Quantifying Systemic Risk in Europe

A Bayesian Approach to Map Financial Contagion Through CDS Spreads

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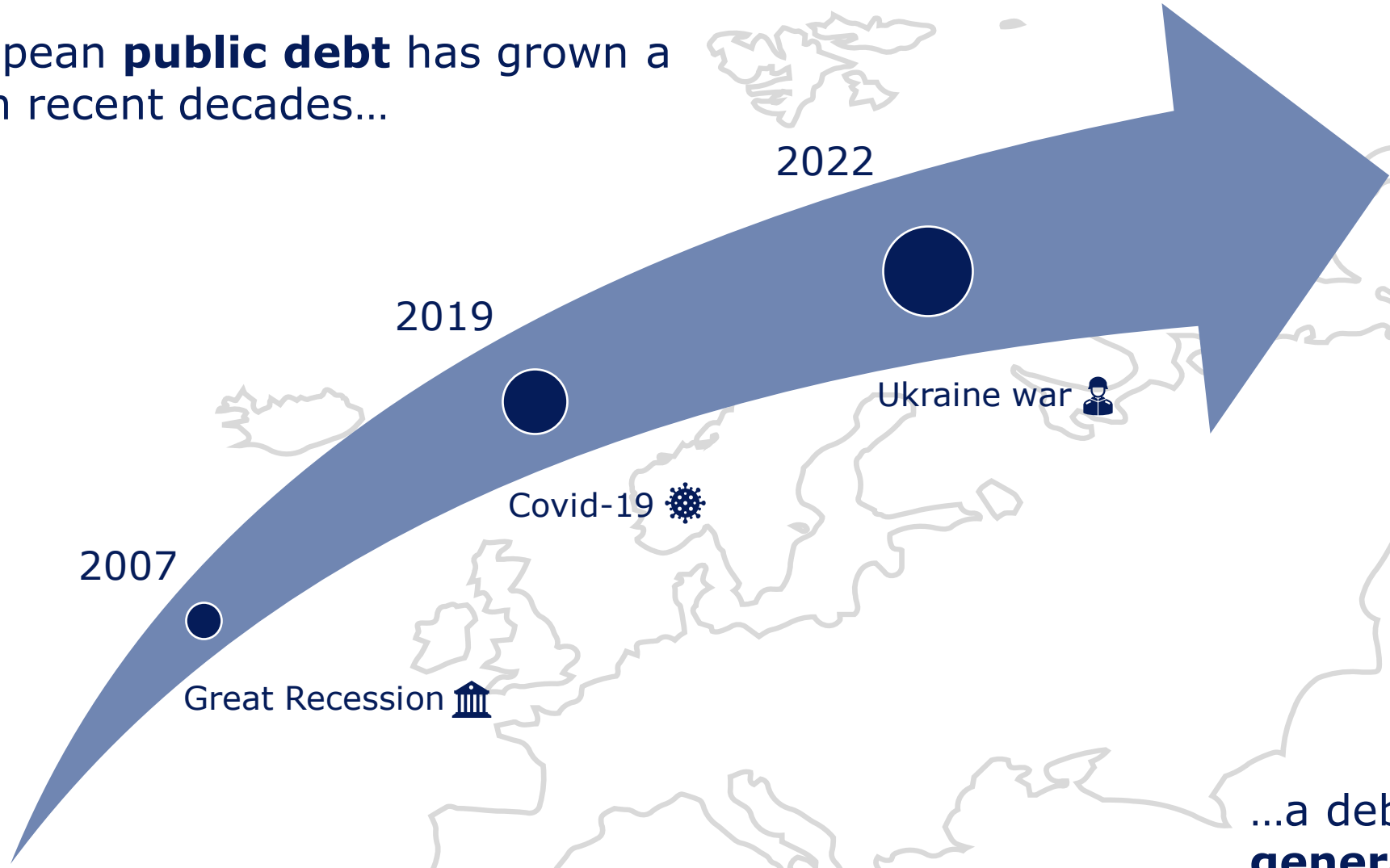
Motivations - Public Debt

European **public debt** has grown a lot in recent decades…



91% of GDP

62% of GDP

…a debt burdening on **future generations** more than ever…

Source: Eurostat

Motivations - Great Recession

…**economic growth** is cardinal for diminishing countries' debts…

90s

- Low inflation
- Low interest rates
- Ample liquidity

2000s

Subprime mortgage → House purchased → Borrower defaults → Foreclosure

2008

Lehman Brothers bankruptcy and **AIG** bailout

Losses in the value of global listed companies: **€16 trillion** (1.5 EU GDP)

2009

Greece international **bailout**

2010

…but **financial instability** can become a serious impediment.

Motivations - Systemic Risk

"Regulators and supervisors focused on the micro-prudential supervision of individual financial institutions and not sufficiently on the **macro-systemic risks** of a contagion of correlated horizontal shocks." *-The Larosière Report, EU, 2009-*

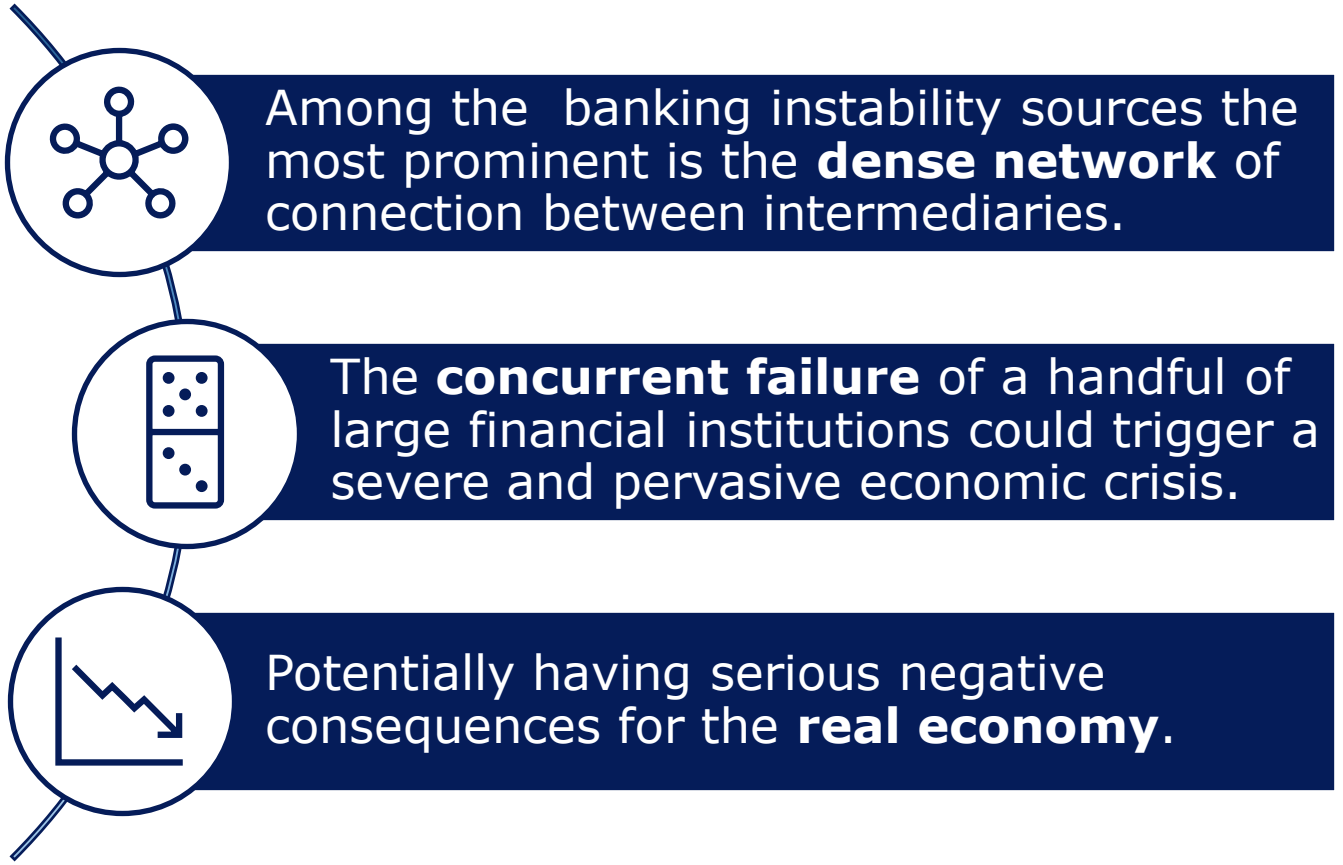
"With respect to macroeconomic policy, policymakers failed to take sufficiently into account growing macroeconomic imbalances that contributed to the buildup of **systemic risks** in the financial system and in housing markets." *–Annual Report, IMF, 2009-*

"The financial and economic crisis that has shaken the world economy for more than two years illustrates the relevance of **systemic risk**."…"The objective is to characterise the phenomenon of **systemic risk** from an academic research perspective."…"three main "forms" of **systemic risk**: the contagion risk, the risk of macro shocks causing simultaneous problems and the risk of the unravelling of imbalances that have built up over time." *-Financial Stability Review, ECB, 2009-*

Systemic Risk - Financial Contagion

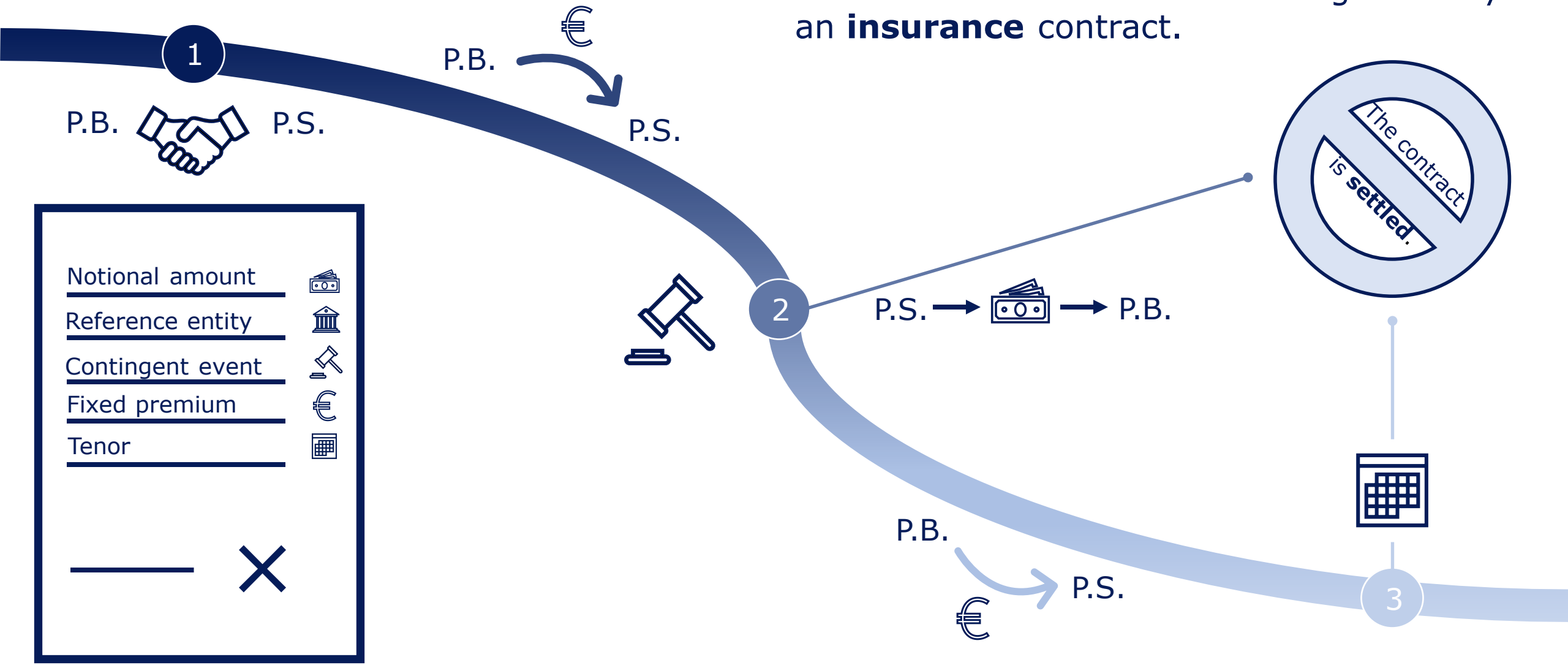
*Systemic risk means a risk of **disruption** in the financial system with the potential to have serious negative consequences for the internal market and **the real economy**. All types of financial intermediaries, markets and infrastructure may be potentially systemically important to some degree.*

-EU Regulation 1092/2010-



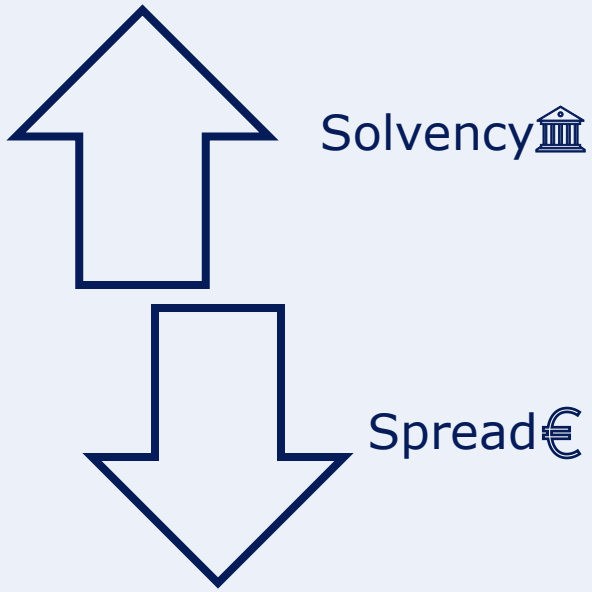
Credit Default Swap - Functioning

It is a financial derivative working similarly to an **insurance** contract.

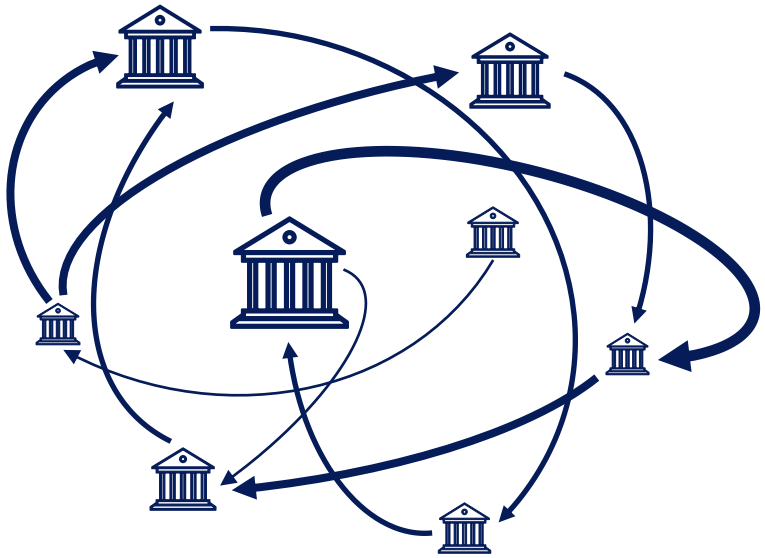


Credit Default Swap - A Proxy for Financial Contagion

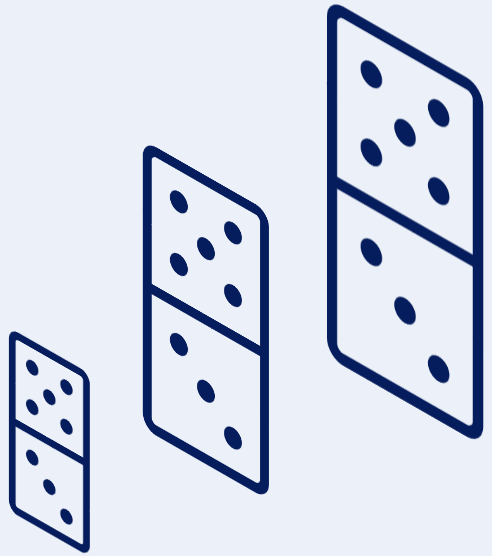
The spread incorporates information on how the market perceives the **creditworthiness** of a reference entity.



Spreads co-movements carry information on the reference entities level of **interdependence.**



A tightly interconnected network of institutions fosters the rapid spread of **financial contagion**, posing systemic risk. High interdependence among market participants amplifies shocks across the system.



Credit Default Swap - Datasets

IHS Markit

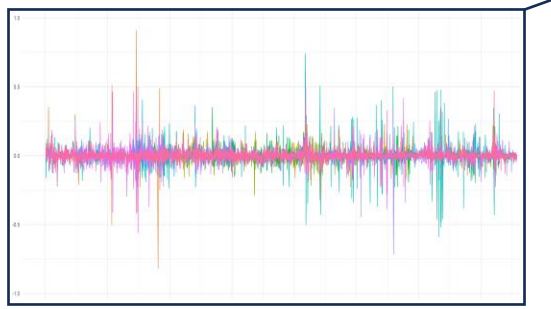
5 years

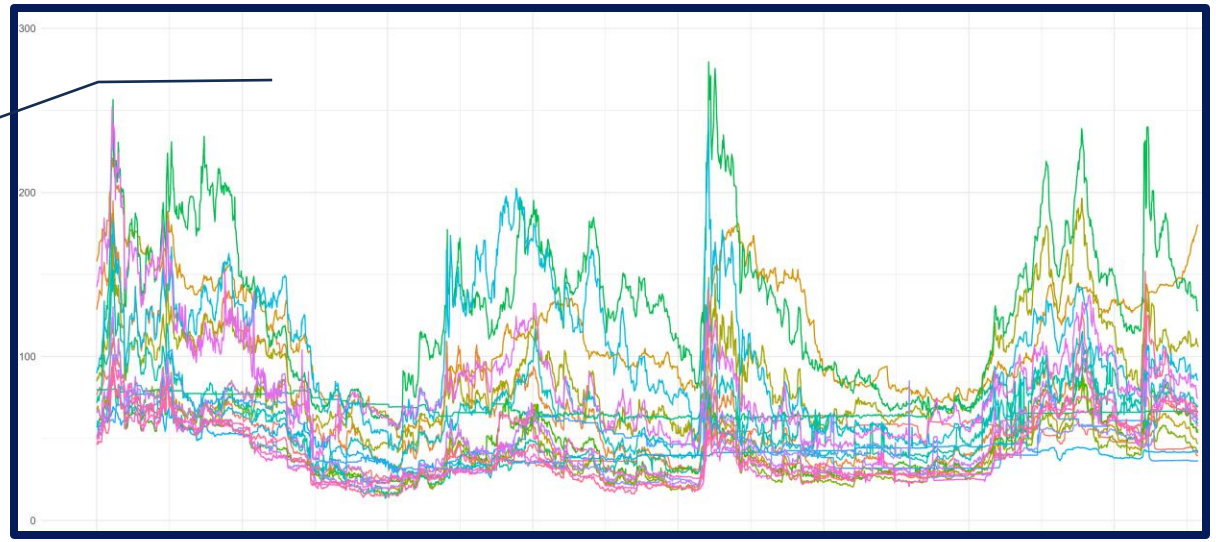
21 European **banks**

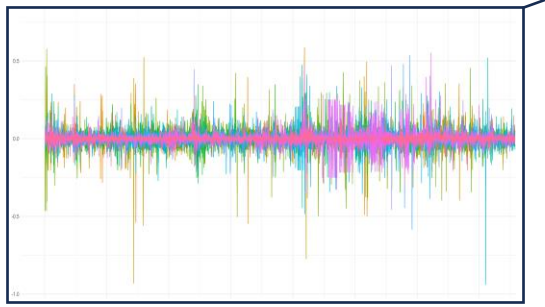
29 European **countries**

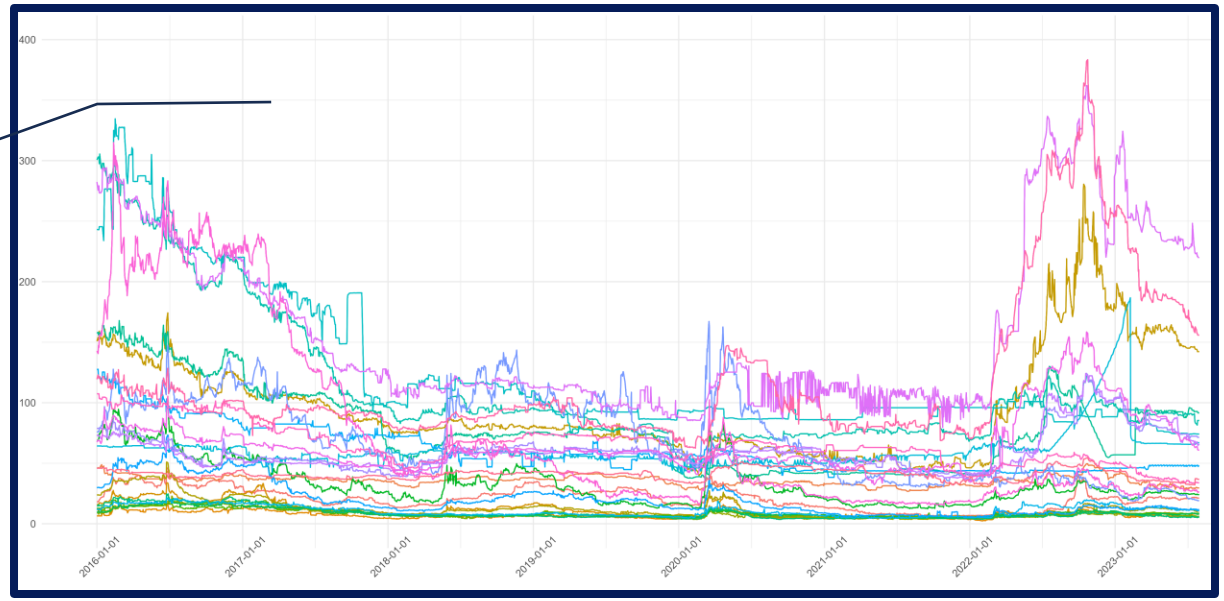
Daily

[01/01/2016-31/07/2023]









Vector Autoregression - Model

The VAR model is a well established model for estimating **multivariate time series**…

$$\mathbf{y_t} = \boldsymbol{\beta_0} + B_1\mathbf{y_{t-1}} + B_2\mathbf{y_{t-2}} + \cdots + B_p\mathbf{y_{t-p}} + \boldsymbol{\epsilon_t}, \quad t = 1, 2, \ldots, T$$

$\mathbf{y_t}$: n×1 — $\boldsymbol{\beta_0}$: n×1 — $B_1, B_2, \ldots, B_p$: n×n — $\boldsymbol{\epsilon_t}$: n×1

Spread entity 1 time t

Spread entity n lag p

$$\begin{aligned}
y_{1t} &= \beta_{0t} + \beta_{11}^{(1)} y_{1,t-1} + \cdots + \beta_{1n}^{(1)} y_{n,t-1} + \beta_{11}^{(2)} y_{1,t-2} + \cdots + \beta_{1n}^{(2)} y_{n,t-2} + \cdots + \beta_{1n}^{(p)} y_{n,t-p} + \epsilon_{1t} \\
&\vdots \qquad\qquad \vdots \qquad\qquad \vdots \qquad\qquad \vdots \\
y_{nt} &= \beta_{0t} + \beta_{n1}^{(1)} y_{1,t-1} + \cdots + \beta_{nn}^{(1)} y_{n,t-1} + \beta_{n1}^{(2)} y_{1,t-2} + \cdots + \beta_{nn}^{(2)} y_{n,t-2} + \cdots + \beta_{nn}^{(p)} y_{n,t-p} + \epsilon_{nt}
\end{aligned}$$

Effect entity 1 lag 2 on entity n

Residual entity n time t

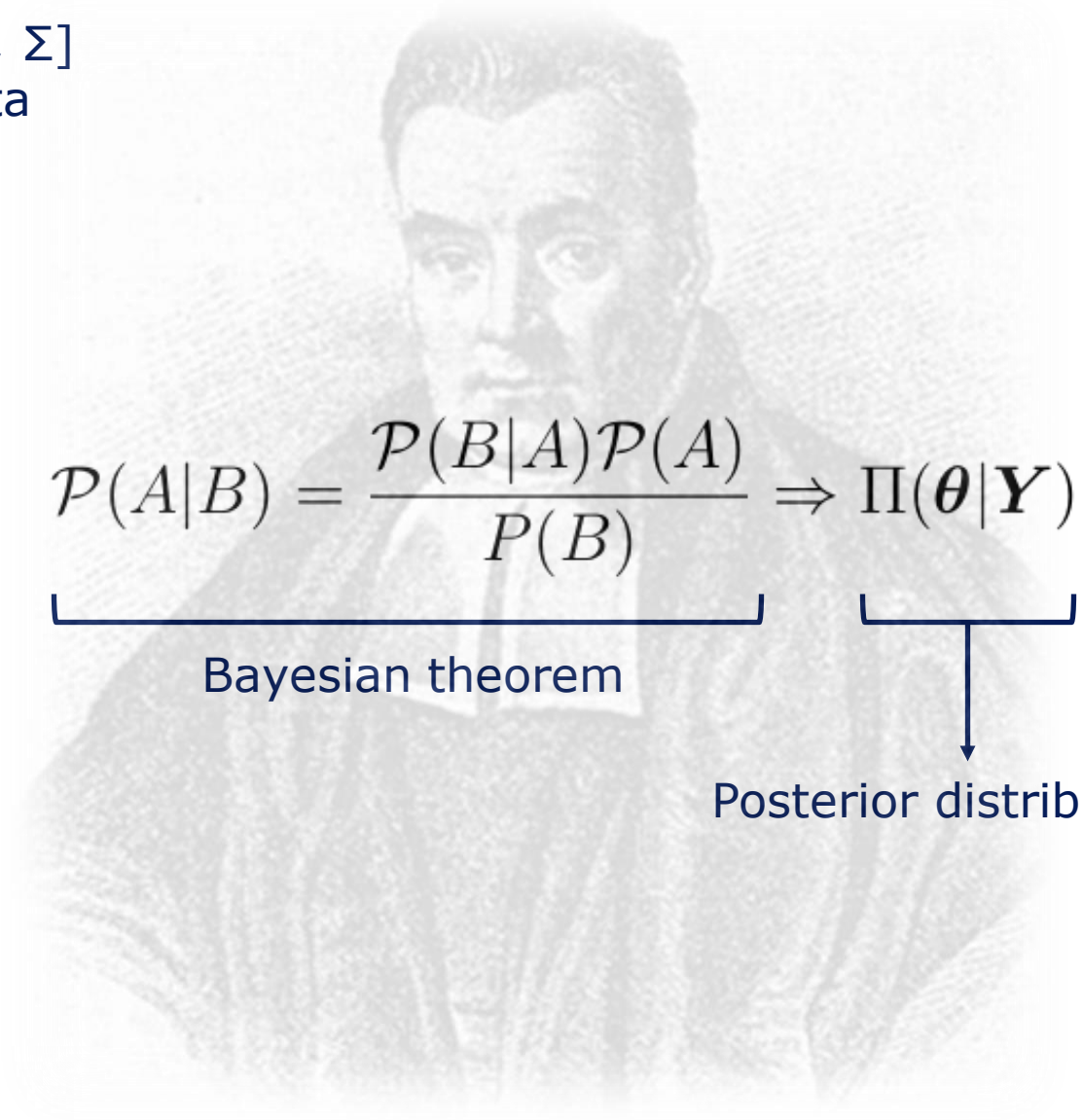
Parameters to be estimated

$$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{B} + \boldsymbol{E} \quad \text{where} \quad E \overset{\text{iid}}{\sim} N(0, I_T \otimes \Sigma)$$

…each variable is modeled as a **linear combination** of its past values as well as the past values of all other variables in the system.

Bayesian VAR - Parameters estimation

Θ=[**B**; Σ]
Y=Data



$$\mathcal{P}(\boldsymbol{B}) = \frac{1}{\sqrt{2\pi\Omega}} exp\left\{-\frac{1}{2}\,(\boldsymbol{B}-\mu)'\Omega^{-1}(\boldsymbol{B}-\mu)\right\}$$

$$\mathcal{P}(\Sigma) = \frac{|\zeta|^{\frac{\nu}{2}}}{2^{\frac{\nu n}{2}}\Gamma_n(\frac{\nu}{2})}|\Sigma|^{-\frac{\nu+n+1}{2}} exp\left\{-\frac{1}{2}tr(\zeta\Sigma^{-1})\right\}$$

$$\underbrace{\mathcal{P}(A|B) = \frac{\mathcal{P}(B|A)\mathcal{P}(A)}{P(B)}}_{\text{Bayesian theorem}} \Rightarrow \underbrace{\Pi(\boldsymbol{\theta}|\boldsymbol{Y})}_{\text{Posterior distribution}} = \frac{\mathcal{P}(\boldsymbol{\theta})\mathcal{L}(\boldsymbol{Y}|\boldsymbol{\theta})}{P(\boldsymbol{Y})} \propto \mathcal{P}(\boldsymbol{\theta})\mathcal{L}(\boldsymbol{Y}|\boldsymbol{\theta})$$

$$\mathcal{L}(\boldsymbol{Y}|\boldsymbol{B},\Sigma) \propto |\Sigma|^{-\frac{T}{2}} exp\left\{-\frac{1}{2}(\boldsymbol{Y}-\boldsymbol{X}\boldsymbol{B})'\Sigma^{-1}(\boldsymbol{Y}-\boldsymbol{X}\boldsymbol{B})\right\}$$

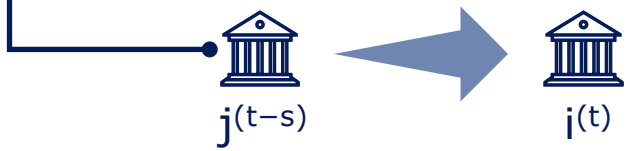
Minnesota Prior – Shrinking distribution

To handle the typical VAR **overparameterization** issue…

$$\mu_{ij}^{(s)} = \begin{cases} 1, & \text{if } i = j \text{ and } s = 1, \\ 0, & \text{otherwise}, \end{cases}$$

$$\beta_{ij}^{(s)} \sim N(\mu_{ij}^{(s)}, \Omega_{ij}^{(s)})$$

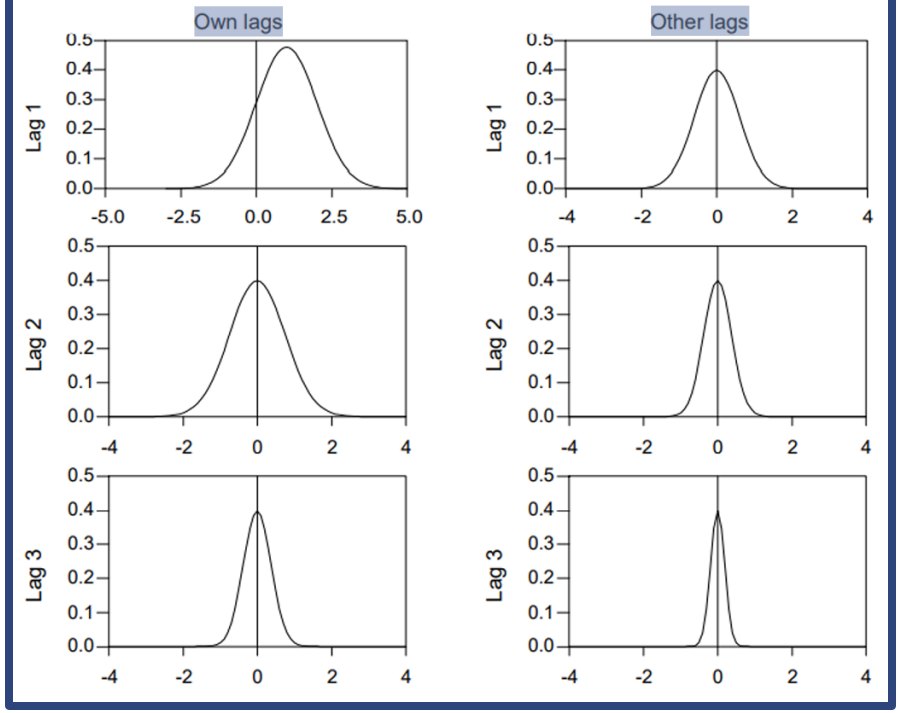
$$\Omega_{i,j}^{(s)} = \begin{cases} \omega^2, & \text{if } s = 1 \text{ and } i = j, \\ (\omega \cdot f(s^{-1}))^2, & \text{if } s \geq 2 \text{ and } i = j, \\ (\kappa \cdot \omega \cdot \tau_{i,j} \cdot f(s^{-1}))^2, & \text{if } i \neq j \text{ and } \forall s \geq 1, \end{cases}$$



$$\beta_{ii}^{(1)} \sim N(1, \omega^2), \qquad \beta_{ij}^{(1)} \sim N(0, (\kappa \cdot \omega \cdot \tau_{ij})^2),$$

$$\beta_{ii}^{(2)} \sim N(0, (\tfrac{\omega}{2})^2), \qquad \beta_{ij}^{(2)} \sim N(0, (\tfrac{\kappa \cdot \omega \cdot \tau_{ij}}{2})^2),$$

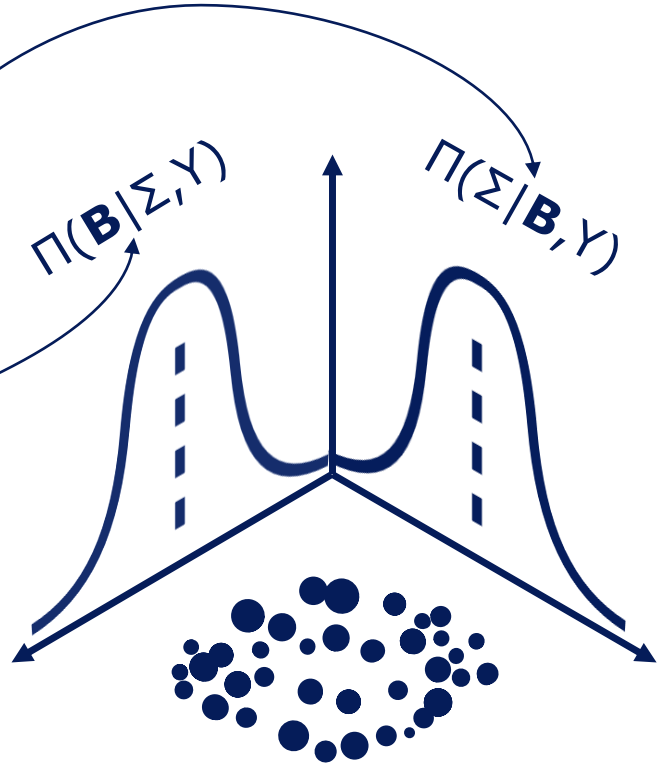
$$\beta_{ii}^{(3)} \sim N(0, (\tfrac{\omega}{3})^2), \qquad \beta_{ij}^{(3)} \sim N(0, (\tfrac{\kappa \cdot \omega \cdot \tau_{i,j}}{3})^2),$$



Gibbs Sampling - Estimation

Algorithm 1: Gibbs Sampler

1 Initialize $Draws\boldsymbol{B}$ and $Draws\Sigma$ as empty matrices of dimensionality $[n \cdot (n \cdot p + 1) \times 9000]$ and $[(n \cdot n) \times 9000]$ respectively.
2 Set the counter $i = 1$.
3 Initialize $\Sigma^{(0)} = I_{[n \times n]}$
4 For i in 1:10000 do:
  (I) Draw $\boldsymbol{B}^{(i)}$ from the posterior $\Pi(\boldsymbol{B}^{(i)}|\Sigma^{(0)}, \boldsymbol{Y})$
  (II) Draw $\Sigma^{(i+1)}$ from the posterior $\Pi(\Sigma^{(i+1)}|\boldsymbol{B}^{(i)}, \boldsymbol{Y})$
5 If i>1000 do:
  (I) Store $\boldsymbol{B}^{(i)}$ in $Draws\boldsymbol{B}$.
  (II) Store $\Sigma^{(i+1)}$ in $Draws\Sigma$.
6 Change the counter i to $i + 1$ and return to step 4.
7 Exit from the loop.



A **M**arkov **C**hain **M**onte **C**arlo method to simulate realizations from the full **posterior distribution**…

Signal Adaptive Variables Selector - Sparsity

…the Signal Adaptive Variable Selector is an automated post-processing technique useful for distinguishing between **signal** and **null** parameters…

Sparse

Shrank

Design matrix

Penalization term

$$\hat{\boldsymbol{B}}^* := \arg\min_{\boldsymbol{B}} \left\{ \frac{1}{2} \|\boldsymbol{X}\hat{\boldsymbol{B}} - \boldsymbol{X}\boldsymbol{B}\|_2^2 + \sum_{i=1}^{r} \sum_{j=1}^{c} \mu_j |\beta_{i,j}| \right\}$$

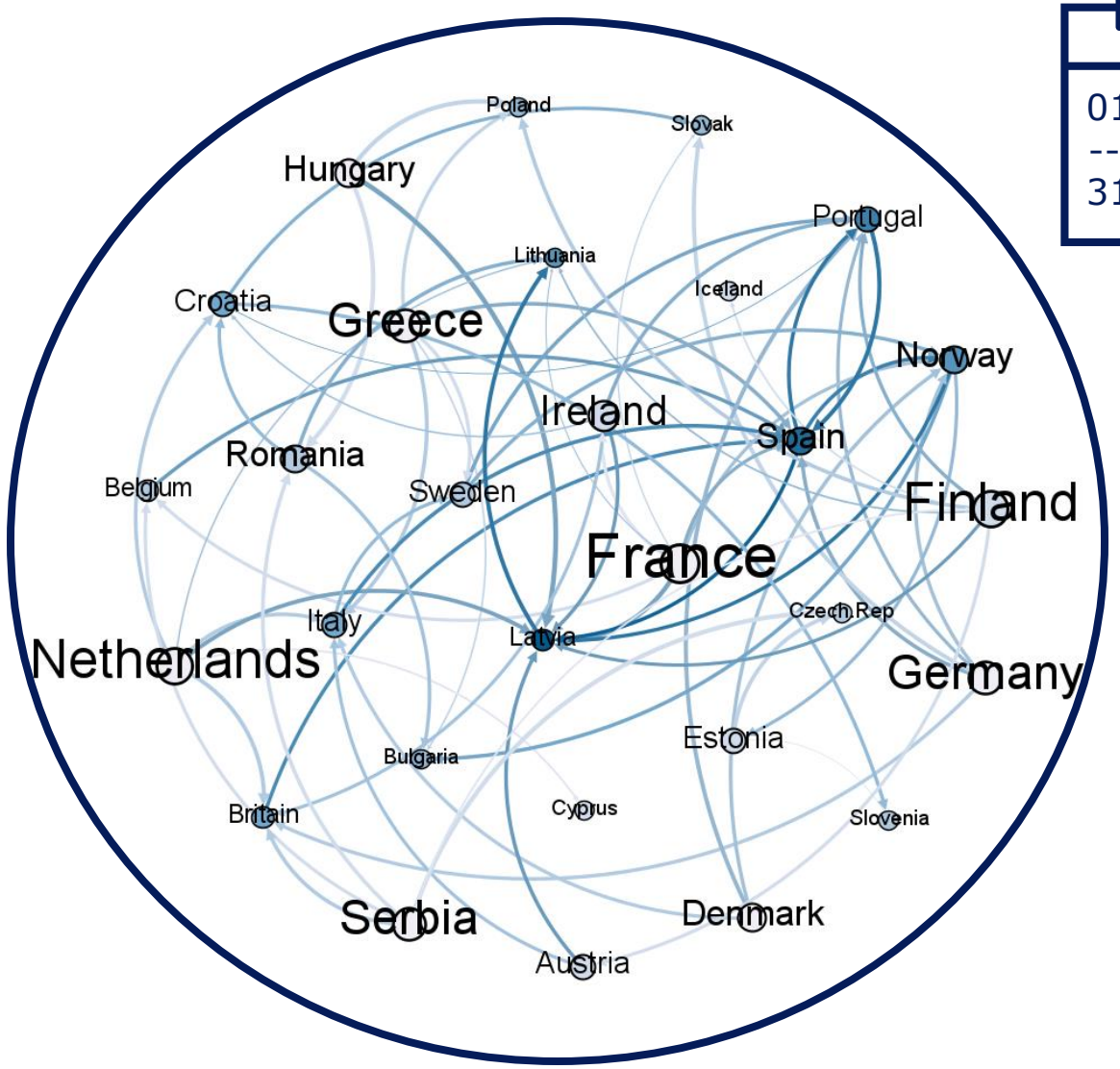
Algorithm 2: Signal Adaptive Variable Selector

1 Input: posterior estimate $\hat{\boldsymbol{B}}^p$ and design matrix $\boldsymbol{X}$.
2 Set the counter $i = 1$.
3 For i in 1:r do:
  Set the counter $j = 1$.
4 For j in 1:c do:
  $\mu_j = \frac{1}{|\hat{\beta}_{i,j}|^2}$
5 If $|\hat{\beta}_{i,j}|^2 \cdot \|\boldsymbol{X_j}\|_2^2 \leq \mu_j$ do:
  $\hat{\beta}^*_{i,j} = 0$
6 Else do:
  $\hat{\beta}^*_{i,j} = sign(\hat{\beta}_{i,j}) \|\boldsymbol{X_j}\|_2^{-2} (|\hat{\beta}_{i,j}|^2 \cdot \|\boldsymbol{X_j}\|_2^2 - \mu_j)$
7 Change the counter j to j+1 and return to step 4.
8 Change the counter i to i+1 and return to step 3.
9 Output: sparse estimate $\hat{\boldsymbol{B}}^*$

$$\begin{pmatrix} 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix} \rightarrow \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

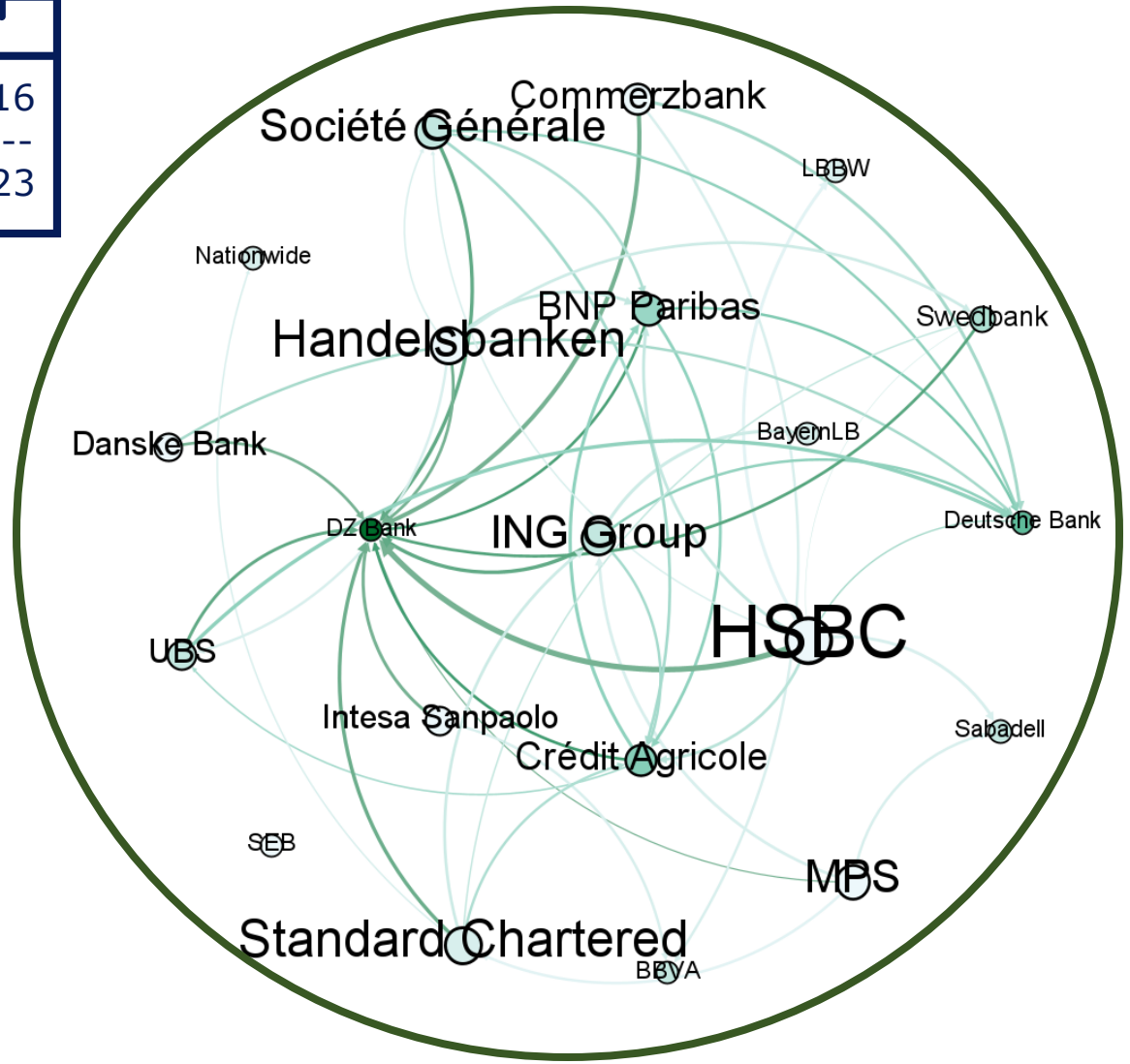
…the matrix of estimated coefficients is **sparsified** to enhance interpretability.

Results - Full Period BVAR



01/01/2016

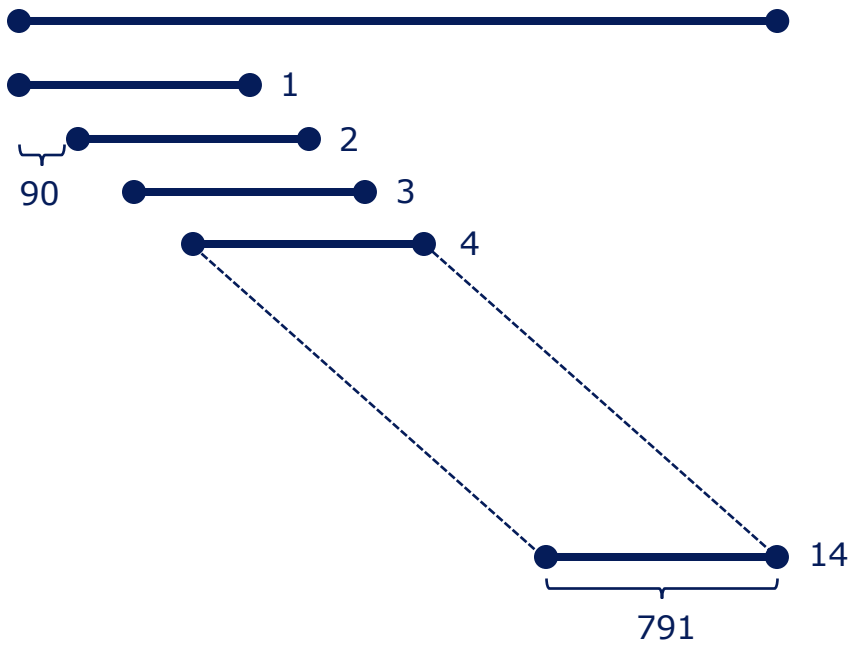
31/07/2023



Results - Rolling Window BVAR: Densities

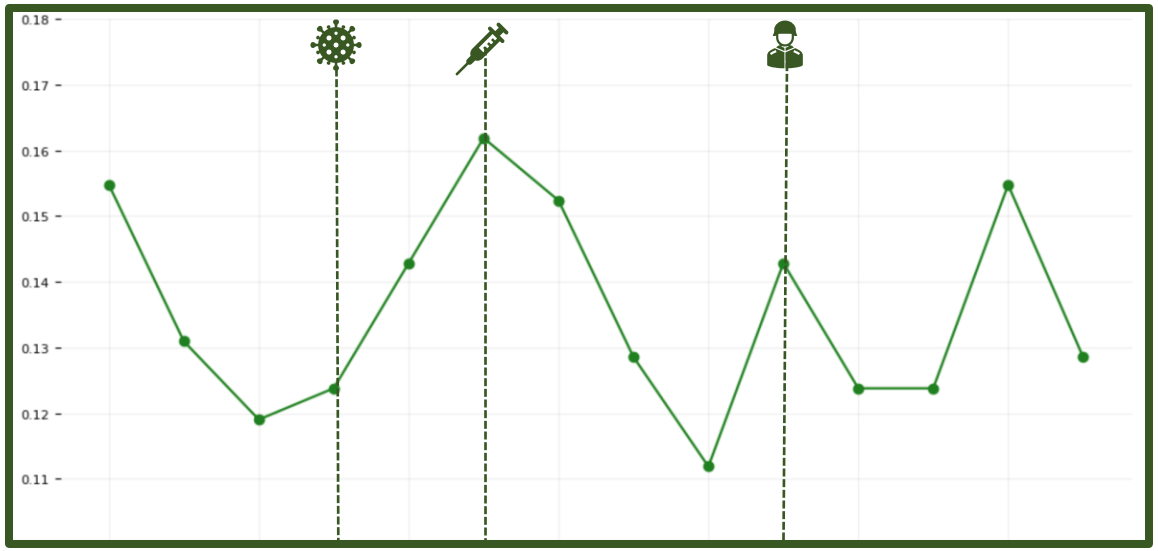
01/01/2016

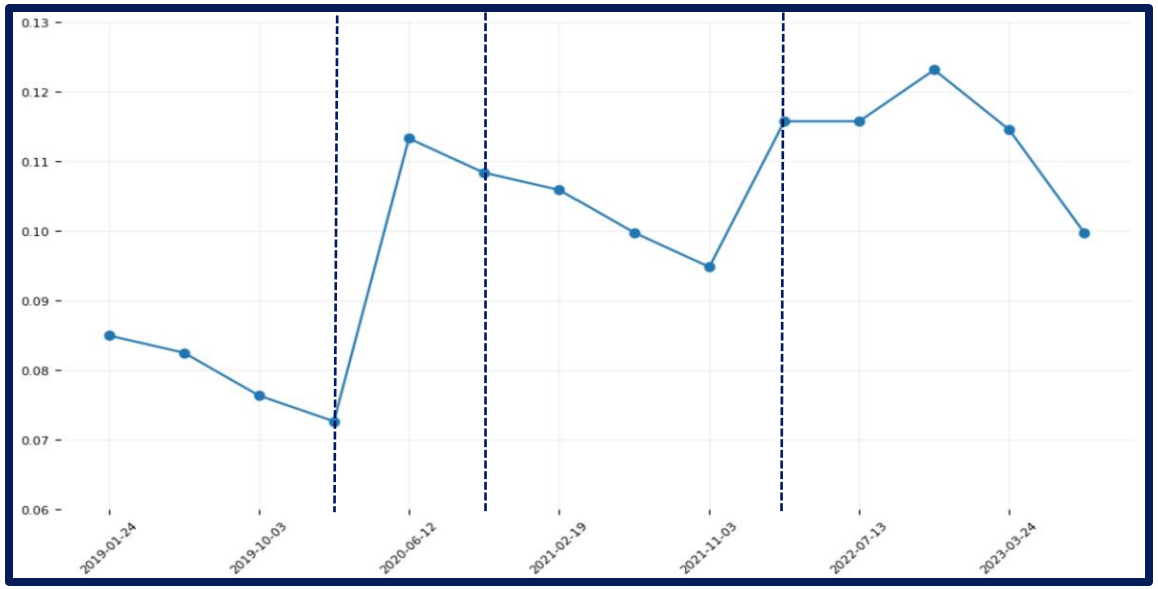
31/07/2023



To determine how the networks describing spreads co-movements **evolve** through time.

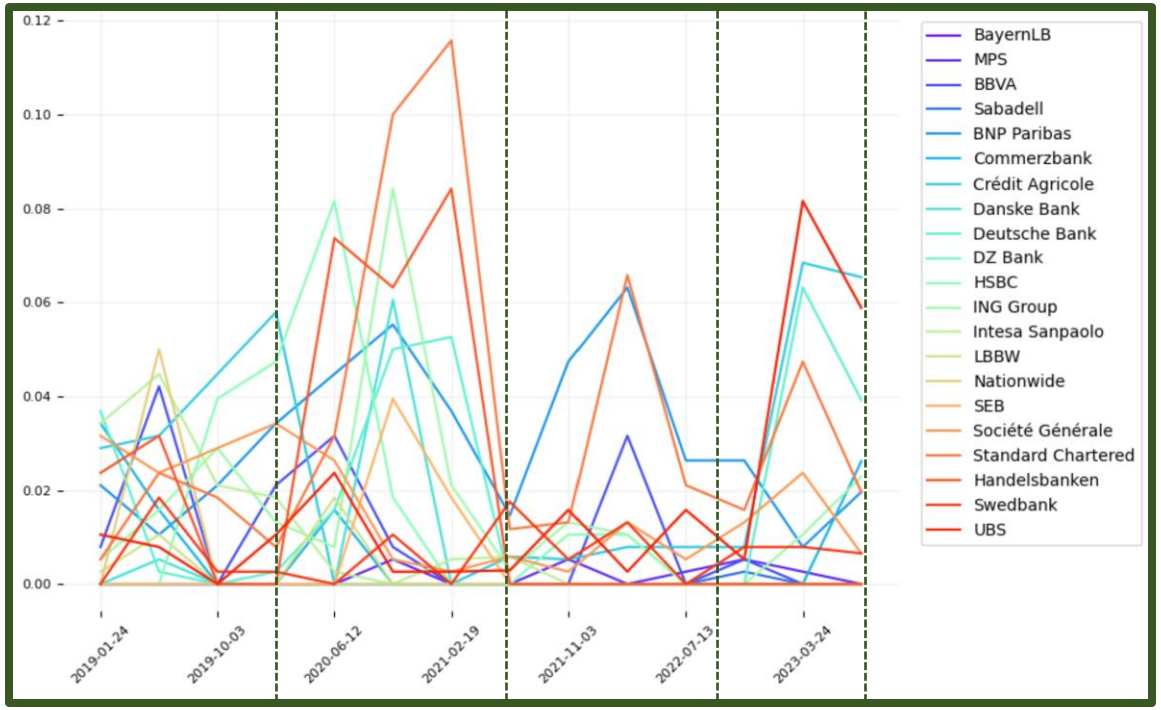
DENSITIES





Results - Rolling window BVAR: Betweenness Centrality

Measures the extent to which a node lies on **paths** between other vertices…

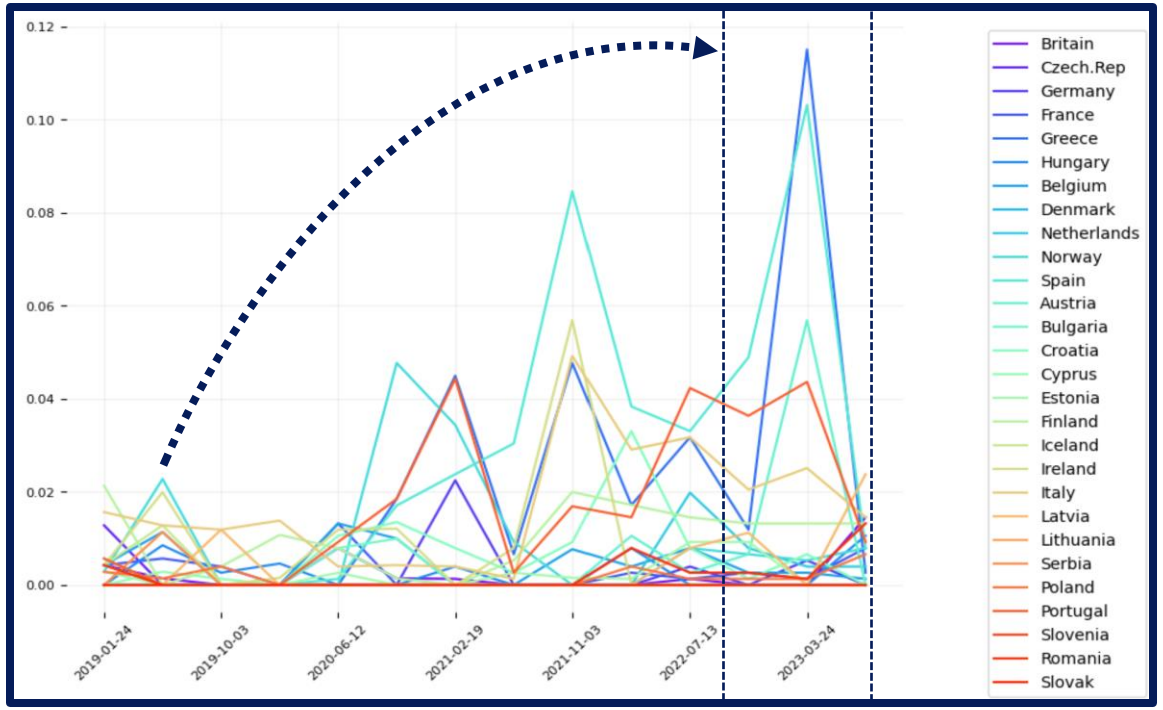


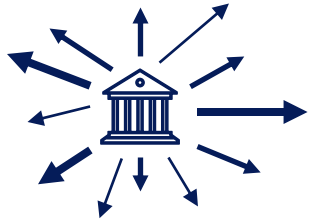
1-S.Chartered
2-Handlesbanken
3-ING Group
4-HSBC

1-S.Chartered
2-BNP Paribas

1-UBS
2-Cr.Agricole
3-Deutsche Bk

1-Greece
2-Spain

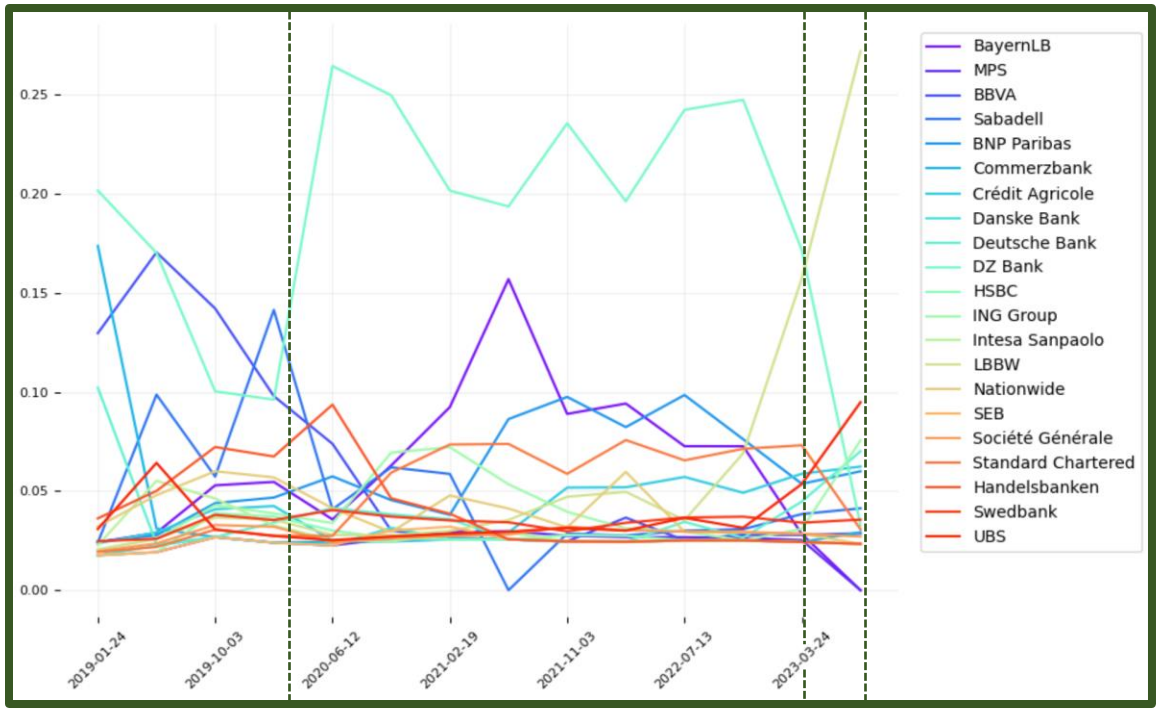


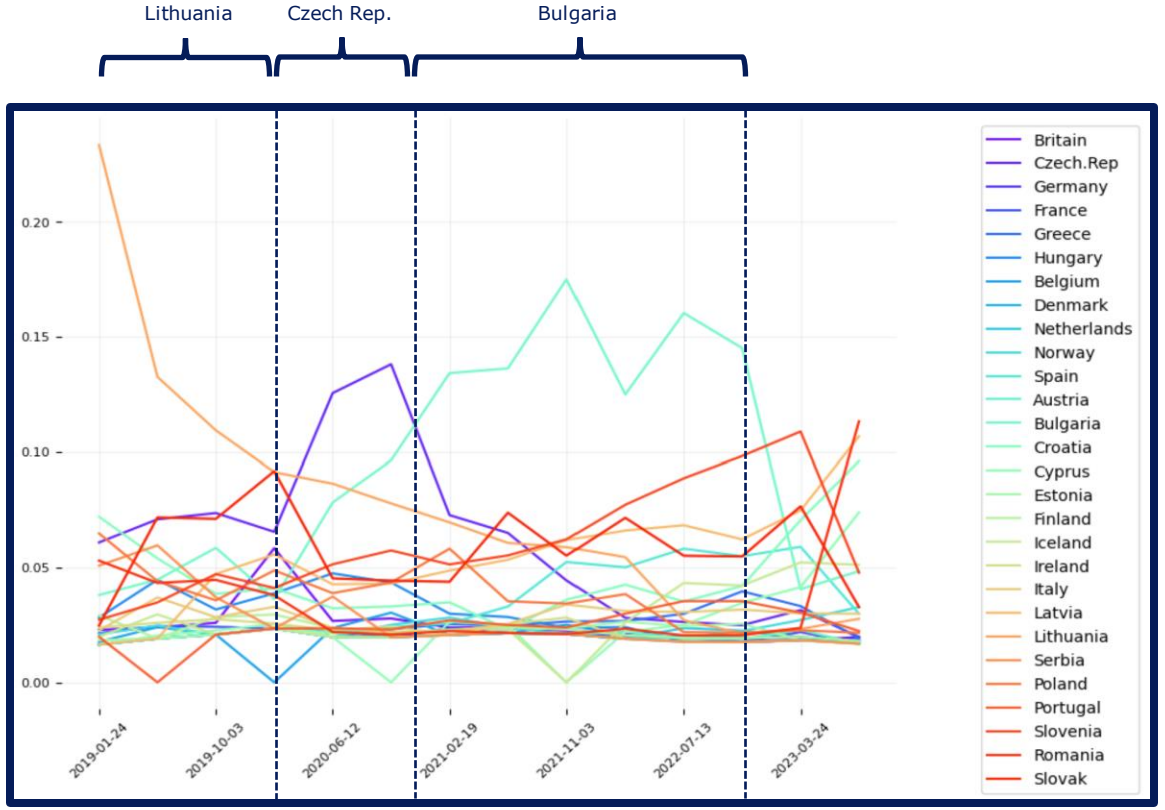


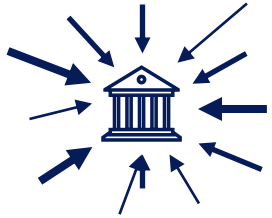
…nodes with high betweenness have considerable **influence** within a network.

Results - Rolling Window BVAR: Page Rank

It quantifies how **influenceable** is a node within a network, by considering how influenceable are the connected nodes…

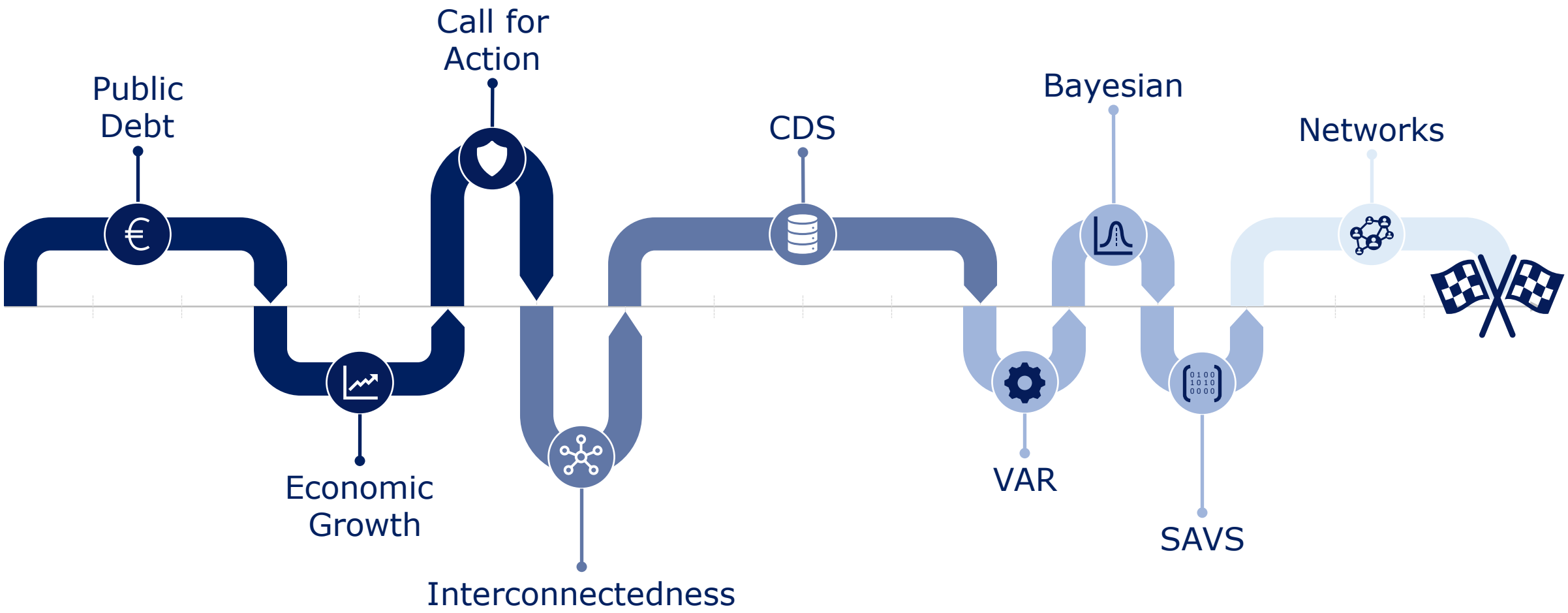






…to determine the **vulnerability** of each node, thus its level of exposure with respect the others.

Conclusions - Recap



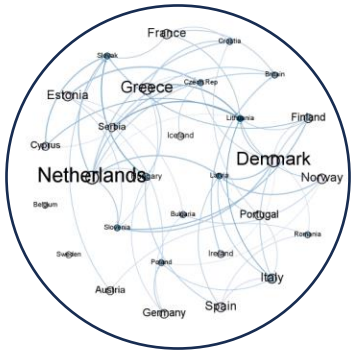
Appendix - Sovereign Networks

2019-01-24

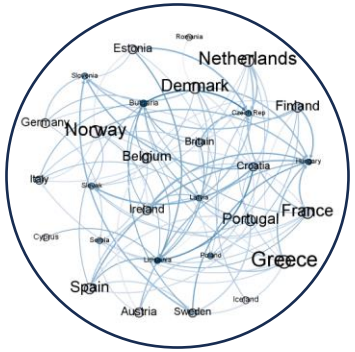
2019-05-30

2019-10-03

2020-02-06



2020-06-12



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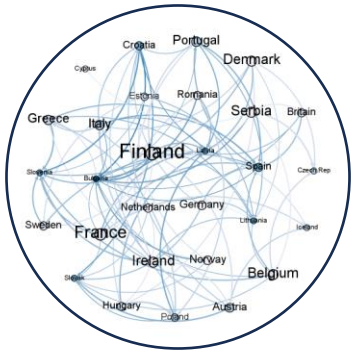
2021-02-19

2021-06-29

2021-11-03

2022-03-09



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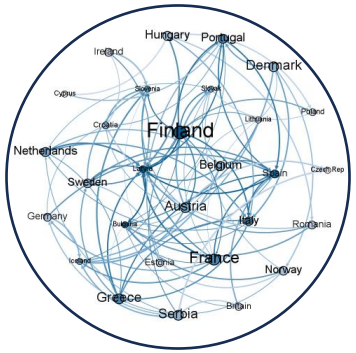

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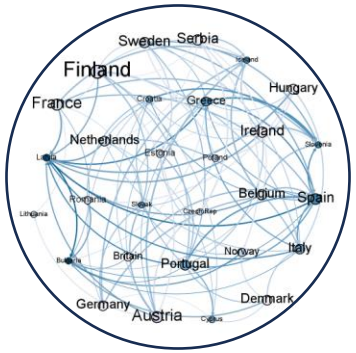

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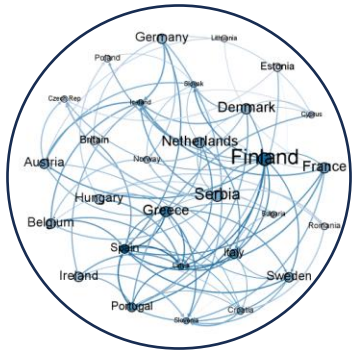
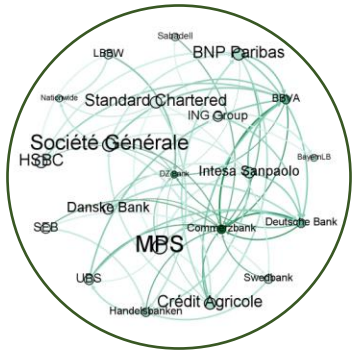


2023-07-28

Appendix - Banking Networks

2019-01-24



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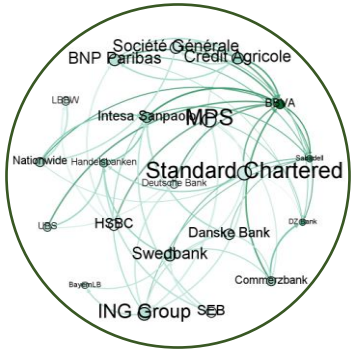
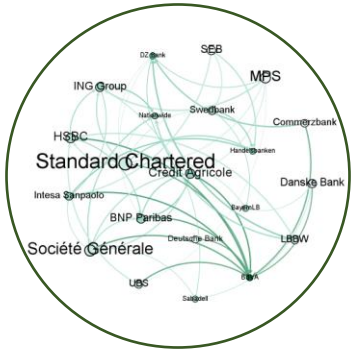
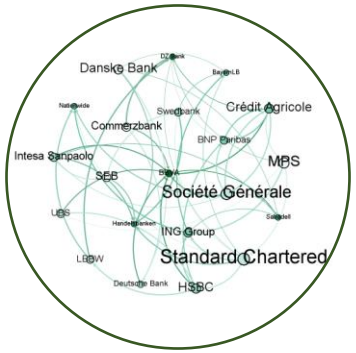


2019-10-03



2020-02-06



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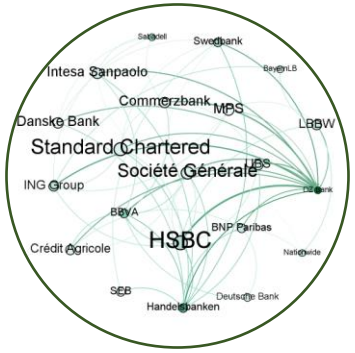
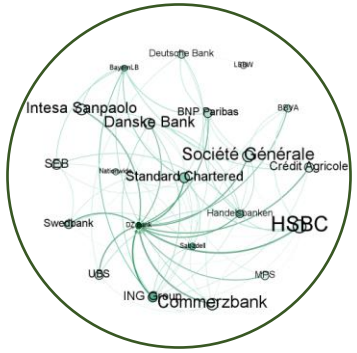


2020-10-16



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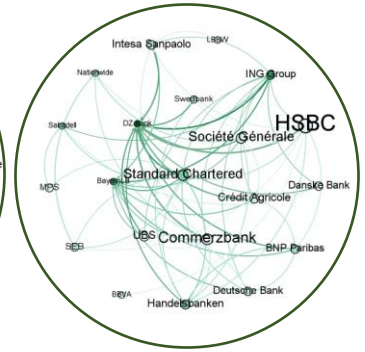

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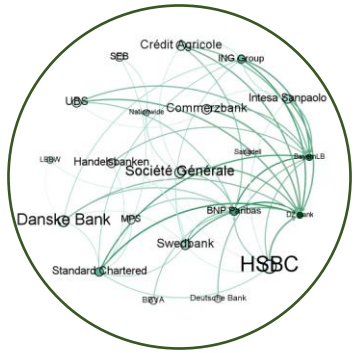

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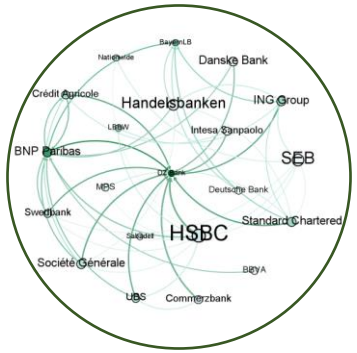

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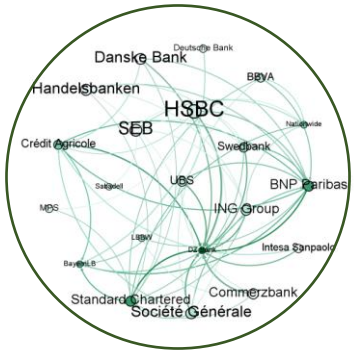

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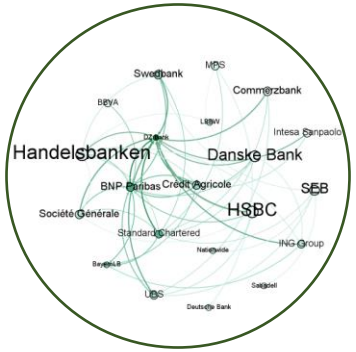

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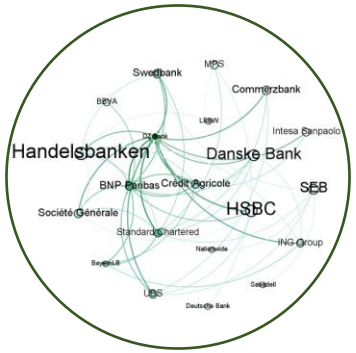

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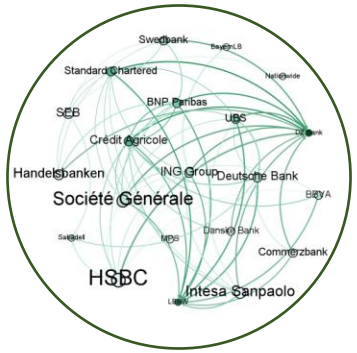

2023-07-28