average form: $y_t = \mu + \sum_{h \geq \mathbf{0}} \Phi_h \varepsilon_{t-h}$, $\Phi_{\mathbf{0}} = I$, $\Phi_h = \sum_{l=\mathbf{1}}^{p} A_l \Phi_{h-l}$ ($\Phi_h = 0$ for $h < 0$)
  - e_i: the i-th unit vector
- Lag order: every window keeps $p = 2$, the order BIC selects on the full sample
  - in the windows BIC picks $p = 1$ every time
  - with $p = 1$ the index has correlation 0.99 with the one shown

Back

Diagnostics of the VAR Residuals

- For each equation: the residual regressed on the VAR regressors and on its own 20 lags
  - HAC Wald test (20 lags) of the 20 lags, Holm correction over the 13 equations
- VAR(2), the order BIC selects: rejection in 13 of 13 equations after Holm
  - VAR(5) and VAR(10): still 13 and 13 of 13
  - VAR(22): 3 rejections at 5%, 1 after Holm
- Full-sample total connectedness falls with the VAR order
  - 63.9% ($p = 2$), 61.4% ($p = 5$), 60.0% ($p = 10$), 59.6% ($p = 22$)
- With autocorrelated residuals, C is a reproducible number of the specification
  - as a share of forecast error variance it needs serially uncorrelated innovations
  - A block bootstrap of the residuals does not turn autocorrelated residuals into innovations

Back

Regularised VARs: the Elastic Net

- Demirer et al. (2018): each VAR equation by the adaptive elastic net
  - λ chosen equation by equation by validation on 10 consecutive time blocks, 20 days removed on each side of the test block (5 in the 150-day windows)
  - $\hat{\beta} = \arg\min_\beta \sum_t \left(y_t - \sum_i \beta_i x_{it}\right)^2 + \lambda \sum_i w_i \left(\frac{1}{2}|\beta_i| + \frac{1}{2}\beta_i^2\right)$, $w_i = 1/|\hat{\beta}_{i,\mathrm{OLS}}|$
  - w_i: adaptive weights, larger for coefficients small in OLS, re-estimated in each training sample
  - The $|\beta_i|$ part sets coefficients to zero, the β_i^2 part shrinks them
  - Rolling 150-day windows: plain elastic net, $w_i = 1$, with $p = 1$ (the order BIC selects in 100% of the windows) and $H = 10$
- Why: selection and shrinkage in the VAR coefficients
  - without forcing a sparse **network** (links also come through Σ)
- On the full sample we keep the BIC order of our OLS VAR, $p = 2$
- With about 4 000 days the penalty hardly matters
  - it matters in short windows

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Granger-Causality Networks and Multiple Testing (1/2)

- Billio, Getmansky, Lo & Pelizzon (2012) draw an edge $j \to i$ when j Granger-causes i at 5%
  - with 13 banks this is $13 \times 12 = 156$ tests
  - j Granger-causes i if the past of j improves the forecast of i
  - In $X_{i,t} = c + aX_{i,t-\mathbf{1}} + gX_{j,t-\mathbf{1}} + u_t$ we test $H_\mathbf{0}$: $g = 0$
  - Even with no links at all, about 7.8 edges would appear by chance

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Granger-Causality Networks and Multiple Testing (2/2)

- Our tests: bivariate regressions, one lag, HAC Wald statistics (Newey–West, 9 lags)
  - Daily returns: 58 edges at 5%, 19 after the Holm (1979) correction, 57 with the BH (Benjamini–Hochberg, procedure) procedure at the nominal 5% level Benjamini & Hochberg (1995)
  - Holm with 5 or 20 HAC lags: 21 and 21 edges; with heteroskedasticity-robust errors only: 33
  - The Benjamini & Yekutieli (2001) procedure, valid under any dependence: 38 edges
  - Log volatility, highly persistent: one extra lag that is not tested Toda & Yamamoto (1995), as in the lag-augmented tests of Shi, Hurn & Phillips (2020), valid only with a correct order p: 153, 149 and 153 edges
- Holm controls the chance of any false edge under arbitrary dependence
- The FDR is the **expected** share of false edges among those drawn
  - the BH (Benjamini–Hochberg) procedure guarantees it for independent tests Benjamini & Hochberg (1995)
  - but tests on overlapping bank pairs are dependent: the 5% level of BH is only nominal here
- Daily returns of banks in different time zones
  - many "causal" edges only reflect that New York closes after Frankfurt

Back

Worked Example: Reverse Stress Test with Two Factors

- Betas $b = (1.2, 0.8)$, target loss $\ell^* = 20\%$
  - four-week covariance of the factors $h\Sigma = \begin{pmatrix} 16 & 6 \\ 6 & 9 \end{pmatrix}$ (%²)
  - $h\Sigma\, b = (1.2 \cdot 16 + 0.8 \cdot 6,\ 1.2 \cdot 6 + 0.8 \cdot 9) = (24, 14.4)$
  - $b^\top h\Sigma\, b = 1.2 \cdot 24 + 0.8 \cdot 14.4 = 40.32$, standard deviation 6.35%
- Most plausible scenario and its distance
  - $f^* = -20 \cdot (24, 14.4)/40.32 = (-11.9\%, -7.1\%), \quad d^* = 20/6.35 = 3.15$
  - Normal probability of a loss at least this large: $\Phi(-3.15) = 0.08\%$ per four weeks
- The scenario loads more on the factor with the larger beta and variance
  - both factors fall together because they are correlated

Back

Sectors, Factors and Lag Order

- Data (Section 3): the 17 financial sectors
  - A financial sector = equal-weighted CDS of its banks and insurers with assets of at least USD 10 (US dollar) billion, 199 institutions in all
- Factors (Eq. (8), Figure 2)
  - Residual pairs with $|\rho| < 0.25$: 91.6% with factors, fewer than half without
- Lag order and horizon (Sections 2.2 and 4)
  - VAR(1) chosen by BIC at the mean and kept at every quantile; $h = 5$ days
  - The quantile is held fixed along the forecast horizon

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Further Results

- Of the 1 122 bilateral spillovers, 568 are below 1% at the mean and 829 at the median (Figure 7)
  - Away from the mean, the network has many weak links rather than a few strong ones
  - In the tails these weak links add up to strong average spillovers
- RTD over time (Section 4.3, Figure 11)
  - RTD rises with the Bear Stearns fund losses of 2007
  - It falls after the US bank rescue programme and the negative rates of the ECB: a fragility signal the mean hides

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Replication Specification and Limits Stated by the Authors

- Specification for the replication on the 13 banks
  - VAR order by BIC, factors by Eq. (8), $h = 5$, $\tau \in \{0.05, 0.5, 0.95\}$ and the mean, $w = 250$, RTD
- Further limits stated by the authors
  - 250 days are too few to select factors window by window, so their number is fixed (Section 4.3, Appendix B of the paper)
  - Shorter windows leave too few effective tail observations
  - Only direct spillovers of idiosyncratic shocks are measured, not propagation through the common factors (footnote 2)
  - Greece is left out for a gap in its CDS data (Section 3, Appendix A of the paper)

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The Discovery Loop, Reusable Prompts (1/2)

- **Literature**: map what is known, then verify every reference
  - `"Which papers test whether connectedness indices predict bank distress out of sample, beyond volatility? Give DOI, sample, horizon and controls."`
- **Hypotheses**: competing readings of a rise in connectedness, each with its own test
  - `"Give competing interpretations of a rise in total connectedness (common shock, contagion, artefact of rolling windows) and a test that discriminates between them."`

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The Discovery Loop, Reusable Prompts (2/2)

- **Data and code**: on the course data, replicating a known number first
  - "Fit a VAR(2) to the log Parkinson volatilities of the 13 banks of the course data on 250-day windows and compute the generalized total connectedness with H = 10."
- **Robustness**, fixed before the predictive regressions are run
  - "Pre-register: horizons 21/63/126 days, volatility and VIX controls, windows 150/250/500 days, HAC lags at least the overlap, out-of-sample evaluation from 2018."
- **Critique**: ask the assistant to attack the result
  - "Act as a referee: is the predictive power of connectedness just the persistence of volatility? Which regression would show it?"

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What the Researcher Must Check (1/2)

- **Non-stationary inputs**: a VAR on price levels, or on trending series, produces spurious connectedness
  - Test: unit-root tests on every input
  - All eigenvalues of the companion matrix of the fitted VAR strictly inside the unit circle in every window
- **Ordering**: Cholesky decompositions change with the order of the banks
  - Test: permute the columns; the generalized table must not change

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What the Researcher Must Check (2/2)

- **Look-ahead**: a window labelled by its first date, or a lag order chosen on the full sample
  - Test: the index at t must not move when data after t are deleted
- **Overlap**: rolling indices and forward outcomes overlap
  - so OLS t-statistics are inflated
  - Test: Newey–West lags at least equal to the overlap, or a block bootstrap
- **Dimension**: 13 banks and $p = 2$ give 27 coefficients per equation from 250 days
  - more banks need shrinkage Demirer et al. (2018)
  - Test: compare with a LASSO VAR
  - Unstable edges signal estimation noise, not structure

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Further Study on Quantinar

Advanced courses on quantinar.com

- Financial Risk Meter for Emerging Markets
- Dynamic Crypto Networks
- Network Centrality

Code and data

- Quantlets: github.com/danpele/MFM/tree/main/Quantlets/Ch_18

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Acronyms used in this material (1/2)

- **AI**: Artificial Intelligence
- **BAC**: Bank of America Corporation (NYSE ticker)
- **BET**: Bucharest Exchange Trading (index)
- **BH**: Benjamini–Hochberg (procedure)
- **BIC**: Bayesian Information Criterion
- **BNP**: BNP Paribas SA (Euronext Paris ticker; Banque Nationale de Paris)
- **BVB**: Bursa de Valori București — *the Bucharest Stock Exchange*
- **CATFIN**: CATastrophic risk in the FINancial sector
- **CDS**: Credit Default Swap
- **CI**: Confidence Interval
- **CoVaR**: Conditional Value-at-Risk (of the system, given an institution)
- **COVID-19**: COronaVIrus Disease 2019
- **CV**: Cross-Validation
- **DBK**: Deutsche Bank AG (Xetra ticker)
- **DCC**: Dynamic Conditional Correlation
- **EBA**: European Banking Authority
- **ECB**: European Central Bank
- **ES**: Expected Shortfall
- **ETF**: Exchange-Traded Fund
- **EU**: European Union
- **FDIC**: Federal Deposit Insurance Corporation
- **FDR**: False Discovery Rate
- **FEVD**: Forecast Error Variance Decomposition
- **FRM**: Financial Risk Meter
- **GAAP**: Generally Accepted Accounting Principles (US)
- **GACV**: Generalized Approximate Cross-Validation
- **GARCH**: Generalised AutoRegressive Conditional Heteroskedasticity
- **GFC**: Global Financial Crisis (2007–2009)

Acronyms used in this material (2/2)

- **GJR**: Glosten–Jagannathan–Runkle (asymmetric GARCH)
- **GS**: The Goldman Sachs Group, Inc. (NYSE ticker)
- **HAC**: Heteroskedasticity and Autocorrelation Consistent (standard errors)
- **HSBA**: HSBC Holdings plc (London Stock Exchange ticker)
- **HSBC**: HSBC Holdings plc (originally the Hongkong and Shanghai Banking Corporation)
- **IFRS**: International Financial Reporting Standards
- **ING**: ING Groep (Internationale Nederlanden Groep) — *the Dutch banking group ING*
- **INGA**: ING Groep N.V. (Euronext Amsterdam ticker)
- **JPM**: JPMorgan Chase & Co. (NYSE ticker)
- **LASSO**: Least Absolute Shrinkage and Selection Operator
- **LRMES**: Long-Run Marginal Expected Shortfall
- **MES**: Marginal Expected Shortfall
- **MS**: Morgan Stanley (NYSE ticker)
- **OLS**: Ordinary Least Squares
- **QFVAR**: Quantile Factor Vector AutoRegression
- **QML**: Quasi-Maximum Likelihood
- **RTD**: Relative Tail Dependence
- **SAN**: Banco Santander SA (Bolsa de Madrid ticker)
- **SG**: Société Générale — *the French banking group Société Générale*
- **SRISK**: Systemic RISK (capital shortfall measure)
- **SVB**: Silicon Valley Bank
- **TENET**: Tail-Event driven NETwork risk
- **TLV**: Banca Transilvania (BVB ticker)
- **US**: United States
- **VAR**: Vector AutoRegression
- **VaR**: Value-at-Risk
- **VIX**: CBOE Volatility IndeX
- **WFC**: Wells Fargo & Company (NYSE ticker)

References (1/5)

- Acharya, V.V., Engle, R., Richardson, M. (2012). Capital shortfall: a new approach to ranking and regulating systemic risks. *American Economic Review*, 102(3), 59–64.
- Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M. (2017). Measuring systemic risk. *Review of Financial Studies*, 30(1), 2–47.
- Adrian, T., Brunnermeier, M.K. (2016). CoVaR. *American Economic Review*, 106(7), 1705–1741.
- Allen, L., Bali, T.G., Tang, Y. (2012). Does systemic risk in the financial sector predict future economic downturns?. *Review of Financial Studies*, 25(10), 3000–3036.
- Ando, T., Bai, J. (2020). Quantile co-movement in financial markets: a panel quantile model with unobserved heterogeneity. *Journal of the American Statistical Association*, 115(529), 266–279.
- Ando, T., Greenwood-Nimmo, M., Shin, Y. (2022). Quantile connectedness: modeling tail behavior in the topology of financial networks. *Management Science*, 68(4), 2401–2431.
- Banulescu-Radu, D., Hurlin, C., Leymarie, J., Scaillet, O. (2021). Backtesting marginal expected shortfall and related systemic risk measures. *Management Science*, 67(9), 5730–5754.
- Basel Committee on Banking Supervision (2018). Global systemically important banks: revised assessment methodology and the higher loss absorbency requirement. Bank for International Settlements.

References (2/5)

- Belloni, A., Chernozhukov, V. (2011). ℓ_1-penalized quantile regression in high-dimensional sparse models. *Annals of Statistics*, 39(1), 82–130.
- Ben Amor, S., Althof, M., Härdle, W.K. (2022). Financial Risk Meter for emerging markets. *Research in International Business and Finance*, 60, 101594.
- Benjamini, Y., Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society B*, 57(1), 289–300.
- Benoit, S., Colliard, J.-E., Hurlin, C., Pérignon, C. (2017). Where the risks lie: a survey on systemic risk. *Review of Finance*, 21(1), 109–152.
- Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3), 535–559.
- Bolton, P., Després, M., Pereira da Silva, L.A., Samama, F., Svartzman, R. (2020). The green swan: central banking and financial stability in the age of climate change. Bank for International Settlements.
- Brownlees, C., Engle, R.F. (2017). SRISK: a conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, 30(1), 48–79.
- Castro, C., Ferrari, S. (2014). Measuring and testing for the systemically important financial institutions. *Journal of Empirical Finance*, 25, 1–14.
- Chernozhukov, V., Fernández-Val, I. (2011). Inference for extremal conditional quantile models, with an application to market and birthweight risks. *Review of Economic Studies*, 78(2), 559–589.
- Danielsson, J., James, K.R., Valenzuela, M., Zer, I. (2016). Model risk of risk models. *Journal of Financial Stability*, 23, 79–91.
- Demirer, M., Diebold, F.X., Liu, L., Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1), 1–15.

References (3/5)

- Diebold, F.X., Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, 119(534), 158–171.
- Diebold, F.X., Yilmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.
- Diebold, F.X., Yilmaz, K. (2014). On the network topology of variance decompositions: measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119–134.
- ECB Banking Supervision (2022). Banks must sharpen their focus on climate risk, ECB supervisory stress test shows. Press release, 8 July 2022.
- Engle, R. (2002). Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339–350.
- Engle, R., Jondeau, E., Rockinger, M. (2015). Systemic risk in Europe. *Review of Finance*, 19(1), 145–190.
- FDIC (2023). FDIC creates a Deposit Insurance National Bank of Santa Clara to protect insured depositors of Silicon Valley Bank, Santa Clara, California. Press release, 10 March 2023.
- Federal Reserve Board (2023). Federal Reserve Board announces it will make available additional funding to eligible depository institutions. Press release, 12 March 2023.
- Franke, J., Härdle, W.K., Hafner, C.M. (2019). Statistics of Financial Markets: An Introduction, 5th ed. Springer.
- Giglio, S., Kelly, B., Pruitt, S. (2016). Systemic risk and the macroeconomy: an empirical evaluation. *Journal of Financial Economics*, 119(3), 457–471.
- Girardi, G., Ergün, A.T. (2013). Systemic risk measurement: multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance*, 37(8), 3169–3180.

References (4/5)

- Glosten, L.R., Jagannathan, R., Runkle, D.E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48(5), 1779–1801.
- Gouriéroux, C., Laurent, J.P., Scaillet, O. (2000). Sensitivity analysis of values at risk. *Journal of Empirical Finance*, 7(3–4), 225–245.
- Härdle, W.K., Chen, C.Y.-H., Overbeck, L. (Eds.) (2017). Applied Quantitative Finance, 3rd ed. Springer.
- Härdle, W.K., Wang, W., Yu, L. (2016). TENET: Tail-Event driven NETwork risk. *Journal of Econometrics*, 192(2), 499–513.
- Hall, P., Horowitz, J.L., Jing, B.-Y. (1995). On blocking rules for the bootstrap with dependent data. *Biometrika*, 82(3), 561–574.
- Hendricks, W., Koenker, R. (1992). Hierarchical spline models for conditional quantiles and the demand for electricity. *Journal of the American Statistical Association*, 87(417), 58–68.
- Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 6(2), 65–70.
- Jiang, E.X., Matvos, G., Piskorski, T., Seru, A. (2024). Monetary tightening and U.S. bank fragility in 2023: mark-to-market losses and uninsured depositor runs?. *Journal of Financial Economics*, 159, 103899.
- Koenker, R., Bassett, G. (1978). Regression quantiles. *Econometrica*, 46(1), 33–50.
- Koenker, R., Bassett, G. (1982). Tests of linear hypotheses and ℓ_1 estimation. *Econometrica*, 50(6), 1577–1583.
- Koop, G., Pesaran, M.H., Potter, S.M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1), 119–147.
- Mainik, G., Schaanning, E. (2014). On dependence consistency of CoVaR and some other systemic risk measures. *Statistics & Risk Modeling*, 31(1), 49–77.
- Mihoci, A., Althof, M., Chen, C.Y.-H., Härdle, W.K. (2020). FRM Financial Risk Meter. In *The Econometrics of Networks*, Advances in Econometrics 42, Emerald, 335–368.

References (5/5)

- Nucera, F., Schwaab, B., Koopman, S.J., Lucas, A. (2016). The information in systemic risk rankings. *Journal of Empirical Finance*, 38, 461–475.
- Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business*, 53(1), 61–65.
- Pele, D.T., Lazar, E., Dufour, A. (2017). Information entropy and measures of market risk. *Entropy*, 19(5), 226.
- Pesaran, H.H., Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17–29.
- Ren, R., Althof, M., Härdle, W.K. (2025). Financial Risk Meter for cryptocurrencies and tail risk network-based portfolio construction. *Singapore Economic Review*, 70(4), 901–927.
- Ren, R., Lu, M., Li, Y., Härdle, W.K. (2022). Financial Risk Meter FRM based on expectiles. *Journal of Multivariate Analysis*, 189, 104881.
- Scaillet, O. (2004). Nonparametric estimation and sensitivity analysis of expected shortfall. *Mathematical Finance*, 14(1), 115–129.
- Shi, S., Hurn, S., Phillips, P.C.B. (2020). Causal change detection in possibly integrated systems: revisiting the money–income relationship. *Journal of Financial Econometrics*, 18(1), 158–180.
- Toda, H.Y., Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66(1–2), 225–250.
- Toma, F.-M., Dima, D.M., Grecu, R., Pele, D.T., Lessmann, S. (2026). Energy Financial Risk Meter: systemic risk in the EU energy sector. SSRN working paper.
- Wang, R., Althof, M., Härdle, W.K. (2023). A financial risk meter for China. *Emerging Markets Review*, 56, 101052.