








# Statistics of Financial Markets

## Chapter 15: Systemic risk




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# Acronyms used in this material (1/2)

- **AI**: Artificial Intelligence
- **AIG**: American International Group
- **ASF**: Autoritatea de Supraveghere Financiară (the Financial Supervisory Authority of Romania)
- **AT1**: Additional Tier 1 (capital instruments)
- **BET**: Bucharest Exchange Trading (index)
- **BIC**: Bayesian Information Criterion
- **BIS**: Bank for International Settlements
- **BNP**: Banque Nationale de Paris (BNP Paribas) — the French banking group BNP Paribas
- **BNR**: Banca Națională a României (the National Bank of Romania)
- **BVB**: Bursa de Valori București (the Bucharest Stock Exchange)
- **CET1**: Common Equity Tier 1 (capital)
- **CNSM**: Comitetul Național pentru Supravegherea Macroprudențială (the National Committee for Macroprudential Oversight)
- **COVID-19**: COronaVIrus Disease 2019
- **DGC**: Degree of Granger Causality
- **ECB**: European Central Bank
- **EODHD**: EOD Historical Data (market-data provider)
- **ES**: Expected Shortfall
- **ESRB**: European Systemic Risk Board

# Acronyms used in this material (2/2)

- **EU**: European Union
- **FINMA**: Eidgenössische Finanzmarktaufsicht (the Swiss Financial Market Supervisory Authority)
- **FRM**: Financial Risk Meter
- **FSB**: Financial Stability Board
- **GARCH**: Generalised AutoRegressive Conditional Heteroskedasticity
- **HSBC**: Hongkong and Shanghai Banking Corporation
- **IFRS**: International Financial Reporting Standards
- **IMF**: International Monetary Fund
- **ING**: Internationale Nederlanden Groep (the Dutch banking group ING)
- **JPM**: JPMorgan Chase (ticker symbol)
- **LRMES**: Long-Run Marginal Expected Shortfall
- **MES**: Marginal Expected Shortfall
- **NYU**: New York University
- **OLS**: Ordinary Least Squares
- **SRISK**: Systemic RISK (capital shortfall in a crisis)
- **SVB**: Silicon Valley Bank
- **TENET**: Tail-Event driven NETwork risk
- **UBS**: Union Bank of Switzerland (former name of UBS)
- **US**: United States
- **VAR**: Vector AutoRegression
- **VIX**: CBOE Volatility IndeX

## Today's Question and Route

- **Question**: when does the loss of one bank become a loss of the whole financial system, and how do we measure it from market data?
  - Chapter 10 measured the risk of one position (VaR 1%, ES 2.5%); this chapter measures the risk that one institution adds to the system
- **Route** of the chapter
  - what systemic risk is: contagion, common exposures, fire sales, too big and too interconnected to fail
  - four crises in the data: 2008, the euro area in 2011–2012, March 2020, March 2023
  - measures: correlation and tail dependence, CoVaR and $\Delta$CoVaR, MES and SRISK, networks
  - macroprudential policy: Basel III buffers, the ESRB, the BNR

## Learning Outcomes

- Explain the channels of systemic risk and recognise them in the crises of 2008, 2011–2012, 2020 and 2023
- Estimate CoVaR 1% and $\Delta$CoVaR by linear quantile regression and interpret them next to VaR 1%
- Compute MES 5%, LRMES and SRISK, and explain the role of leverage
- Distinguish contagion from interdependence (the Forbes–Rigobon correction) and read a tail-dependence estimate
- Read a Granger-causality network and a Diebold–Yilmaz connectedness table
- Name the macroprudential tools of Basel III and the institutions that apply them in the EU and in Romania

## Reading and Tools

- Textbook: Franke, Härdle & Hafner (2019), Ch. 16 (VaR) and Ch. 17 (copulae); surveys: Bisias, Flood, Lo & Valavanis (2012); Benoit, Colliard, Hurlin & Pérignon (2017)
  - the landmark papers of the chapter: Adrian & Brunnermeier (2016); Acharya, Pedersen, Philippon & Richardson (2017); Brownlees & Engle (2017); Billio, Getmansky, Lo & Pelizzon (2012); Diebold & Yilmaz (2014)
- Python Quantlets of this chapter: Quantlets/Ch_15
- Lecture notebook: open in Google Colab
- Video courses: Financial Risk Meter for Emerging Markets; Dynamic Crypto Networks

## Definition of Systemic Risk

- **Systemic risk**: the risk that the financial system as a whole stops working (lending, payments, trading), with large costs for the real economy IMF, BIS & FSB (2009)
  - the definition of the IMF (International Monetary Fund), the BIS and the FSB (Financial Stability Board) for the G-20 in 2009
- Three criteria for a **systemically important** institution IMF, BIS & FSB (2009)
  - **size**: how much of the system's services it provides
  - **substitutability**: whether others can take over its activity quickly
  - **interconnectedness**: how many others it would drag down
- Key point: systemic risk is a property of the **system**, not of a single balance sheet

## Limitations of VaR Computed Bank by Bank

- VaR 1% of a bank (Chapter 10): the loss of **this** bank exceeded with probability 1%
  - it ignores what happens to the others when this bank is in trouble
- **Fallacy of composition**: if every bank sells risky assets to cut its own VaR, prices fall for all and the risk of all rises
  - a small bank with a high VaR can matter less than a large, connected bank with a moderate VaR
- We need measures of the **tail of the system given the institution**, or of the **institution given the tail of the system**
  - CoVaR: the system given that the bank is in distress Adrian & Brunnermeier (2016)
  - MES and SRISK: the bank given that the market crashes Acharya, Pedersen, Philippon & Richardson (2017); Brownlees & Engle (2017)

## Channel 1: Direct Contagion

- **Contagion**: the failure of one institution causes losses or failures at others
  - direct exposures: interbank loans, derivatives, deposits held at other banks
  - a network of balance sheets: a loss travels along the links Allen & Gale (2000)
- Network structure matters Allen & Gale (2000); Haldane & May (2011)
  - many links spread small shocks thin, so the system absorbs them
  - the same links transmit large shocks everywhere: "robust yet fragile"
- **Too interconnected to fail**: an institution whose failure would hit many counterparties at once

## Channel 2: Common Exposures and Fire Sales

- **Common exposures**: banks hold the same assets (mortgages, government bonds), so one shock hits all of them at once
  - no link between the banks is needed: the correlation comes from the assets
- **Fire sales**: a bank that must sell quickly sells below the fundamental value Shleifer & Vishny (2011)
  - the lower price is a loss for every holder of the asset (marked to market)
  - **liquidity spiral**: losses $\rightarrow$ higher margins $\rightarrow$ more sales $\rightarrow$ lower prices Brunnermeier & Pedersen (2009)
- **Leverage** amplifies everything: with assets 20 times equity, a 5% fall in asset value wipes out the equity

# Channel 3: Bank Runs and Information Contagion

- **Bank run**: depositors withdraw at once because they fear that others will withdraw first Diamond & Dybvig (1983)
  - a bank holds long, illiquid loans and short, liquid deposits: it cannot pay everyone at once
  - a run can hit a solvent bank; deposit insurance removes the reason to run
- **Information contagion**: trouble at one bank makes investors doubt similar banks
  - Northern Rock (United Kingdom), September 2007: the first run on a British bank in over a century




Depositors queue outside a Northern Rock branch, September 2007

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

## Too Big to Fail

- **Too big to fail**: a bank whose failure would damage the economy so much that the state rescues it
  - the expected rescue lowers its funding cost: an implicit subsidy
  - moral hazard: the bank takes more risk because losses are shared with taxpayers
- The regulatory answer after 2008 BCBS (2018)
  - G-SIBs (global systemically important banks): a list published every year, with extra capital for each bank
  - resolution plans: a failing bank must be wound down without taxpayers' money
- Market measures (CoVaR, SRISK) let us rank banks without waiting for a failure

## Summary of the Systemic Risk Measures

| Measure | Question | Tool |
|---|---|---|
| correlation, tail dependence | do banks and markets crash together? | pseudo-observations, t copula |
| CoVaR, $\Delta$CoVaR | how much worse is the system when the bank is in distress? | quantile regression |
| MES | how much does the bank lose on the market's worst days? | conditional average |
| SRISK | how much capital would the bank miss in a crisis? | MES, leverage |
| networks | who transmits shocks to whom? | Granger tests, variance decompositions |

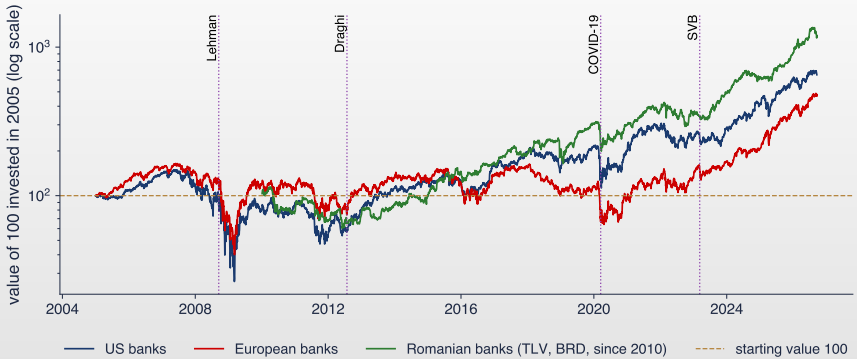
- All measures use only market prices: they are available daily, for any listed bank
- Their weakness: market prices can be calm while risk builds up (2006–2007)

## Data of the Chapter

| Group | Banks | Market index |
|---|---|---|
| US banks | JPMorgan Chase, Bank of America, Citigroup, Goldman Sachs, Morgan Stanley, Wells Fargo | S&P 500 |
| European banks | Deutsche Bank, BNP Paribas, Santander, ING, HSBC | Euro Stoxx 50 |
| Romanian banks | Banca Transilvania (TLV), BRD (since 2010) | BET |

- Daily adjusted closes of the banks and closes of the indices from EODHD, January 2005 – 18 September 2026; the VIX as a stress indicator
- Prices are joined on common days first, then daily log returns in %: $r_t = 100(\ln P_t - \ln P_{t-1})$
- BVB banks from 2010: before, many days have no trades; TLV without 30–31 May 2016 (a price adjustment applied one day late, Chapter 2)
- Bank portfolio of a group: equal weights, rebalanced daily

# Bank Portfolios since 2005




- Value of 100 invested in each equal-weighted portfolio (log scale); dotted lines: Lehman, Draghi's speech, COVID-19, the failure of SVB
- Maximum drawdown: US banks −82% (6 March 2009), European banks −76% (9 March 2009), Romanian banks −47% (5 June 2012)

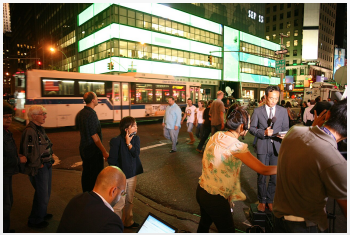
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## Interpretation of the Bank Portfolios

- 2008–2009: US and European banks lost about four fifths of their value; the trough came in March 2009, six months after Lehman
  - a systemic crisis is a process that lasts months, not a single bad day
- European banks stayed below their 2005 level for most of the period: the euro-area crisis and low interest rates
- Romanian banks: their worst fall came in the euro-area crisis of 2011–2012 (the parent banks of many Romanian banks are in the euro area)
- March 2020 and March 2023: sharp falls, but short; central banks and governments reacted within days

# 2008: Lehman Brothers

- 15 September 2008: Lehman Brothers files for bankruptcy, the largest bankruptcy in US history (assets above 600 billion USD)
  - 16 September: AIG, an insurer that had sold protection on mortgage debt to many banks, is rescued by the Federal Reserve
  - the same day, a money market fund holding Lehman debt "breaks the buck" and investors run from such funds
- All three channels at once
  - direct exposures (derivatives with Lehman), common exposures (mortgages), a run on short-term funding
- From the end of August to the trough in November: US banks −59%, European banks −54%, S&P 500 −41%



Lehman Brothers headquarters, New York, 15 September 2008

Photo: Robert Scoble (2008); CC BY 2.0; Wikimedia Commons

# 2010–2012: The Euro-Area Crisis

- Greece (2010), then Ireland, Portugal, Spain and Italy: doubts about government debt
  - **the bank–sovereign loop**: banks hold their own government's bonds, and the government stands behind its banks
  - a fall in bond prices weakens the banks; rescuing the banks weakens the state
- 26 July 2012: Mario Draghi, President of the ECB (European Central Bank): "the ECB is ready to do whatever it takes to preserve the euro" Draghi (2012)
  - a promise, not a purchase, stopped the spiral: the role of expectations
- July 2011 – September 2012, worst point: European banks −41%, US banks −37%, Romanian banks −34%

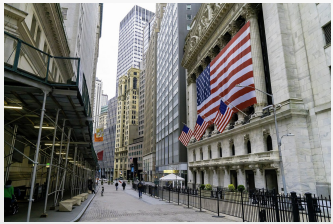


The ECB building in Frankfurt am Main

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

# March 2020: The Dash for Cash

- COVID-19 lockdowns: everyone wanted cash at the same time, even government bonds were sold
  - the stress started outside the banks: funds, firms, the bond market
  - banks were better capitalised than in 2008 (Basel III) and became part of the solution (credit lines)
- Fast policy response: central banks bought assets and lent in dollars to other central banks
  - trough on 23 March 2020: US banks −48%, European banks −48%, Romanian banks −35%, S&P 500 −34%



The Financial District of New York, 25 March 2020

Photo: Billie Grace Ward (2020); CC BY 2.0; Wikimedia Commons

# March 2023: SVB

- SVB (Silicon Valley Bank): deposits of technology firms, mostly above the insured limit, invested in long-term bonds
  - rising interest rates in 2022 created large unrealised losses on the bonds
  - 9 March 2023: depositors tried to withdraw about 42 billion USD in one day; 10 March: the bank is closed Federal Reserve (2023); FDIC (2023)
- A run in the age of mobile banking: faster than any run before
  - a mid-sized bank became systemic through information contagion: other regional banks fell the next days



Silicon Valley Bank headquarters, Santa Clara, 13 March 2023

Photo: Minh Nguyen (2023); CC BY-SA 4.0; Wikimedia Commons

# March 2023: Credit Suisse

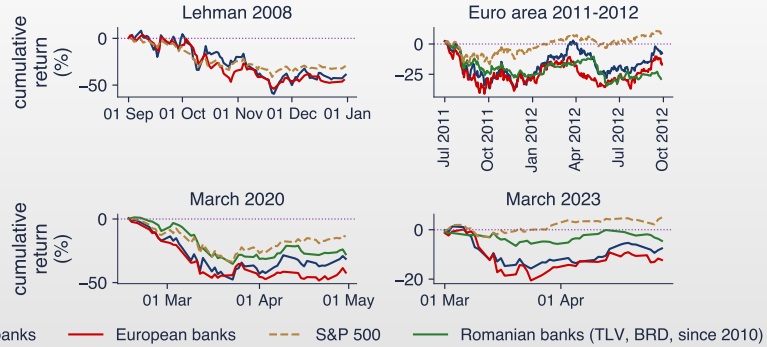
- Credit Suisse: a G-SIB that had lost clients and money for years (scandals, losses on hedge-fund clients)
  - after SVB, investors and depositors left quickly
- 19 March 2023: takeover by UBS, approved by the Swiss supervisor FINMA FINMA (2023)
  - AT1 bonds (additional tier 1 capital) of about 16 billion CHF were written down to zero
  - a rescue by merger, not a resolution: too big to fail was still alive
- From the end of February to the trough: European banks $-21\%$, US banks $-16\%$, Romanian banks $-7\%$



The Credit Suisse headquarters at Paradeplatz, Zürich

Photo: Thomas Wolf, www.foto-tw.de (2013); CC BY-SA 3.0 DE; Wikimedia Commons

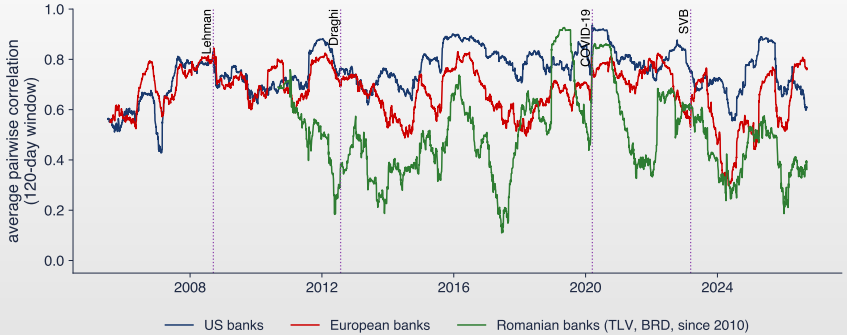
# Four Episodes Side by Side




- Cumulative return from the start of each window; the Romanian banks enter the data in 2010
- Interpretation: in 2008 and 2011–2012 the banks fell much more than the S&P 500 (the banks were the problem); in 2020 they fell with the market; in 2023 they fell while the market rose

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# Correlation between Banks in Crises




- Average of the pairwise correlations of daily returns within each group, on 120-day windows
- US banks: 0.59 before the crisis (July 2005 – June 2007), up to 0.94 (16 March 2020); TLV and BRD: 0.31 in 2017, 0.85 in April–June 2020, maximum 0.93 (9 May 2019)

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## Interpretation: Limits of Diversification in Crises

- In crises, the banks move together: a portfolio of several banks is almost one bank
  - the common factor (the market, funding stress) dominates the bank-specific news
- The two Romanian banks: low correlation in 2017, very high in 2020; the maximum (9 May 2019) falls outside any crisis
  - in calm years the BVB stocks are driven by their own news and by low liquidity; in a crisis, by the common shock
- Caution: a rolling correlation estimated on 120 days is noisy (for two stocks, it can peak in a calm year), and a rise in correlation does not prove contagion (next slide)

## Contagion and Interdependence: Forbes and Rigobon (1/2)

- If $y = \beta x + e$ with fixed $\beta$, the correlation of $x$ and $y$ rises **automatically** when the variance of $x$ rises Forbes & Rigobon (2002)
  - $x$: the return of the source market; $y$: the return of the other market; $\beta$: the strength of the link; $e$: a shock of $y$ unrelated to $x$
  - a higher correlation in a crisis may be the same link seen in a more volatile period: **interdependence**
  - **contagion**: the link itself becomes stronger
- Corrected correlation:

$$\rho^* = \frac{\rho}{\sqrt{1 + \delta(1 - \rho^2)}}, \qquad \delta = \frac{\sigma^2_{\text{crisis}}}{\sigma^2_{\text{calm}}} - 1$$

- Notation
  - $\rho$: the correlation measured in the crisis; $\sigma^2$: the variance of the source market in each period
  - $\delta$: the relative rise of that variance; $\rho^*$: the crisis correlation that the calm-period volatility would give
  - compare $\rho^*$ with $\rho_{\text{calm}}$: $\rho^* > \rho_{\text{calm}}$ points to contagion

## Contagion and Interdependence: Forbes and Rigobon (2/2)

- Worked example
  - US bank portfolio (source) and European bank portfolio: calm January 2005 – June 2007 ($n = 506$), crisis 15 September – 31 December 2008 ($n = 72$)
  - $\rho_{\text{calm}} = 0.40$, $\rho_{\text{crisis}} = 0.60$; variance $0.89 \to 75.4$, so $\delta = 83.7$
  - $\rho^* = 0.60/\sqrt{1 + 83.7 \times 0.638} = 0.60/\sqrt{54.4} = 0.08$
- Interpretation: after the correction there is no rise in correlation: the data are consistent with interdependence, not with a stronger link

## Tail Dependence (Chapter 10) (1/2)

- **Pseudo-observations**: $U = \text{rank}/(n+1)$, the rank of a return among the $n$ returns of its series, scaled to $(0, 1)$
  - $U \leq 0.05$: one of the worst 5% of days of that series; the marginal distributions no longer matter
- **Lower tail dependence** at level $q$: $\lambda(q) = P(U_1 \leq q \mid U_2 \leq q)$
  - $U_1$: the bank; $U_2$: the market; $\lambda(q)$: the probability that the bank is in its worst $q$ days, given that the market is in its worst $q$ days
  - under independence $\lambda(q) = q$; the limit $\lambda_L = \lim_{q \to 0} \lambda(q)$ is the tail-dependence coefficient
- For systemic risk: tail dependence measures how often a bank and the market are in their worst days **together**

## Tail Dependence (Chapter 10) (2/2)

- The t copula (Chapter 10) has a positive tail-dependence coefficient Demarta & McNeil (2005); the Gaussian copula has $\lambda_L = 0$

$$\lambda_L = 2\, t_{\nu+1}\Big( - \sqrt{(\nu+1)(1-\rho)/(1+\rho)}\Big) > 0$$

- Notation
  - $t_{\nu+1}$: the distribution function of a Student-t with $\nu + 1$ degrees of freedom
  - $\rho$: the correlation parameter of the copula; $\nu$: its degrees of freedom; a small $\nu$ gives strong joint crashes
- Estimation
  - $\rho = \sin(\pi\tau/2)$ from Kendall's $\tau$, a rank correlation; $\nu$ by maximum likelihood
  - $\tau = (C - D)/\binom{n}{2}$; $C$, $D$: the numbers of concordant and discordant pairs of days (both series move in the same or in opposite directions)

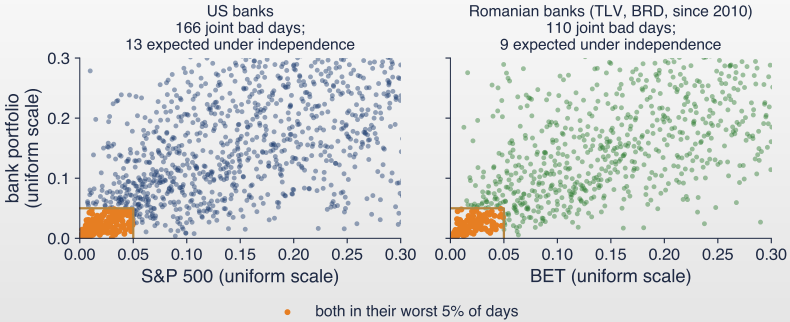
# Tail Dependence of Banks and Markets

| Pair | $n$ | corr. | $\lambda(5\%)$ | $\lambda(1\%)$ | $\hat{\nu}$ | $\lambda_L$ (t) |
|---|---|---|---|---|---|---|
| US banks, S&P 500 | 5 229 | 0.79 | 0.64 | 0.63 | 3.2 | 0.49 |
| European banks, Euro Stoxx 50 | 5 212 | 0.86 | 0.72 | 0.67 | 3.1 | 0.59 |
| Romanian banks, BET | 3 414 | 0.86 | 0.65 | 0.62 | 4.3 | 0.53 |
| European banks, US banks | 4 895 | 0.59 | 0.43 | 0.50 | 3.0 | 0.36 |

- $\lambda(q)$: empirical; $\hat{\nu}$ and $\lambda_L$: t copula; under independence $\lambda(5\%) = 0.05$ and $\lambda(1\%) = 0.01$
- Interpretation: on more than half of the market's worst days the banks are also in their worst days; the small $\hat{\nu}$ (about 3–4) means strong joint crashes, which a Gaussian copula misses entirely
- $\lambda(1\%)$ rests on a few dozen days: an imprecise estimate

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# Joint Large Losses




- Lower-left corner of the pseudo-observations; orange: both the bank portfolio and the index in their worst 5% of days
- US: 166 joint bad days against 13 under independence (about 13 times more); Romania: 110 against 9

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## Definition of CoVaR

- $X^i$: return of institution $i$; $X^{sys}$: return of the system; level $\alpha$ = probability of the tail (Chapter 10)
  - $q_\alpha(X^i)$: the $\alpha$-quantile of $X^i$; $\mathrm{VaR}^i_\alpha = -q_\alpha(X^i)$: the loss of $i$ exceeded with probability $\alpha$
- **CoVaR** (conditional VaR of the system) Adrian & Brunnermeier (2016)

$$\mathrm{CoVaR}^{sys|i}_\alpha = -q_\alpha\left(X^{sys} \mid X^i = q_\alpha(X^i)\right)$$

  - $q_\alpha(X^{sys} \mid \cdot)$: the $\alpha$-quantile of the system return, conditional on what follows the bar
  - the VaR 1% of the system on a day when institution $i$ is at its own VaR 1%: "CoVaR 1%"
- **$\Delta$CoVaR**: the contribution of $i$ to systemic risk

$$\Delta\mathrm{CoVaR}^{sys|i}_\alpha = \mathrm{CoVaR}^{sys|X^i=q_\alpha}_\alpha - \mathrm{CoVaR}^{sys|X^i=q_{\mathbf{50\%}}}_\alpha$$

  - $q_{50\%}$: the median of $X^i$, a normal day of the institution
  - reading: how much the VaR of the system rises when $i$ moves from a normal day (its median) to distress

## Quantile Regression (Chapter 13)

- Linear quantile regression Koenker & Bassett (1978): $q_\alpha(Y \mid X = x) = a_\alpha + b_\alpha x$
  - $a_\alpha$: the intercept (constant term); $b_\alpha$: the slope
  - estimated by minimising $\sum_t \rho_\alpha(y_t - a - bx_t)$, with the check loss $\rho_\alpha(u) = u(\alpha - 1\{u < 0\})$
  - $u$: the residual; $1\{u < 0\}$: 1 if the point is below the line, 0 otherwise
  - for $\alpha = 1\%$, a residual below the line costs 99 times more than one above it: the line passes below 99% of the points
- Same idea as VaR 1% by quantile regression in Chapter 13, now with another institution as the regressor
  - the slope $b_\alpha$ can differ from the OLS slope: the tail can react more strongly than the centre

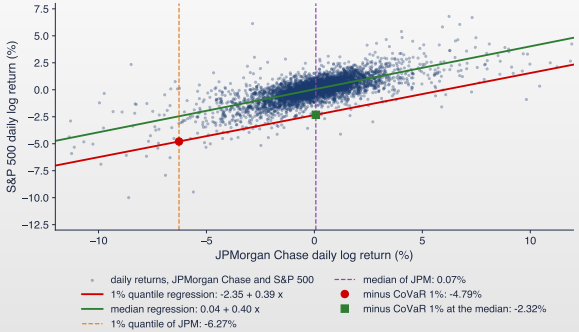
## Estimating CoVaR in Three Steps

- **Step 1**: quantile regression of the system on the institution at level $\alpha$: $X_t^{sys} = a + bX_t^i + \varepsilon_t$ Adrian & Brunnermeier (2016)
  - $\hat{a}$, $\hat{b}$: the estimated intercept and slope; the $\alpha$-quantile of the error $\varepsilon_t$ is zero by construction
- **Step 2**: the empirical quantiles of the institution: $\hat{q}_\alpha(X^i)$ (distress) and $\hat{q}_{50\%}(X^i)$ (median)
- **Step 3**: plug in
  - $\mathrm{CoVaR}_\alpha = -(\hat{a} + \hat{b}\,\hat{q}_\alpha(X^i))$
  - $\Delta\mathrm{CoVaR}_\alpha = \hat{b}\left(\hat{q}_{50\%}(X^i) - \hat{q}_\alpha(X^i)\right)$: only the slope and the distance between the two quantiles matter
- Here the system is proxied by the regional equity index (S&P 500, Euro Stoxx 50, BET); Adrian and Brunnermeier use the portfolio of all financial institutions

## Worked Example: JPMorgan Chase and the S&P 500

- Daily log returns, 2005–2026 ($n = 5\,229$); quantile regression at 1%: $\hat{a} = -2.35$, $\hat{b} = 0.39$
  - JPM: $\hat{q}_{1\%} = -6.27\%$ (so VaR 1% of JPM $= 6.27\%$), median $\hat{q}_{50\%} = 0.07\%$
- **CoVaR 1%** $= -(-2.35 + 0.39 \times (-6.27)) = 2.35 + 2.445 = 4.795\%$
  - from the unrounded estimates: 4.79% (the value in the chart); CoVaR at the median of JPM: 2.32%
- **$\Delta$CoVaR 1%** $= 0.39 \times (0.07 - (-6.27)) = 0.39 \times 6.34 = 2.47\%$
  - the unconditional VaR 1% of the S&P 500 is 3.53%
- Interpretation: when JPM is in distress, the loss of the index exceeded with probability 1% is 4.79%, against 2.32% on a normal JPM day

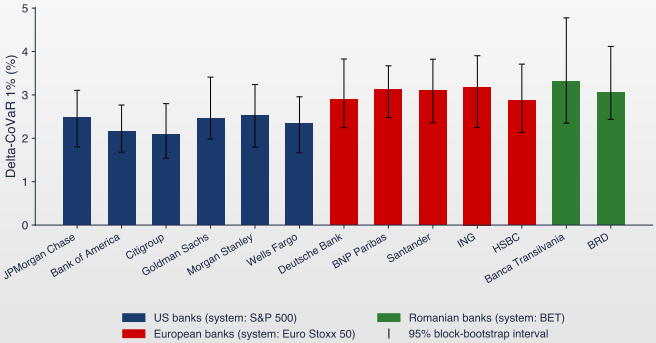
# CoVaR: a Graphical Illustration




- Red line: the 1% quantile of the S&P 500 given JPM; green line: the median; dashed: the 1% quantile and the median of JPM
- $\Delta$CoVaR is the vertical distance between the red dot and the green square on the red line: 2.47%

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# ΔCoVaR 1% of 13 Banks




- System: the regional index; 95% intervals from a moving-block bootstrap (blocks of 20 days, 200 resamples)
- US banks: 2.1–2.5%; European banks: 2.9–3.2%; TLV 3.31%, BRD 3.05%; largest: Banca Transilvania

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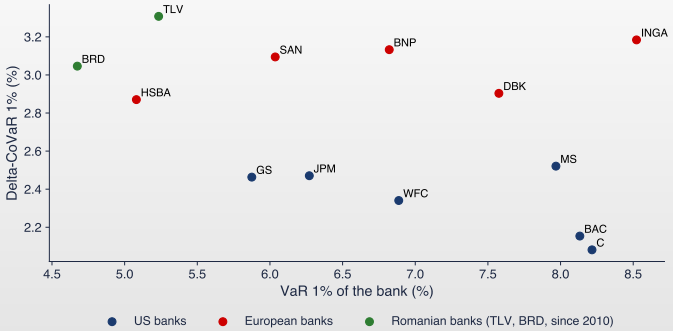
## Interpretation of ΔCoVaR

- The intervals overlap: within a region, the data cannot rank the banks precisely
  - a ranking of systemic importance needs its uncertainty, like any estimate (bootstrap, Chapter 2)
- European and Romanian banks have a larger ΔCoVaR than US banks
  - banks weigh more in the Euro Stoxx 50 and in the BET than in the S&P 500: the index is closer to a banking system
  - TLV and BRD are among the largest stocks of the BET, so the BET partly measures themselves
- Robustness: the ranking at 5% is close to the ranking at 1% (Spearman correlation 0.87)
  - Spearman: the correlation of the ranks, $\rho_S = 1 - 6\sum_i d_i^2/(N(N^2-1))$; $d_i$: the difference of the two ranks of bank $i$; $N$: the number of banks

## Worked Example: Banca Transilvania and the BET

- TLV and the BET, daily log returns since 2010 ($n = 3\,414$); quantile regression at 1%: $\hat{b} = 0.61$
  - TLV: $\hat{q}_{1\%} = -5.23\%$ (VaR 1% of TLV), median 0.18%
- $\Delta$CoVaR 1% $= 0.61 \times (0.18 + 5.23) = 3.31\%$; CoVaR 1% of the BET $= 5.28\%$
  - 95% block-bootstrap interval for $\Delta$CoVaR: [2.35, 4.78]
- Interpretation: a distress day of TLV moves the 1% quantile of the BET down by about 3.31 percentage points
  - part of this is mechanical: TLV is one of the largest weights in the BET; a cleaner system would be the BET without TLV

# VaR and ΔCoVaR Compared



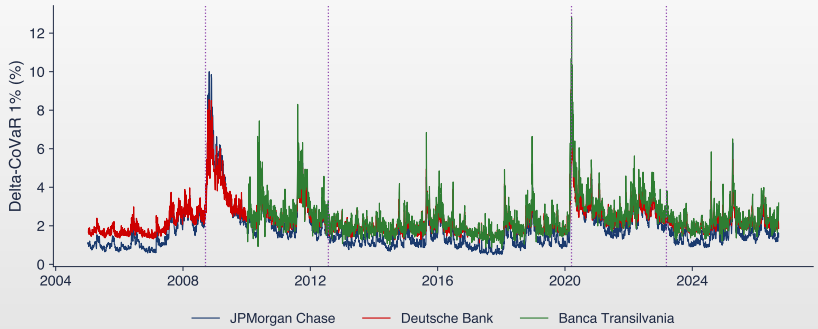

- Each point: a bank, its own VaR 1% (horizontal) and its ΔCoVaR 1% (vertical); Spearman rank correlation $-0.31$
- Interpretation: Citigroup and Bank of America are among the three largest VaR 1% and among the three smallest ΔCoVaR; regulating banks by their own VaR misses systemic risk Adrian & Brunnermeier (2016)

SFM_ch15_covar

## Time-Varying ΔCoVaR

- Adrian and Brunnermeier let the quantiles depend on lagged **state variables** $M_{t-1}$ Adrian & Brunnermeier (2016)
  - $M_{t-1}$: the vector of state variables known at the close of day $t-1$ (market stress, interest rates)
  - $X_t^i = c + \gamma^\top M_{t-1}$ at levels $\alpha$ and 50%: $\hat{q}_{\alpha,t}(X^i)$ and $\hat{q}_{50\%,t}(X^i)$
  - $X_t^{sys} = a + bX_t^i + \delta^\top M_{t-1}$ at level $\alpha$; then $\Delta\mathrm{CoVaR}_t = \hat{b}\,(\hat{q}_{50\%,t} - \hat{q}_{\alpha,t})$
  - $c$, $\gamma$, $a$, $b$, $\delta$: coefficients of the quantile regressions ($\delta$ is not the $\delta$ of Forbes–Rigobon)
- The paper uses seven state variables (VIX, liquidity and credit spreads, interest rates, market and real-estate returns)
  - here, a reduced set: the VIX level and the index return of the previous day
- The slope $\hat{b}$ is fixed; the time variation comes from the distance between the two conditional quantiles of the bank

# ΔCoVaR 1% through Time




- JPMorgan Chase: average 1.86%, maximum 10.07% (18 March 2020); Deutsche Bank: maximum 9.08% (13 March 2020); Banca Transilvania: maximum 12.81% (17 March 2020)
- Interpretation: the contribution of a bank to systemic risk is not a constant; it jumps when the VIX jumps (2008, March 2020) and is small in calm years (JPM in 2017: 0.75%)

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# Case Study: Adrian and Brunnermeier (2016)

- Adrian & Brunnermeier (2016): CoVaR of US financial institutions (commercial and investment banks, insurers, brokers), weekly data 1986–2010
  - the system: the portfolio of all financial institutions; seven state variables
- Findings
  - in the cross-section, the VaR of an institution says little about its $\Delta$CoVaR
  - **forward** $\Delta$CoVaR: size, leverage and maturity mismatch two years earlier predict the contribution in a crisis
  - a basis for countercyclical capital: charge banks when risk is built up, not when it shows



Tobias Adrian

Photo: Chianoo Adrian (2025); CC BY 4.0; Wikimedia Commons



Markus Brunnermeier

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

## Marginal Expected Shortfall

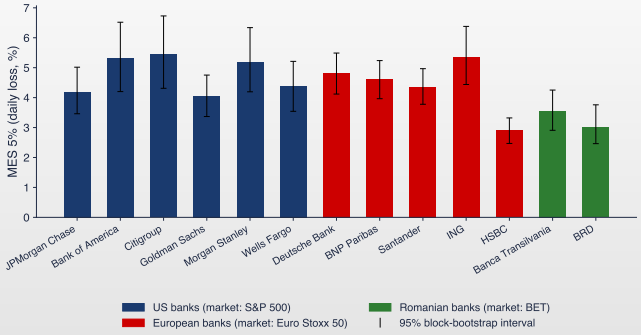
- **MES** Acharya, Pedersen, Philippon & Richardson (2017): the expected loss of institution $i$ on the days when the market is in its tail
  - $\mathrm{MES}^i_\alpha = -E\left[X^i \mid X^m \leq q_\alpha(X^m)\right]$; we use the worst 5% of market days: "MES 5%"
  - $X^m$: the market return; $q_\alpha(X^m)$: its $\alpha$-quantile; the bar: "on the days when"
  - the direction is the opposite of CoVaR: the bank given the market, not the market given the bank
- Why "marginal": ES of the market $= \sum_i w_i \,\mathrm{MES}^i$ when the market is a portfolio with weights $w_i$
  - MES is the contribution of $i$ to the ES of the system (Chapter 10)
- Estimation: sort the days by the market return, take the worst $\lceil n\alpha \rceil$ days, average the bank's returns on those days, change the sign

## Worked Example: MES from Ten Days

| Day | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| market | $-4.0$ | 1.2 | $-0.5$ | 2.1 | $-6.0$ | 0.3 | $-1.1$ | 0.8 | $-2.2$ | 1.5 |
| bank | $-6.5$ | 1.8 | $-0.2$ | 2.9 | $-9.0$ | 0.1 | $-2.0$ | 1.1 | $-3.1$ | 2.4 |

- Level $\alpha = 20\%$: $\lceil 10 \times 0.2 \rceil = 2$ worst market days: day 5 ($-6.0$) and day 1 ($-4.0$)
  - MES 20% $= -(-9.0 - 6.5)/2 = 7.75\%$; ES 20% of the market $= -(-6.0 - 4.0)/2 = 5.00\%$
- Interpretation: on the market's bad days this bank loses about 1.5 times as much as the market: it amplifies the crashes
- Note: MES selects the days by the market return, not by the bank return

# MES 5% of 13 Banks



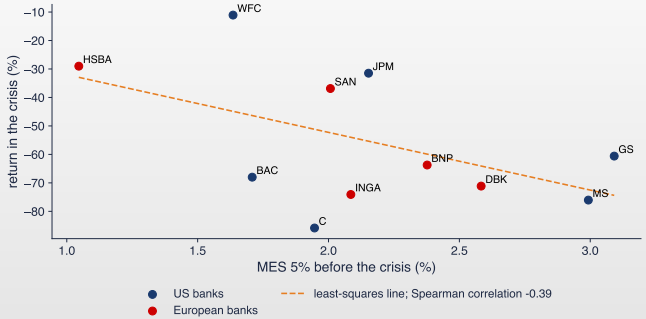

- Average daily loss of each bank on the worst 5% of days of its regional index (US and Europe since 2005, Romania since 2010); 95% block-bootstrap intervals
- Largest: Citigroup (5.44%) and ING (5.35%); smallest: HSBC (2.90%); TLV 3.54%, BRD 3.00%

SFM_ch15_mes_srisk

## Interpretation: MES and $\Delta$CoVaR

- MES is close to a tail beta: the average market loss on its worst 5% of days times the sensitivity of the bank
  - Citigroup: OLS beta 1.66, MES 5.44%; HSBC: beta 0.81, MES 2.90%
- MES and $\Delta$CoVaR rank the 13 banks differently: Spearman correlation $-0.29$
  - they answer different questions: "who suffers in a crash" against "who adds to the crash"
  - a regulator should look at several measures, with their intervals Benoit, Colliard, Hurlin & Pérignon (2017)

# Case Study: MES and the Bank Losses of 2008




- Design of Acharya, Pedersen, Philippon & Richardson (2017): MES 5% measured from June 2006 to June 2007, against the return from July 2007 to December 2008; here 11 US and European banks
- Spearman correlation $-0.39$ ($p = 0.23$, $n = 11$): the sign of the paper (higher MES, larger loss), but not significant with 11 banks; worst return: Citigroup ($-86\%$)

SFM_ch15_mes_srisk

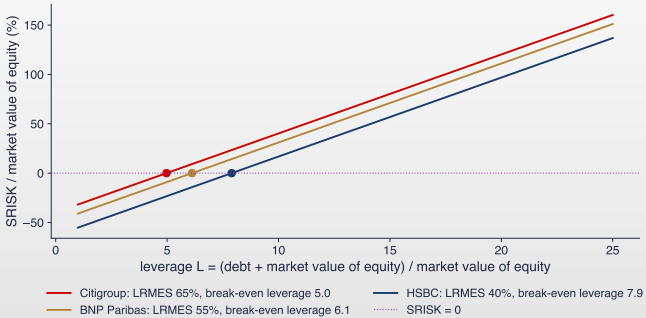
## Long-Run MES (LRMES)

- A crisis lasts months: we need the loss of the bank if the market falls 40% over six months: **LRMES** (long-run MES)
  - approximation of Acharya, Engle & Richardson (2012): $\mathrm{LRMES} \approx 1 - \exp(-18 \times \mathrm{MES})$, with MES the daily loss (as a fraction) on the days when the market falls by more than 2%
  - the factor 18 turns the daily loss on bad days into the loss over a six-month crisis; $1 - e^{-x}$ keeps LRMES between 0 and 1
- Example: MES $= 3\% = 0.03$: $\mathrm{LRMES} = 1 - e^{-0.54} = 1 - 0.583 = 41.7\%$
  - the bank would lose about 41.7% of its market value in such a crisis
- Our 13 banks: LRMES between 40% and 65%; Brownlees and Engle estimate it instead from a dynamic model (GARCH and dynamic correlation) Brownlees & Engle (2017)

## SRISK: the Capital Shortfall in a Crisis

- A bank needs equity of at least a fraction $k$ of its assets; $k = 8\%$ in Brownlees & Engle (2017)
  - $D$: book value of debt; $W$: market value of equity; assets $\approx D + W$
- **SRISK** $= k(D + W_{\text{crisis}}) - W_{\text{crisis}}$ with $W_{\text{crisis}} = (1 - \text{LRMES})W$:
  - $\text{SRISK} = kD - (1 - k)(1 - \text{LRMES})\, W$ Brownlees & Engle (2017)
  - $kD$: the capital required on the debt; $(1 - k)(1 - \text{LRMES})W$: the equity left after the crisis, net of the capital required on it
  - SRISK $> 0$: capital missing in a crisis; the **aggregate SRISK** (sum of the positive values) is what the state might have to cover
- Example: $D = 900$, $W = 100$ (billion), LRMES $= 41.7\%$
  - SRISK $= 0.08 \times 900 - 0.92 \times (1 - 41.7\%) \times 100 = 72 - 53.6 = 18.4$ billion

# SRISK and Leverage




- SRISK$/W = k(L-1) - (1-k)(1-\mathrm{LRMES})$ with leverage $L = (D+W)/W$; SRISK $> 0$ above $L^* = 1 + (1-k)(1-\mathrm{LRMES})/k$
- Interpretation: Citigroup needs capital in a crisis above a leverage of 5.0, HSBC only above 7.9; banks typically have $L$ between 10 and 20, so leverage decides the sign

SFM_ch15_mes_srisk

# Case Study: SRISK and V-Lab

- Brownlees & Engle (2017): SRISK of large US financial firms, with LRMES from a GARCH–DCC model (Chapter 9)
  - aggregate SRISK rose before the failure of Lehman; it helps to forecast falls in industrial production and rises in unemployment
  - the ranking by SRISK in 2007–2008 points to the institutions that later needed public support
- Europe: Engle, Jondeau & Rockinger (2015); a lower $k = 5.5\%$ is used because of the accounting rules (IFRS, International Financial Reporting Standards)
  - published and updated on V-Lab SRISK (NYU Stern) for financial institutions from many countries



Viral Acharya

Photo: MeJudice (2014); CC BY 3.0; Wikimedia Commons



Robert Engle

Photo: Jon Demske (2022); CC BY-SA 4.0; Wikimedia Commons

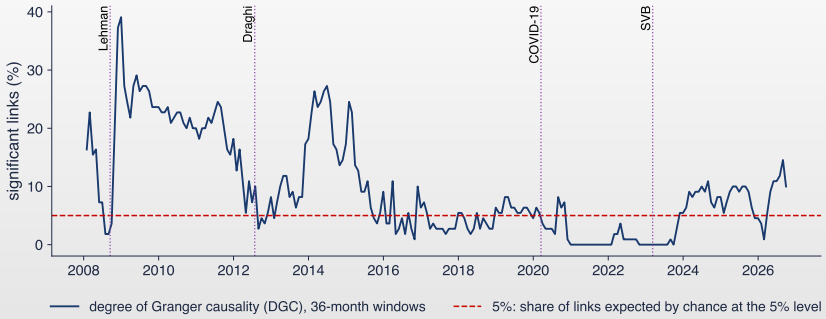
## The Banking System as a Network

- A **network**: nodes (banks) and directed links ("a shock to $i$ affects $j$")
  - real links (interbank loans) are mostly confidential; we estimate links from returns
- Two statistical tools
  - **Granger causality**: do past returns of $i$ help to forecast $j$? Billio, Getmansky, Lo & Pelizzon (2012)
  - **variance decompositions**: what share of the forecast error of $j$ comes from shocks to $i$? Diebold & Yilmaz (2014)
- A statistical link is a co-movement, not a contract: it shows where to look, not why

## Granger Causality

- $x$ **Granger-causes** $y$ if past values of $x$ improve the forecast of $y$ beyond the past of $y$ Granger (1969)
  - regression $y_t = a + b\,y_{t-1} + c\,x_{t-1} + e_t$; test $H_0 : c = 0$ with a $t$ test at 5%
  - $a$: the constant; $b$: the own past of $y$; $c$: the effect of yesterday's $x$; $e_t$: the error; $c \neq 0$: a link from $x$ to $y$
- **Degree of Granger causality** (DGC) Billio, Getmansky, Lo & Pelizzon (2012): the share of the $N(N-1)$ ordered pairs with a significant link
  - $N$: the number of banks; $N(N-1)$: the ordered pairs ($i \to j$ and $j \to i$ count separately)
  - the paper: monthly returns, 36-month rolling windows, lag 1, 5% level
  - the paper also filters each series with a GARCH(1,1) model; with 36 monthly observations per window we report the unfiltered test
- Under no links, about 5% of pairs are significant by chance: DGC must be compared with 5%

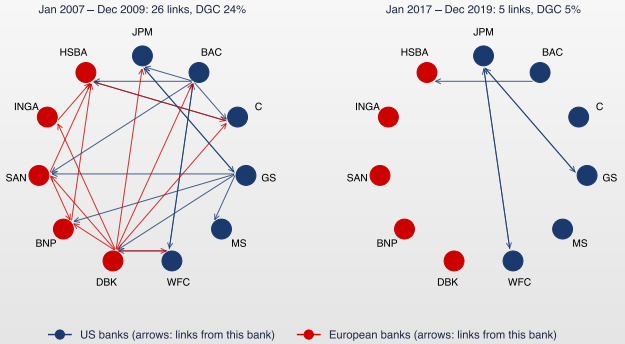
# Granger Networks through Time




- 11 US and European banks, monthly returns since 2005 (260 months); first window ends in January 2008
- DGC: maximum 39% (window ending 31 December 2008), average 10%, minimum 0% (31 December 2020)

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# Two Networks: 2007–2009 and 2017–2019



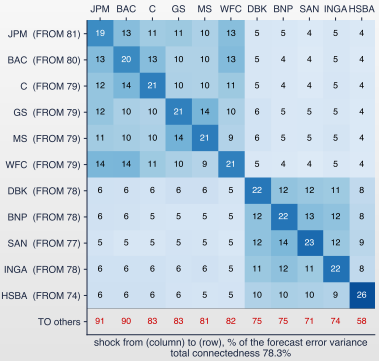

- Arrows: significant Granger-causal links at 5% in a 36-month window; 26 links in the crisis window, 5 in the calm one
- Interpretation: as in Billio, Getmansky, Lo & Pelizzon (2012), the banks became more connected around the crisis; in calm years the network is close to what chance alone would give

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## Diebold–Yilmaz Connectedness

- Fit a VAR (vector autoregression) to the returns of $N$ banks; forecast $H$ days ahead
  - VAR($p$): $x_t = c + \Phi_1 x_{t-1} + \cdots + \Phi_p x_{t-p} + u_t$; $x_t$: the vector of the $N$ returns; $\Phi_j$: $N \times N$ coefficient matrices; $u_t$: the shocks
  - $d_{ij}$: the share of the $H$-day forecast error variance of bank $i$ due to shocks to bank $j$ (generalized decomposition, Pesaran & Shin (1998))
  - each row sums to 100%
- Measures Diebold & Yilmaz (2012); Diebold & Yilmaz (2014)
  - FROM others: $\sum_{j \neq i} d_{ij}$; TO others: $\sum_{j \neq i} d_{ji}$; NET = TO − FROM
  - **total connectedness**: $\frac{1}{N} \sum_{i \neq j} d_{ij}$, the average share of risk that comes from the others
- Here: daily returns of 11 banks since 2005, VAR order by BIC (Bayesian information criterion), $H = 10$ days

# The Connectedness Table



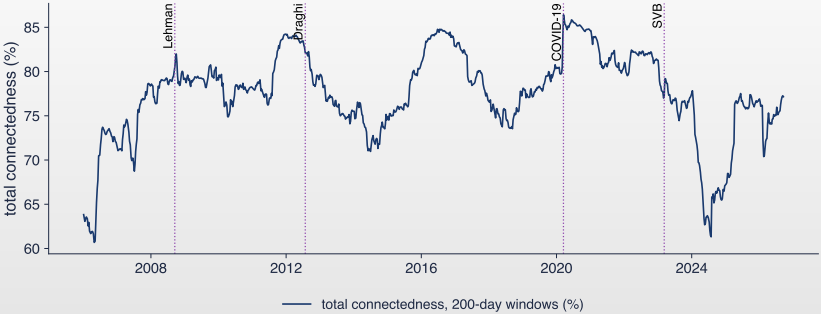

- 4 895 common days, VAR(1); total connectedness 78.3%; two blocks: US banks are connected mostly with US banks, European with European
- Largest transmitter (TO): JPMorgan Chase; smallest: HSBC (NET −15.8)

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## Interpretation of the Connectedness Table

- Each bank receives about four fifths of its forecast error variance from the others (FROM between 74 and 81)
  - daily bank returns are dominated by common shocks; the own share (the diagonal) is only about one fifth
- NET: US banks are net transmitters (JPMorgan Chase $+10.6$), European banks net receivers (HSBC $-15.8$)
  - partly timing: New York closes after Europe, so US news reaches European prices the next day
- Connectedness describes the data; it is not a map of exposures between the banks

# Total Connectedness through Time




- Rolling 200-day windows moved by 5 days; minimum 61% (28 April 2006), maximum 86% (17 March 2020); October 2008 – March 2009: 79%
- Interpretation: connectedness rose during 2007, before Lehman, and reaches its maximum in March 2020; but in 2016, a year without a crisis in the data, it reaches 85%, above the 2008–2009 average: a high level alone does not signal a crisis; it falls when bank-specific news dominate (2006, 2024)

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## Further Reading: the Financial Risk Meter

- **FRM** (Financial Risk Meter) Mihoci, Althof, Chen & Härdle (2020): a daily index of systemic risk from quantile regressions with many regressors
  - for each bank: a lasso quantile regression (Chapter 13) of its returns on the returns of all other banks and on macro variables
  - the penalty $\lambda$ needed to fit the tail is large when the banks move together: FRM = the average $\lambda$
- Extensions
  - TENET (tail-event driven network) Härdle, Wang & Yu (2016): CoVaR with many banks, a network of tail links
  - FRM for emerging markets Ben Amor, Althof & Härdle (2022); the video course on Quantinar (Reading and Tools)

## Micro- and Macroprudential

- **Microprudential**: is each bank safe on its own? (capital, VaR, backtesting, Chapter 10)
- **Macroprudential**: is the system safe? Two dimensions
  - **in time**: risk builds up in booms (credit growth, leverage) and shows in busts: build buffers in good times
  - **across institutions**: larger and more connected banks need more capital
- The measures of this chapter (CoVaR, SRISK, connectedness) are among the tools that central banks use to monitor the second dimension

# Basel III Capital Buffers

- Minimum CET1 (common equity tier 1) capital: 4.5% of risk-weighted assets BCBS (2011); on top of it, buffers Basel Framework, RBC30:
  - **capital conservation buffer**: 2.5%; below it, dividends and bonuses are restricted
  - **countercyclical buffer**: 0–2.5%, raised when credit grows too fast, released in a crisis
- For systemic importance
  - **G-SIB surcharge**: 1% to 3.5%, by a score of size, interconnectedness, substitutability, complexity and cross-border activity BCBS (2018)
  - in the EU: O-SII (other systemically important institutions) buffers and a systemic risk buffer



The BIS tower in Basel

Photo: Taxiarchos228 (2014); CC BY-SA 4.0; Wikimedia Commons

# Macroprudential Authorities: the ESRB and the BNR

- **ESRB** (European Systemic Risk Board), set up in 2010 after the crisis, chaired by the President of the ECB (ESRB website)
  - monitors systemic risk in the EU, issues warnings and recommendations to national authorities
- Romania: **CNSM** (Comitetul Național pentru Supravegherea Macroprudențială), with the BNR, the ASF (financial supervisory authority) and the Government (CNSM website)
  - the BNR sets the capital buffers of the banks (countercyclical, O-SII, systemic risk buffer) on CNSM recommendations
  - the BNR also uses limits on borrowers (loan-to-value, debt service-to-income) and publishes a financial stability report



The BNR palace in Bucharest

Photo: Britchi Mirela (2018); CC BY-SA 4.0; Wikimedia Commons

## An Open Research Question

- **Is the systemic risk of the Romanian banks imported from their euro-area parents, or is it local?**
  - today: $\Delta$CoVaR of TLV peaks in March 2020 (12.81%); BRD belongs to a French group, TLV is Romanian-owned
  - the BET is partly the banks themselves, so a better "system" is needed
- Why it is open: two banks, few crises, different trading hours (Bucharest, Frankfurt, New York), thin trading in some years
- AI tools can speed up such a study; they do not replace checking it Wang et al. (2023)

## Possible Uses of AI Tools

- **Literature**: a list of studies on systemic risk in Central and Eastern Europe and on parent–subsidiary contagion
- **Code**: a first draft of $\Delta$CoVaR of TLV and BRD with the euro-area bank portfolio as the conditioning variable and state variables
- **Robustness**: two-day returns (trading hours), weekly data, CoVaR at 5%, other state variables
- Example prompt
  - `Write Python code that estimates the Delta-CoVaR at 1% of the BET conditional on Banca Transilvania by quantile regression, with the lagged VIX and the lagged Euro Stoxx 50 return as state variables, and adds a moving-block bootstrap interval.`

## What to Check

- The level convention: "CoVaR 1%" and "MES 5%" name the tail probability; CoVaR and MES are positive losses
- The direction of conditioning: CoVaR is the system given the bank, MES is the bank given the market
- $\Delta$CoVaR compares distress with the **median** of the bank, not with the bank's VaR
- Prices joined on common days before returns; BVB days without trades removed; different trading hours
- Uncertainty: quantile regressions at 1% rest on about 1% of the days; report bootstrap intervals
- References: every cited paper must exist; check the DOI

## Project Idea

- **Question**: do the euro-area banks raise the tail risk of the Romanian banks in stress periods?
  - data: TLV, BRD, BET, the five European banks, Euro Stoxx 50, VIX, since 2010 (EODHD)
- Steps
  - $\Delta$CoVaR 1% of each Romanian bank conditional on the European bank portfolio, static and with state variables
  - MES 5% of TLV and BRD with the Euro Stoxx 50 as the market; Diebold–Yilmaz FROM shares on rolling windows
  - compare 2011–2012, March 2020 and March 2023, with block-bootstrap intervals
- Deliverable: one table, one chart, and a paragraph on what the data can and cannot show
- Declare any AI use, and list the errors of the AI that you corrected

## Key Takeaways

- Systemic risk is a property of the system: contagion, common exposures, fire sales and runs, amplified by leverage
- In crises bank correlations and tail dependence rise; correct for volatility before speaking of contagion
- CoVaR 1%: the system given the bank; $\Delta\text{CoVaR} = \hat{b}(\hat{q}_{50\%} - \hat{q}_{\alpha})$ from quantile regression
- MES 5%: the bank given the market; $\text{SRISK} = kD - (1-k)(1-\text{LRMES})W$, driven by leverage
- Networks (Granger, Diebold–Yilmaz) show more connectedness around crises
- Macroprudential policy: Basel III buffers, G-SIB and O-SII surcharges; the ESRB in the EU, the CNSM and the BNR in Romania

# Key Formulas

| Quantity | Formula |
|---|---|
| CoVaR | $\mathrm{CoVaR}_\alpha = -(\hat{a} + \hat{b}\,\hat{q}_\alpha(X^i))$, $X^{sys} = a + bX^i$ at level $\alpha$ |
| ΔCoVaR | $\hat{b}\,(\hat{q}_{50\%}(X^i) - \hat{q}_\alpha(X^i))$ |
| MES | $-E[X^i \mid X^m \le q_\alpha(X^m)]$ |
| LRMES | $1 - \exp(-18\,\mathrm{MES}_{2\%})$ |
| SRISK | $kD - (1-k)(1-\mathrm{LRMES})W$, $L^* = 1 + (1-k)(1-\mathrm{LRMES})/k$ |
| Forbes–Rigobon | $\rho^* = \rho/\sqrt{1+\delta(1-\rho^2)}$ |
| Granger | $y_t = a + by_{t-1} + cx_{t-1} + e_t$, $H_0 : c = 0$ |
| Diebold–Yilmaz | total $= \frac{1}{N}\sum_{i\neq j} d_{ij}$, $\mathrm{NET}_i = \mathrm{TO}_i - \mathrm{FROM}_i$ |

## Self-Assessment

- **Question**: bank A has a larger VaR 1% than bank B. Is A more systemic?
  - **Answer**: not necessarily: systemic importance depends on the link with the system (ΔCoVaR, MES), not on the bank's own tail
- **Question**: a quantile regression at 1% gives $\hat{b} = 0.5$, $\hat{q}_{1\%}(X^i) = -6\%$, $\hat{q}_{50\%}(X^i) = 0$. What is ΔCoVaR?
  - **Answer**: $0.5 \times (0 - (-6)) = 3\%$
- **Question**: why can SRISK be negative?
  - **Answer**: a bank with low leverage keeps enough capital even after a market fall of 40%: it has a capital surplus
- Next: Chapter 16, review

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