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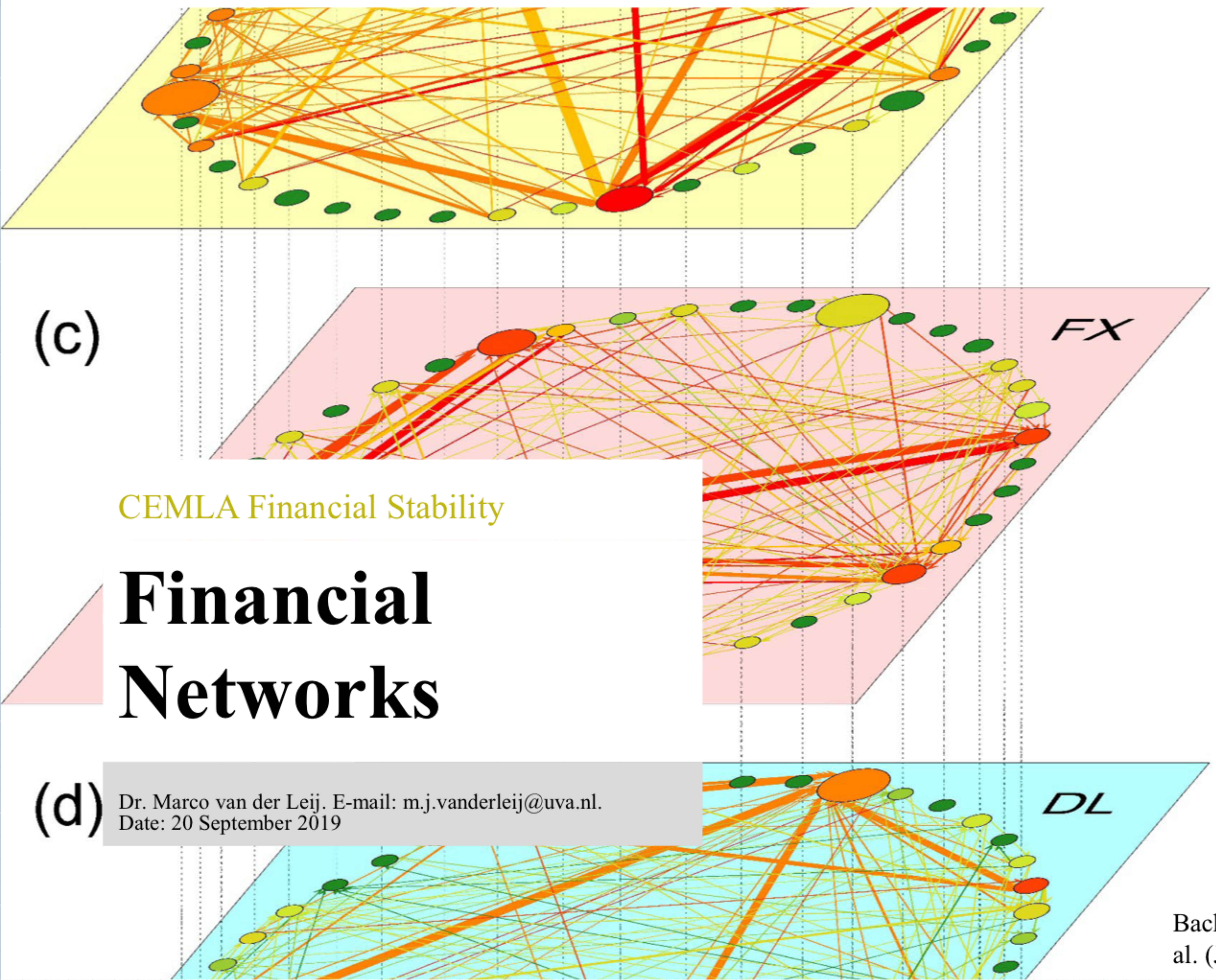

CEMLA Financial Stability

Financial Networks

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Date: 20 September 2019

Background figure from Poledna et al. (JFS, 2015)

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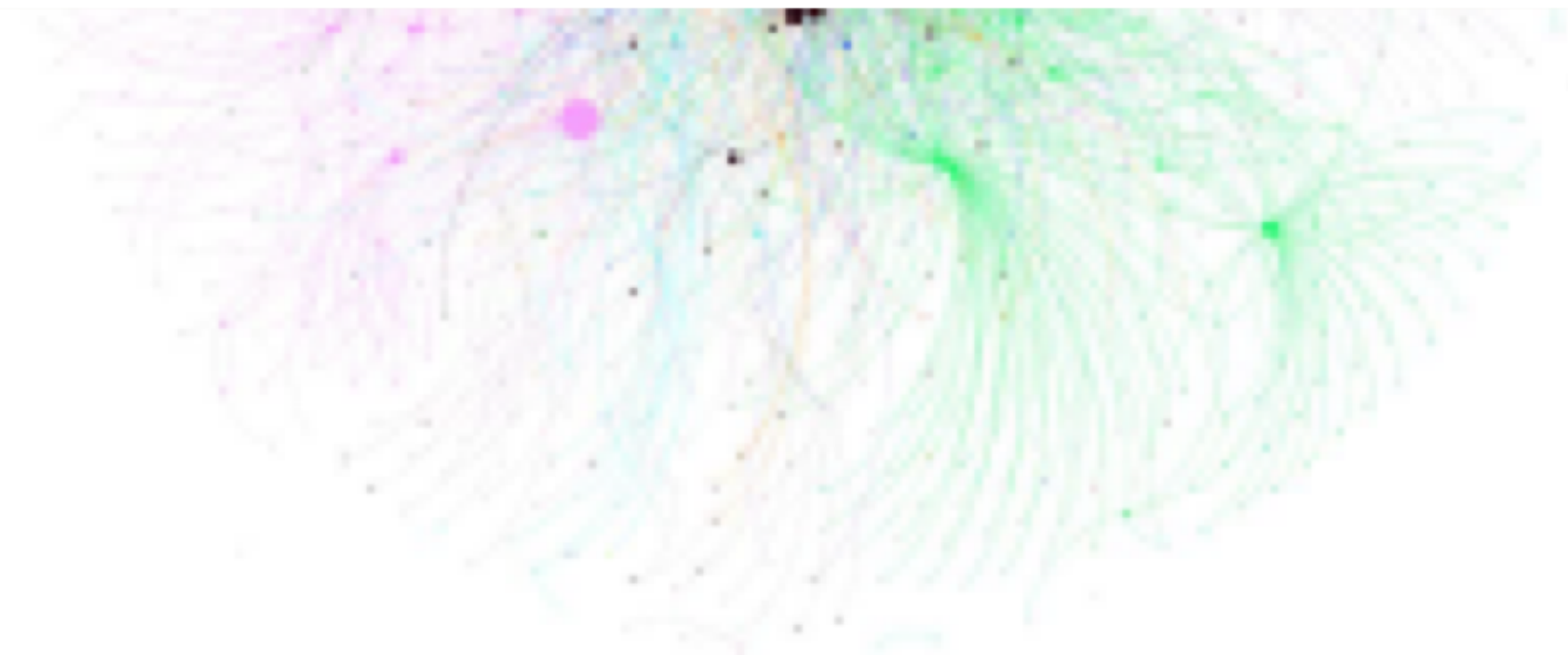
Source: ECB Financial Stability Review, May 2019 – Special Features

Financial networks and financial stability



Sources: ECB supervisory data and ECB calculations.
Notes: The node size captures the weighted in-degree of interconnectedness. The node colour represents the country of origin. The thickness of the links reflects the value of the exposures in € billions. The colour of the links refers to the country of the target, thus also capturing the borrower's perspective.

Modelling systemic events

This special feature uses simulations to examine how different contagion channels might lead to a systemic crisis, using recent real data. We do this by

Learning goals

Part 1

- Explain 3 main channels of financial contagion:
  - Default cascades,
  - Funding contagion / liquidity hoarding
  - Fire sales externality
- Compute by hand:
  - Fictitious default algorithm of Eisenberg & Noe (2001)
  - DebtRank algorithm of Bardoscia, Battiston, Cacciolli et Cardarelli (2015)

Learning goals

Part 2

- Give typical characteristics of large networks
- Construct financial network data from balance sheet data and large exposures
- Compute measures of financial contagion:
  - System level: systemic risk, expected systemic loss
  - Bank level: systemic importance, vulnerability
- Explain what is a multilayer network and why it is important for assessing systemic risk
  - Poledna et al. (JFS, 2015)

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Financial networks and systemic risk

Financial network: set of

- Nodes: financial institutions (banks)
- Links between banks: exposures, common assets, from transactions, funding

Financial contagion:

- Spread of a shock from one bank to other banks through the financial network

Systemic risk:

- Risk that financial stress in one bank leads to financial stress in the whole financial sector

Two approaches to financial networks

Asset price approach

Publicly traded stock market prices of banks

Network estimated from time series dependencies

Examples: SRISK, CoVAR

Key papers:

- Diebold & Yilmaz (2009)
- Billio et al. (2012)
- Brownlees & Engle (2016)
- Adrian-Brunnermeier (2016)

Balance sheet approach

Private data on assets and liabilities of banks

Network is (partly) known

Systemic risk is estimated from assumptions on contagion mechanism

Key papers:

- Eisenberg & Noe (2001)
- Cifuentes et al. (2005)
- Gai et al. (2011)

Bank balance sheet

bank i

Assets	**Liabilities**
Outside assets e_i • Liquid assets • Cash, gov bonds	Outside liabilities b_i • Deposits
• Illiquid assets • Loans to firms/consumers	In-network liabilities p_{ij}
In-network assets p_{ji}	Equity • Capital + reserves w_i

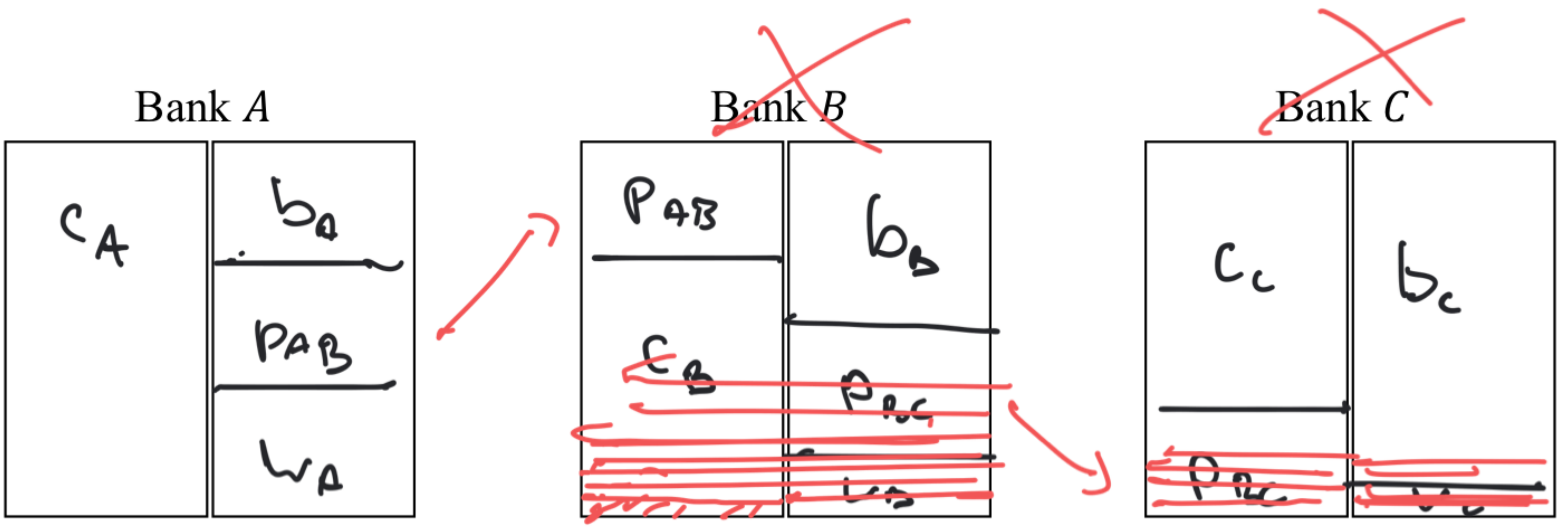
Contagion channels

Types of contagion

- Default cascades
- Funding contagion / liquidity hoarding
- Fire sales externality

Default cascade

Shock leads to default (if $w_i < 0$)



through the asset side

Default cascade

Shock is transmitted through asset side

Default cascade mechanism gets amplified by

- Bankruptcy cost
- Incorporating default risk in the asset values
- Fire sales externality

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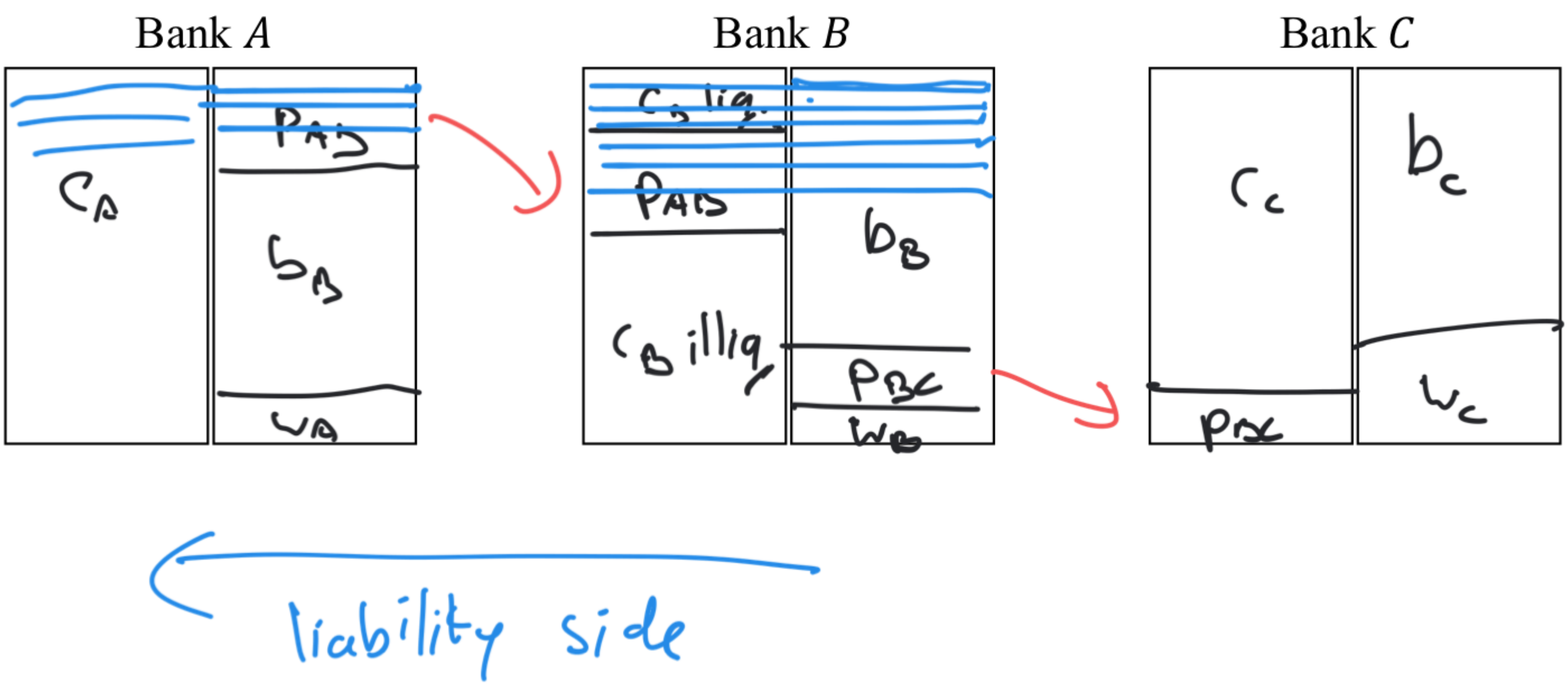
Funding contagion

Shock to external funding b_B



Funding contagion

Shock is transmitted through liability side

Net worth is not directly affected (no defaults)

But mechanism gets amplified by:

- Liquidity hoarding: Bank B converts its remaining loan to A into cash
- Sales of illiquid assets (fire sales)

Fire sales externality

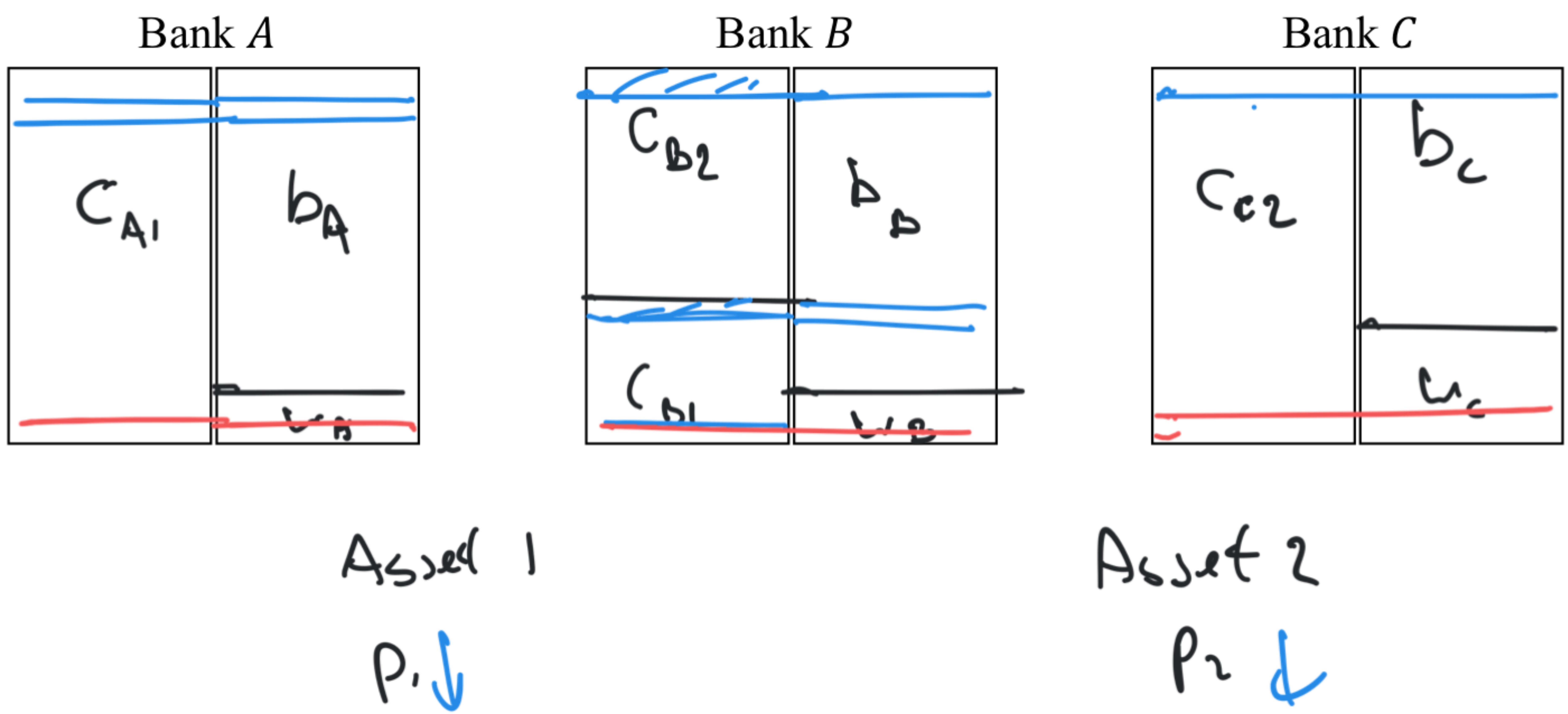
Shock on asset price

Assumptions:

- Banks would like to keep their leverage ratio constant
  - Bank regulation, Internal risk management
- Assets are illiquid: sale leads to drop in price
- Balance sheet assets are valued at mark-to-market

Fire sales externality

Shock on asset price



Contagion channels

Types of contagion

- Default cascades
- Funding contagion / liquidity hoarding
- Fire sales externality
- Other?

DEFAULT CASCADES

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Eisenberg & Noe (2001)

Define:

- Payment that bank *i* owes to *j*: $\bar{p}_{ij}$
- Payment that bank *i* makes to *j*: p_{ij}

Similar distinction for external assets and liabilities

$\bar{b}_i, \bar{c}_i$ b_i, c_i

We are interested in solving for: p_{ij} $\forall ij$

Eisenberg & Noe (2001)

Assumptions:

- External assets are always paid out: $c_i = \bar{c}_i$
- If bank is solvent: $w_i \geq 0$
  - Bank pays what it owes $p_{ij} = \bar{p}_{ij}$ $b_i = \bar{b}_i$
- If bank defaults: $w_i < 0$
  - Bank pays out all its assets $\bar{c}_i + \sum_k p_{ki}$
  - Assets are divided equally among all its creditors (equal seniority)

Eisenberg & Noe (2001)

Define:

- Total payment that bank *i* owes: $\bar{p}_i = \bar{b}_i + \sum_j \bar{p}_{ij}$
- Total payment that bank *i* pays: $p_i = b_i + \sum_j p_{ij}$
- Share of bank *i*'s total payments to bank *j*:

$$\alpha_{ij} = \frac{\bar{p}_{ij}}{\bar{p}_i}$$

Then $p_{ij} = \alpha_{ij} p_i$

$$p_i = \begin{cases} \bar{p}_i & \text{if } \bar{p}_i \le \bar{c}_i + \sum_k p_{ki} \\ \bar{c}_i + \sum_k p_{ki} & \text{otherwise} \end{cases}$$

Eisenberg & Noe (2001)

Payments clear if: Solve p_i $\forall i$

$$p_i = \min\left\{ \bar{p}_i ,\ c_i + \sum_k \alpha_{ki} p_k \right\} \text{ for all } i$$

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Eisenberg & Noe (2001)

Eisenberg & Noe (2001) show that there exist a generically unique payment vector $\vec{p}$ that clears the system of payment equations

If all banks default, then

Computation clearing payment vector

Fictitious default algorithm:

Start with everyone paying what they owe

In each period t

- Check which banks default
- Solvent banks pay what they owe
- Solve the system of price equations for the defaulting banks

Go back to 2 until no further banks default

Exercise: Fictitious default algorithm

Round 1

~~Bank A~~ e

c_A	~~10~~ 3	b_A	5
		p_{AB}	3
		p_{AC}	1
		w_A	~~1~~
Total		Total	

5/9, 1/3, 1/9

Bank B

c_B	4	b_B	4
p_{AB}	3	p_{BC}	2
		w_B	1
Total	7	Total	7

Bank C

c_C	3.8	b_C	6
p_{AC}	1	w_C	0.8
p_{BC}	2		
Total		Total	

round 2

~~Bank A~~

c_A	3	b_A	5/3
		p_{AB}	1
		p_{AC}	1/3
		w_A	
Total	3	Total	3

Bank ~~B~~

c_B	4	b_B	10/3
p_{AB}	1	p_{BC}	5/3
		w_B	
Total	5	Total	5

Bank C

c_C	3.8	b_C	6
p_{AC}	1/3	w_C	2/15
p_{BC}	2		
Total		Total	

round 3

~~Bank C~~

c_C	3.8		
p_{AC}	1/3		
p_{BC}	5/3		
	5.8		

$$\vec{p} = \begin{bmatrix} 3 \\ 5 \\ 5.8 \end{bmatrix}$$

DebtRank (Bardoscia et al., 2015)

Idea:

- The market value of bank A's interbank debt may drop **before** bank A defaults.
- If assets are value at mark-to-market, then a shock of A leads to a loss at other banks that own debt issued by A

DebtRank:

- Market value of debt issued by A decreases **proportionally** to decrease in equity of A

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DebtRank algorithm

Define

- p_{ij} : the "market value" of debt issued by *i* and owned by *j* in round *t*
  - Similarly b_i, c_i

Algorithm

- $t = 0$: Initiate balance sheets $\forall i : c_i(0) = \bar{c}_i,\ p_{ij}(0) = \bar{p}_{ij}$
- $t = 1$: Apply shocks to banks $\forall i : s_i$

$$c_i(1) = \bar{c}_i - s_i$$

$$w_i(1) = \max(\underbrace{0}_{\text{default}},\ \underbrace{w_i(0) - s_i}_{\text{solvent}})$$

DebtRank algorithm

- $t = 0$: Initiate balance sheets
- $t = 1$: Apply shocks to banks
- $t \geq 2$: Revalue interbank assets proportional to drop in debt issuer's equity

$$p_{ij}(t) = p_{ij}(0) \frac{w_i(t-1)}{w_i(0)}$$

$$w_i(t) = \max\Big(\underset{\text{default}}{0}, \; w_i(0) - s_i - \sum_k \big(p_{ki}(0) - p_{ki}(t)\big)\Big)$$

solvent

  - Update equity

Repeat until convergence

Example DebtRank

Round 0: initial situation

Bank A

c_A	10	b_A	4
		p_{AB}	4
		w_A	2
Total		Total	

Bank B

c_B	12	b_B	4
p_{AB}	4	p_{BC}	8
		w_B	4
Total		Total	

Bank C

c_C	4	b_C	10
p_{BC}	8	w_C	2
Total		Total	

~~Round 1: shock to bank A~~

Bank A

c_A	9	b_A	4
		p_{AB}	4
		w_A	1
Total		Total	

Bank B

c_B	12	b_B	4
p_{AB}	2	p_{BC}	8
		w_B	2
Total		Total	

~~Bank C~~

c_C	4	b_C	10
p_{BC}	4	w_C	0
Total		Total	

Bank A Bank B Bank C

DebtRank

Two versions of DebtRank

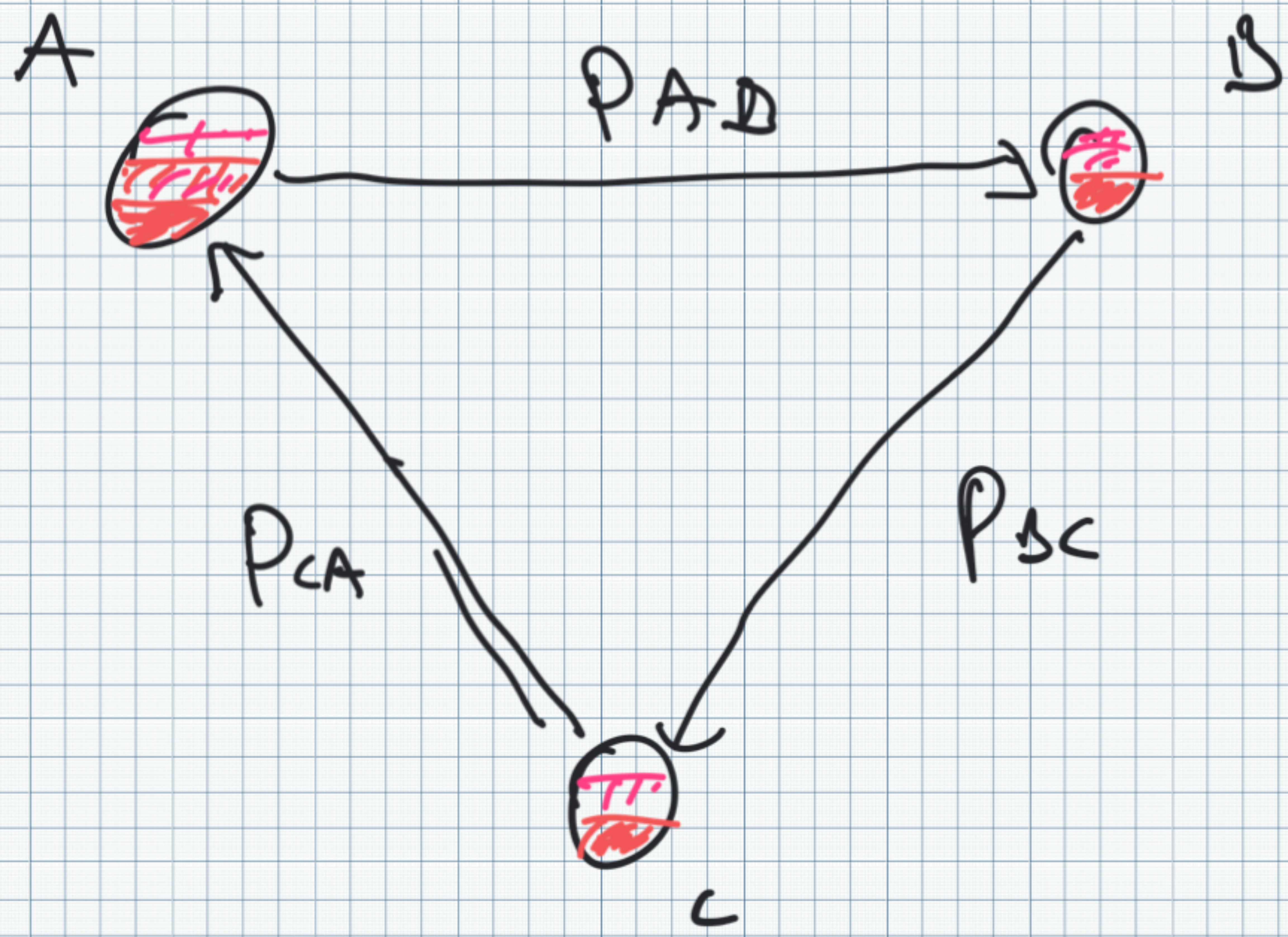
- New: Bardoscia et al. (2015) $p_{ij}(t) = p_{ij}(0) \frac{w_i(t-1)}{w_i(0)}$

- Old: Battiston et al. (2012)

$$p_{ij}(t) = \begin{cases} p_{ij}(0) \frac{w_i(t-1)}{w_i(0)} & \text{if } w_i(s) = w_i(0)\ \forall s < t-1 \\ p_{ij}(t-1) & \text{otherwise} \end{cases}$$

i is hit for first time

i is already hit


A
PAB
B
PCA
PBC
C

DebtRank

Difference between old and new version

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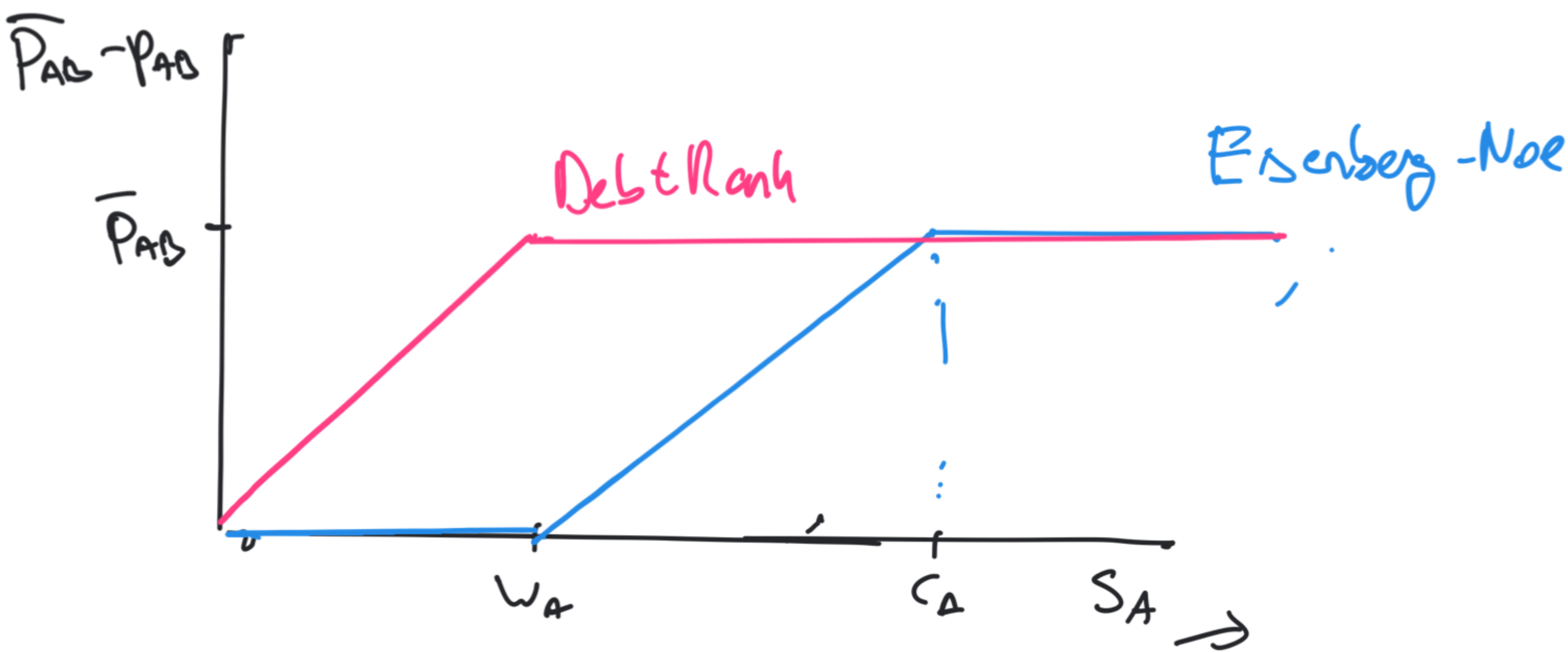
Comparison DebtRank vs Eisenberg-Noe

Bank A

$c_A - s_A$	b_A p_{AB} w_A

Bank B

c_B p_{AB}	b_B w_B



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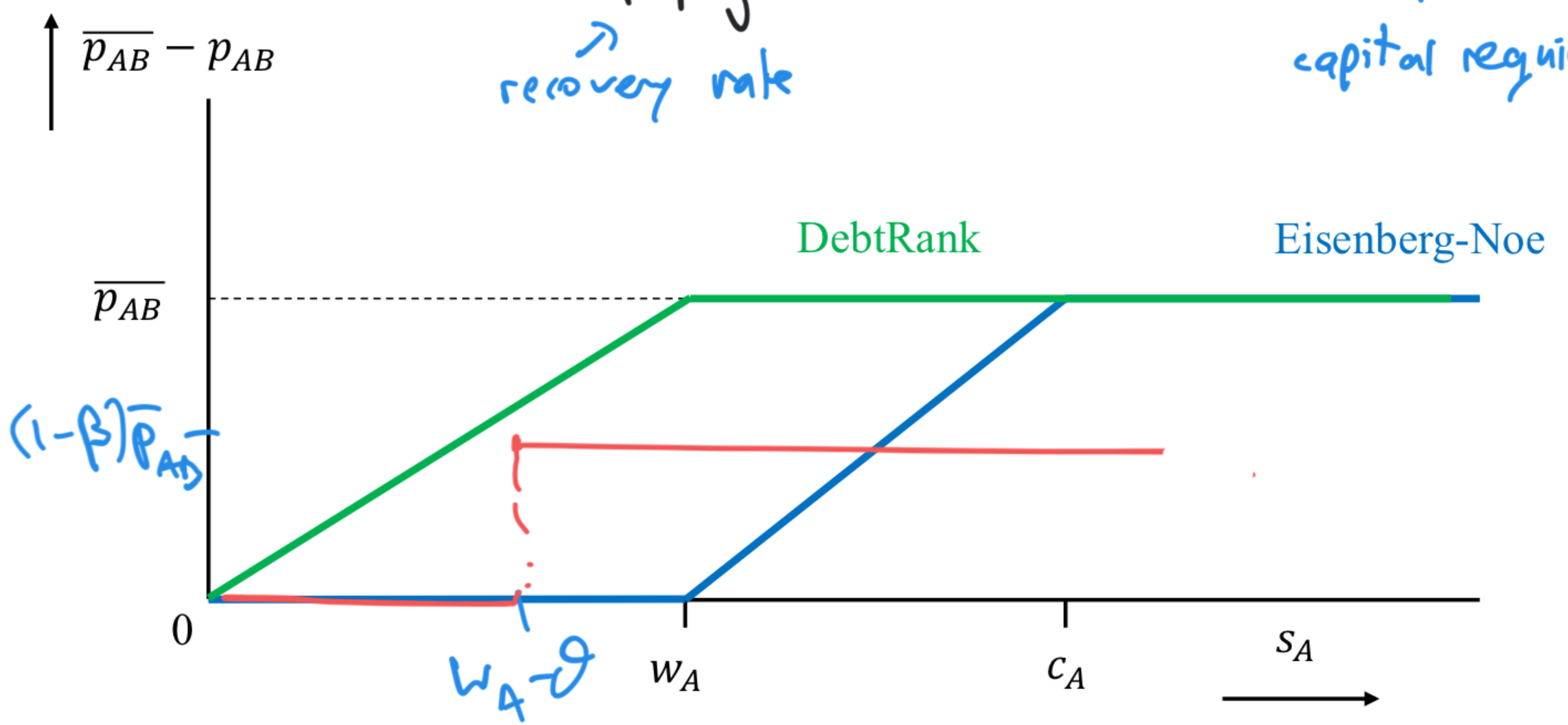
Standard default cascade: (Furfine, 2003)

$$p_{ij}(t) = \begin{cases} \overline{p}_{ij} & \text{if } \quad w_i \geq \vartheta \\ \beta\,\overline{p}_{ij} & \quad\quad w_i < \vartheta \end{cases}$$

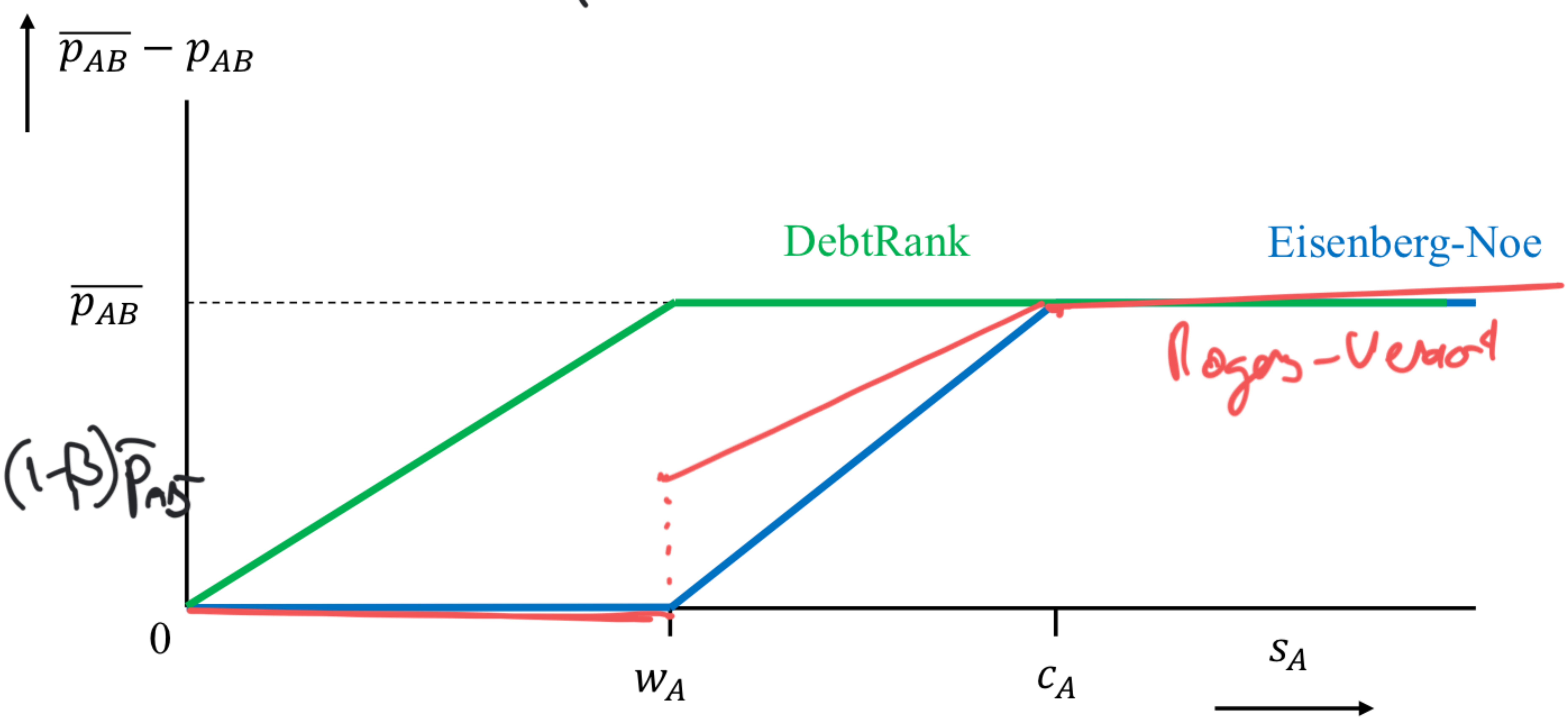
recovery rate

minimum capital requirement

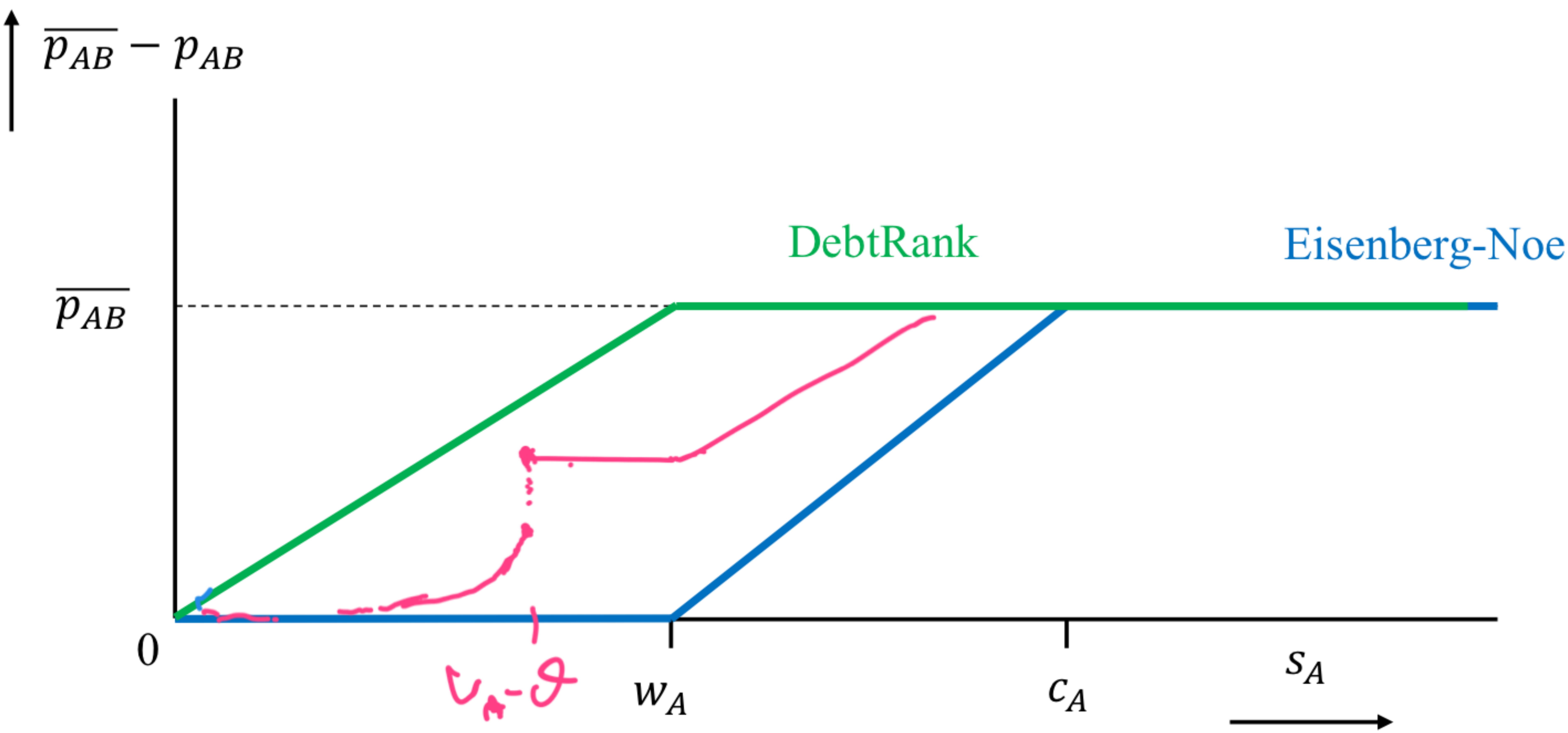


Rogers & Veraart (2013)

$$p_i(t) = \begin{cases} \bar{p}_i & \text{if } \bar{p}_i \le \bar{c}_i + \Sigma_k p_{ki} \\ \beta(\bar{c}_i + \Sigma_k p_{ki}) & \text{otherwise} \end{cases}$$

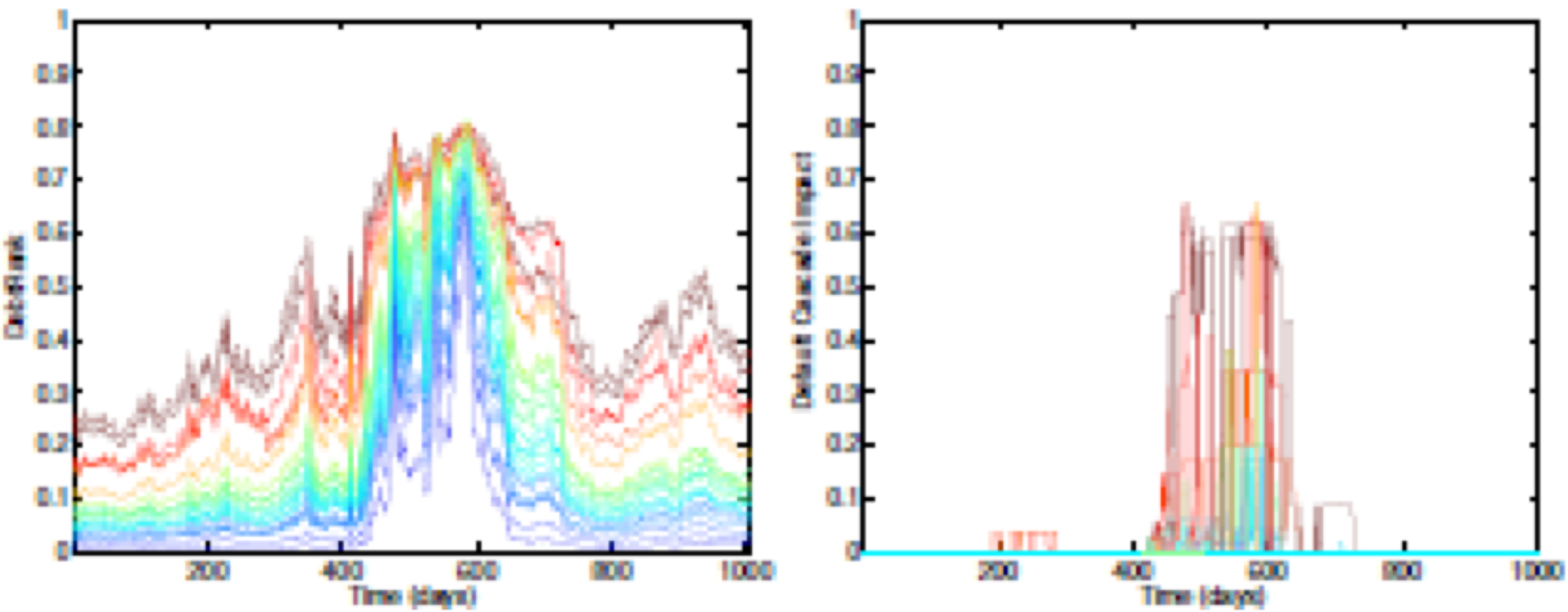


Comparison DebtRank vs Eisenberg-Noe



DebtRank vs Furfine

Source: Battiston et al. 2012, Supplementary Information Figure 16



Comparison DebtRank vs Eisenberg-Noe

DebtRank

- ‘Agent-based’
- Dynamic process
- Upperbound on contagion
- Contagion before default
- Always volatile

Eisenberg-Noe

- Accounting identities
- Fixed point clearing vector
- Lowerbound on contagion
- Contagion only after default
- No contagion in quiet periods

Constructing network data

Financial contagion analysis requires **complete** network data on interbank exposures

Usually information on network data is **incomplete**

- Only for large exposures
- Only for certain registered type of transactions
- Only for banks within own jurisdiction

What to do then?

Constructing network data

Predict network using:

- Bank balance sheet reports:
  - Aggregate interbank assets and liabilities often available

    $\forall i \quad a_i = \sum_k p_{ki} \qquad l_i = \sum_j p_{ij}$
- Available (incomplete) network data
  - Large exposures
- General information on financial network structure

Financial network structure

Common characteristics of financial networks:

- Relatively few links: low density
- Large inequality in # of links among banks
  - Degree distribution has a fat tail
- Short path lenghts
- Core-periphery structure:
  - Few core banks with many links and dense core
  - Many peripheral banks with few links, only to core banks

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Estimation

$$P = \begin{bmatrix} 0 & & \cdot & \cdot & \cdot & \\ & 0 & & \cdot & 60 & \\ & & 0 & & \cdot & \cdot \\ & \cdot & & 0 & & \\ \cdot & 70 & & & 0 & \\ & & & \cdot & \cdot & 0 \end{bmatrix} \begin{matrix} 300 \\ 240 \\ \\ \\ \\ \\ \end{matrix}$$

0 140

Gandy & Veraart (2017) propose a Bayesian approach

- Prior: information on
  - Aggregate interbank assets and liabilities
  - Known links
  - Some random network model (Erdös-Renyi, scale-free, etc.)
- Posterior: <u>distribution</u> of potential networks

Networks can be sampled from the posterior using Gibbs-sampling

- Package in R: systemicrisk

Evaluating systemic risk

Typical simulation

- If network data is incomplete, randomly draw K financial networks from posterior distribution

For each financial network:

- For each bank *i*
  - Let bank *i* default (large random shock)
  - Run some contagion algorithm
  - Measure contagion effect on system

Measuring contagion

- # additional default triggered by i's default
  - Direct contagion after 1 round
  - Indirect contagion in further rounds
- Welfare loss triggered by i's default
  - Loss of total asset value
  - Direct and indirect contagion

systemic importance
of i

Measuring contagion

Suppose we have N simulations, one for each bank

- Systemic Risk at system level

$\rightarrow SR =$ average # default M simulation

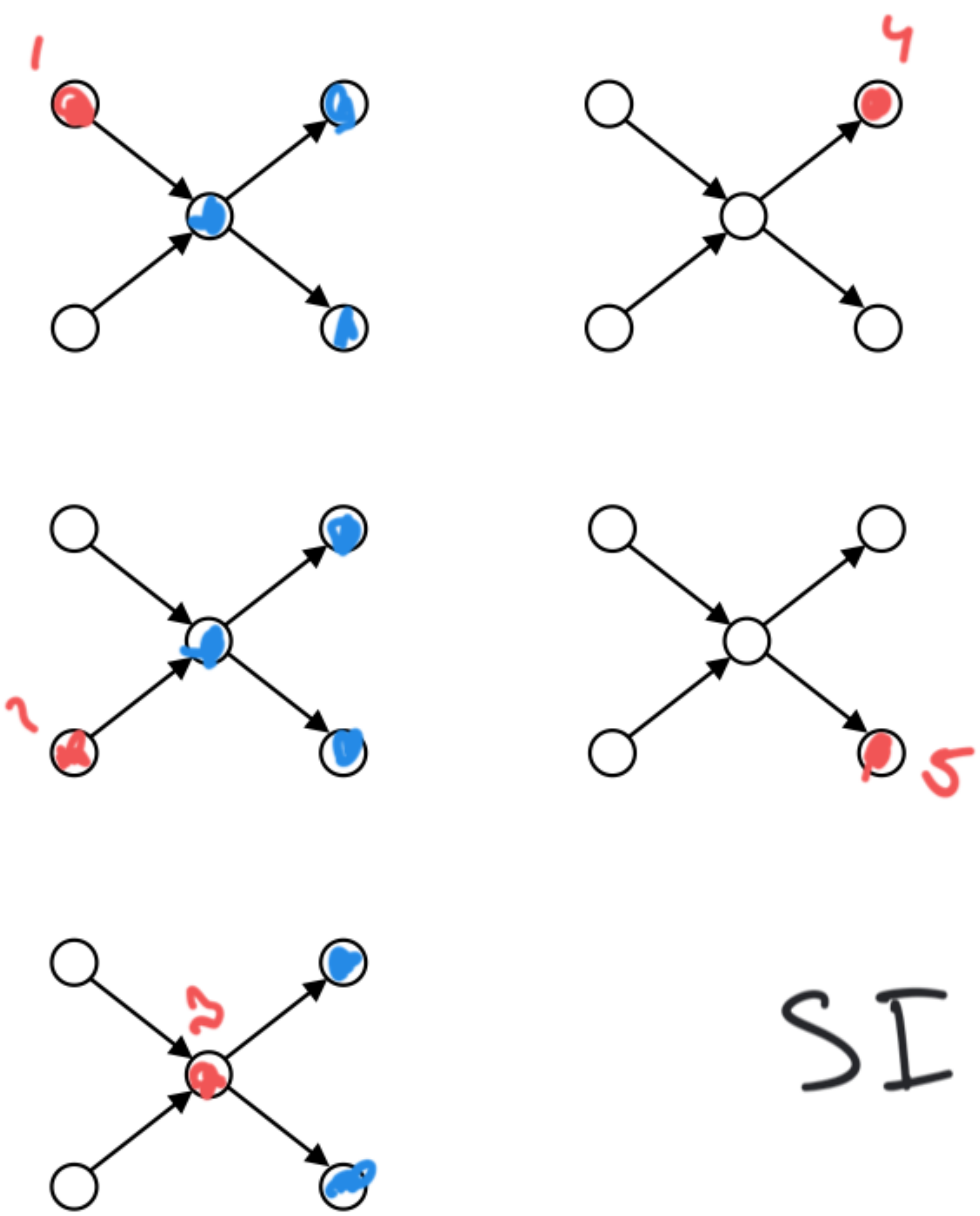
$\rightarrow SR = \sum_i \hat{p}_i R_i$ ← welfare loss due to i's default

idiosyncratic prob. default

Bank level

- Systemic importance
- Vulnerability
  - # simulations in which i defaults
  - Average loss incurred by i in simulations

Systemic importance and vulnerability



- Most systemically important:

  1, 2

- Most vulnerable: 4, 5

$$SI = \underbrace{SR(g)}_{\text{systemic risk}} - SR(g \setminus \underbrace{\{i\}}_{\text{network with } i \text{ being "saved"}})$$

The multi-layer network nature of financial systemic risk and its implications

Sebastian Poledna[1] José Luis Molina-Borboa[2] Serafín Martínez-Jaramillo[2] Marco van der Leij[3] Stefan Thurner[1,4]

[1]Medical University of Vienna [2]Banco de México [3]University of Amsterdam, Tinbergen Institute, and De Nederlandsche Bank
[4]Santa Fe Institute, and IIASA

Views expressed in this presentation are our own and do not necessarily reflect the views of the Banco de México, De Nederlandsche Bank or any of the authors' affiliations.

Course CEMLA Financial Stability
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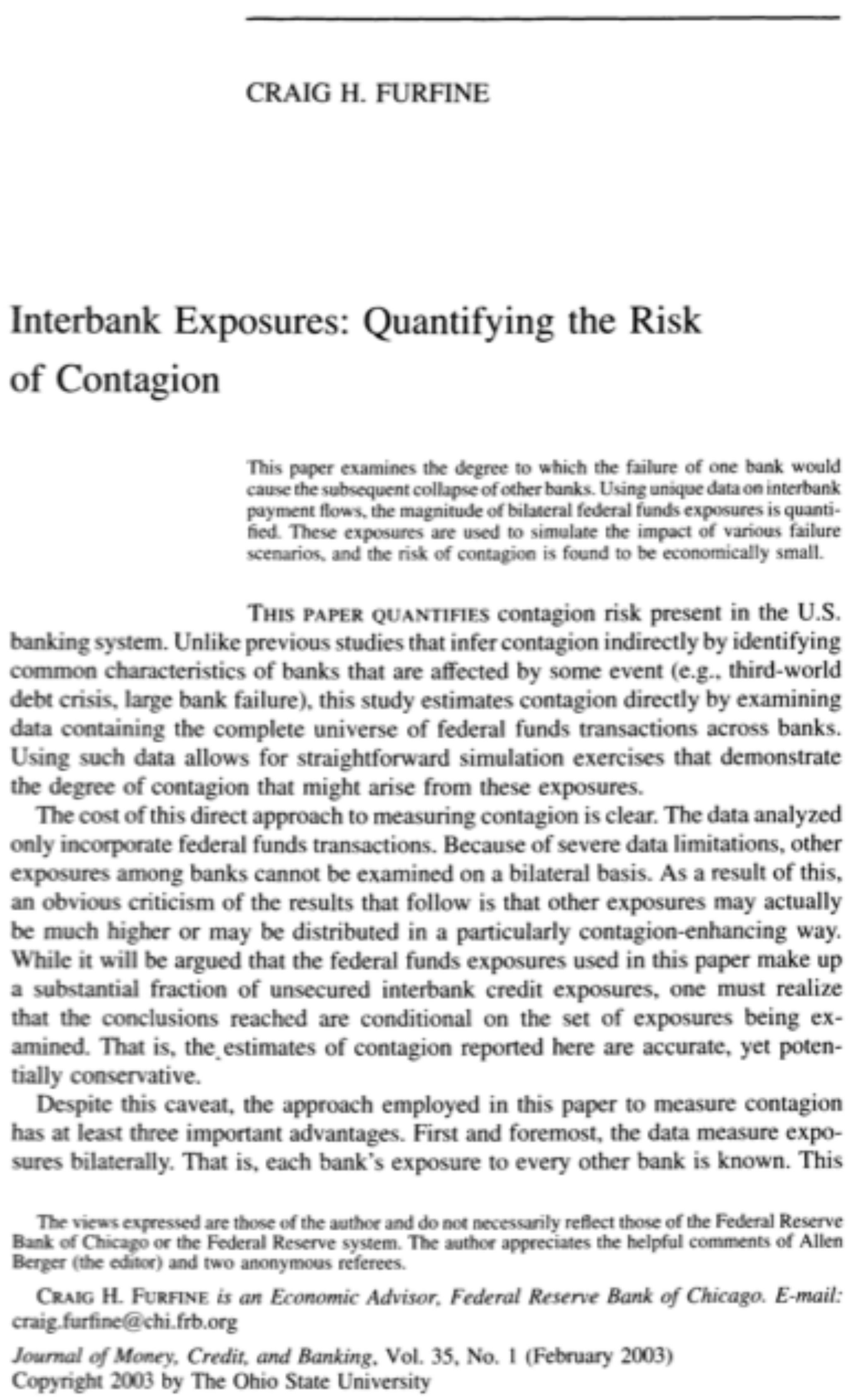

CRAIG H. FURFINE

Interbank Exposures: Quantifying the Risk of Contagion

This paper examines the degree to which the failure of one bank would cause the subsequent collapse of other banks. Using unique data on interbank payment flows, the magnitude of bilateral federal funds exposures is quantified. These exposures are used to simulate the impact of various failure scenarios, and the risk of contagion is found to be economically small.

THIS PAPER QUANTIFIES contagion risk present in the U.S. banking system. Unlike previous studies that infer contagion indirectly by identifying common characteristics of banks that are affected by some event (e.g., third-world debt crisis, large bank failure), this study estimates contagion directly by examining data containing the complete universe of federal funds transactions across banks. Using such data allows for straightforward simulation exercises that demonstrate the degree of contagion that might arise from these exposures.

The cost of this direct approach to measuring contagion is clear. The data analyzed only incorporate federal funds transactions. Because of severe data limitations, other exposures among banks cannot be examined on a bilateral basis. As a result of this, an obvious criticism of the results that follow is that other exposures may actually be much higher or may be distributed in a particularly contagion-enhancing way. While it will be argued that the federal funds exposures used in this paper make up a substantial fraction of unsecured interbank credit exposures, one must realize that the conclusions reached are conditional on the set of exposures being examined. That is, the estimates of contagion reported here are accurate, yet potentially conservative.

Despite this caveat, the approach employed in this paper to measure contagion has at least three important advantages. First and foremost, the data measure exposures bilaterally. That is, each bank's exposure to every other bank is known. This

The views expressed are those of the author and do not necessarily reflect those of the Federal Reserve Bank of Chicago or the Federal Reserve system. The author appreciates the helpful comments of Allen Berger (the editor) and two anonymous referees.

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Journal of Money, Credit, and Banking, Vol. 35, No. 1 (February 2003)

Furfine (2003), *Interbank Exposures: Quantifying the Risk of Contagion*, JMCB

"This paper examines the degree to which the failure of one bank would cause the subsequent collapse of other banks. Using unique data on interbank payment flows [in the U.S.], the magnitude of bilateral federal funds exposures is quantified. These exposures are used to simulate the impact of various failure scenarios, and the risk of contagion is found to be economically small."

What was missing?

Contagion mechanism

- Eisenberg-Noe fictitious default algorithm using book value (no behavior)
- Underestimation of contagion
- Late developments: new mechanisms, e.g. DebtRank

Data

- Only one type of exposure: uncovered interbank loans in the U.S.
- Banks have different types of exposures: Financial multilayer (multiplex) network
- How does the multilayer nature of financial networks matter for estimating systemic risk?

Introduction

In this paper we

- consider a data set of different exposures between banks in Mexico
- analyze individual layers and the combined multilayer network
- using systemic risk measures based on DebtRank

Introduction

We find that

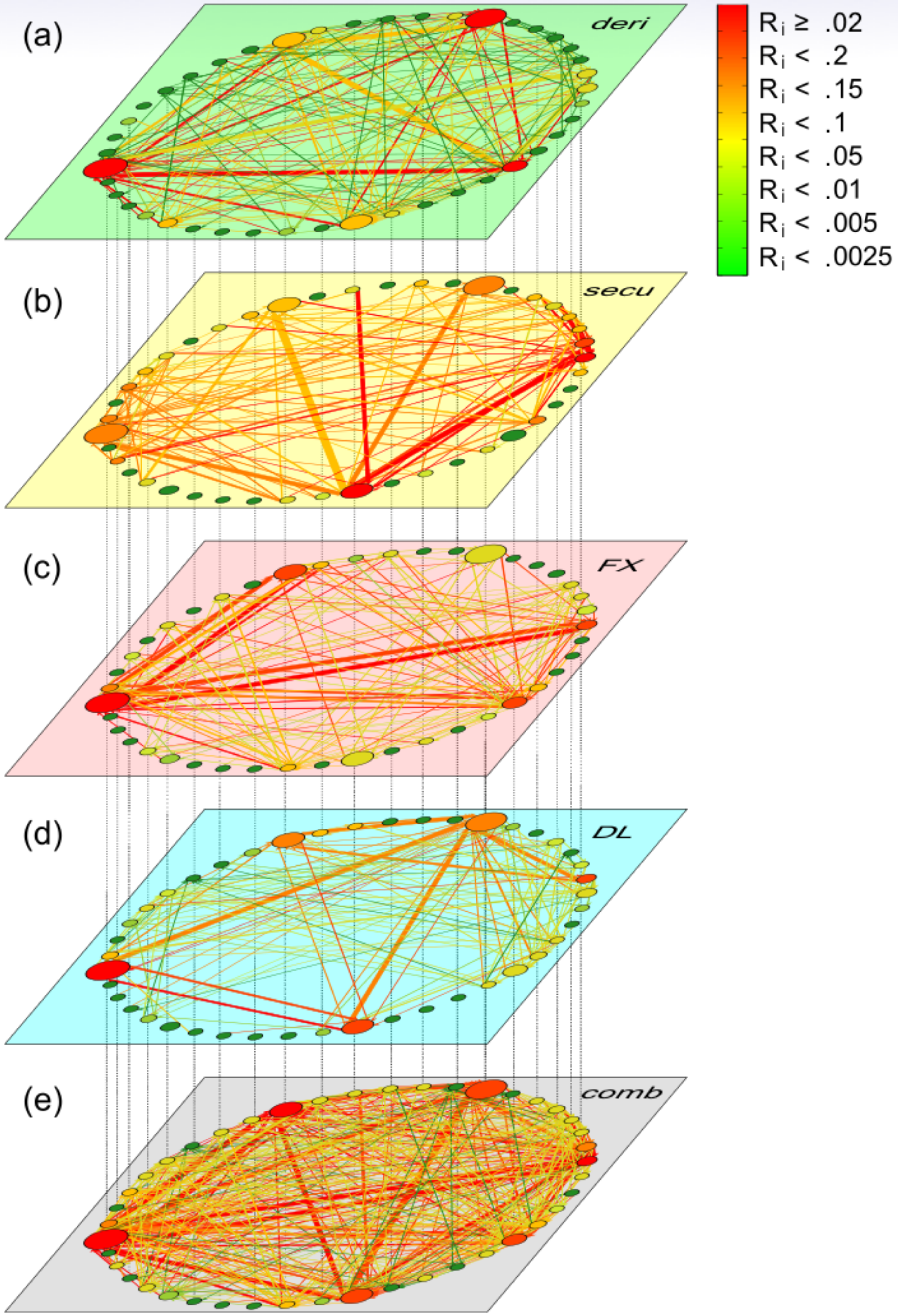
- Using only the layer of interbank loans underestimates systemic risk by 90%
- Systemic risk of the combined exposure network is higher than the sum of the 4 layers: *non-linear effect of combining layers*
- Financial markets underestimates current systemic risk
- The contribution of a credit transaction to expected systemic loss is up to a hundred times higher than the corresponding credit risk

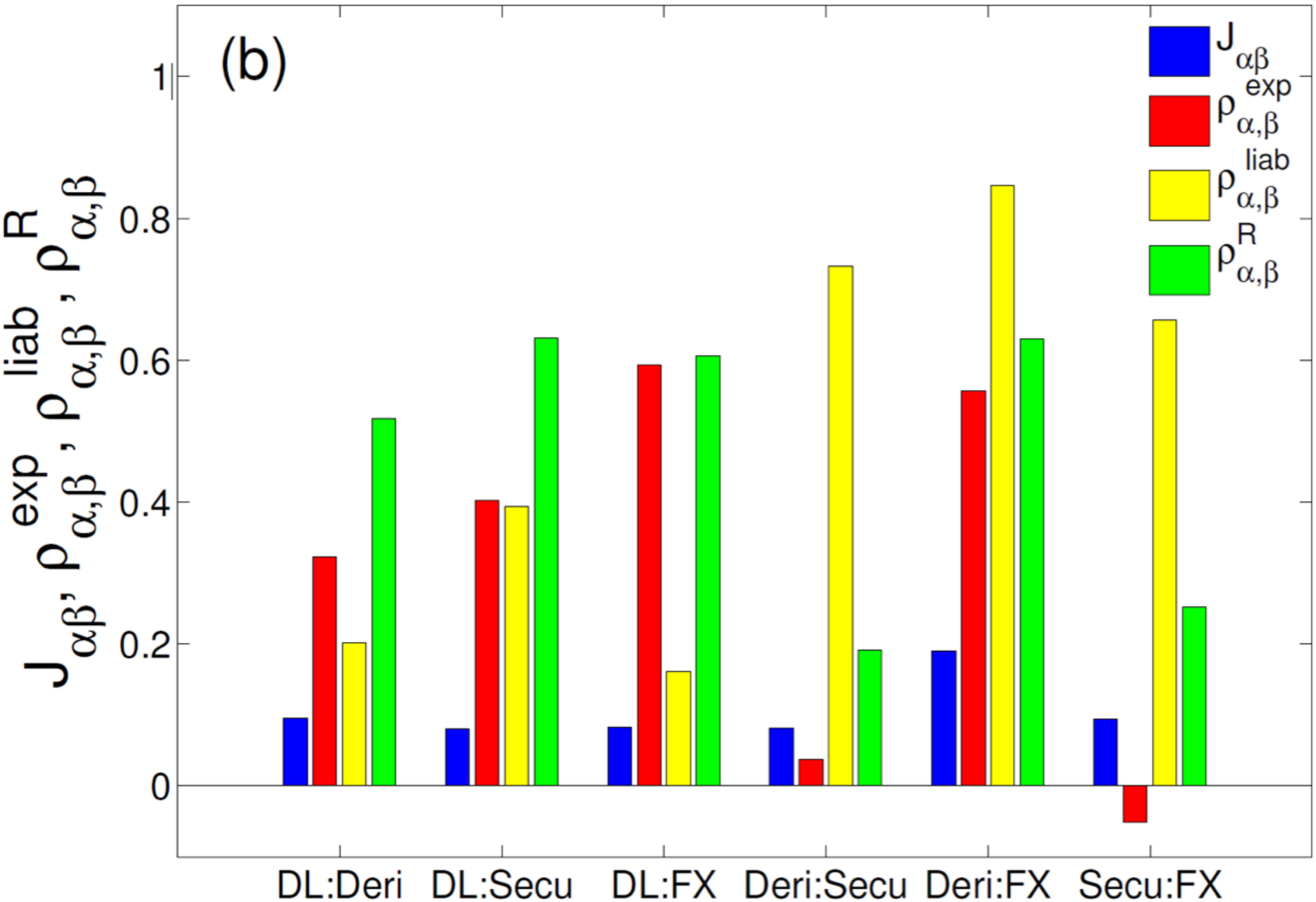
Data

Daily bilateral exposures on 43 banks in Mexico (from January 2, 2007 to May 30, 2013) arising from

1. Derivatives: valuation of derivatives transactions (swaps, forwards and options), repo transactions and securities trading.
2. Securities: securities issued by one bank that are held by another bank
3. Foreign Exchange: exposures from FX transactions
4. Deposits & Loans: Interbank deposits and loans in local and foreign currency, credit lines extended for settlement purposes.

The *combined* network of exposure is obtained by *aggregating the individual layer exposures*.

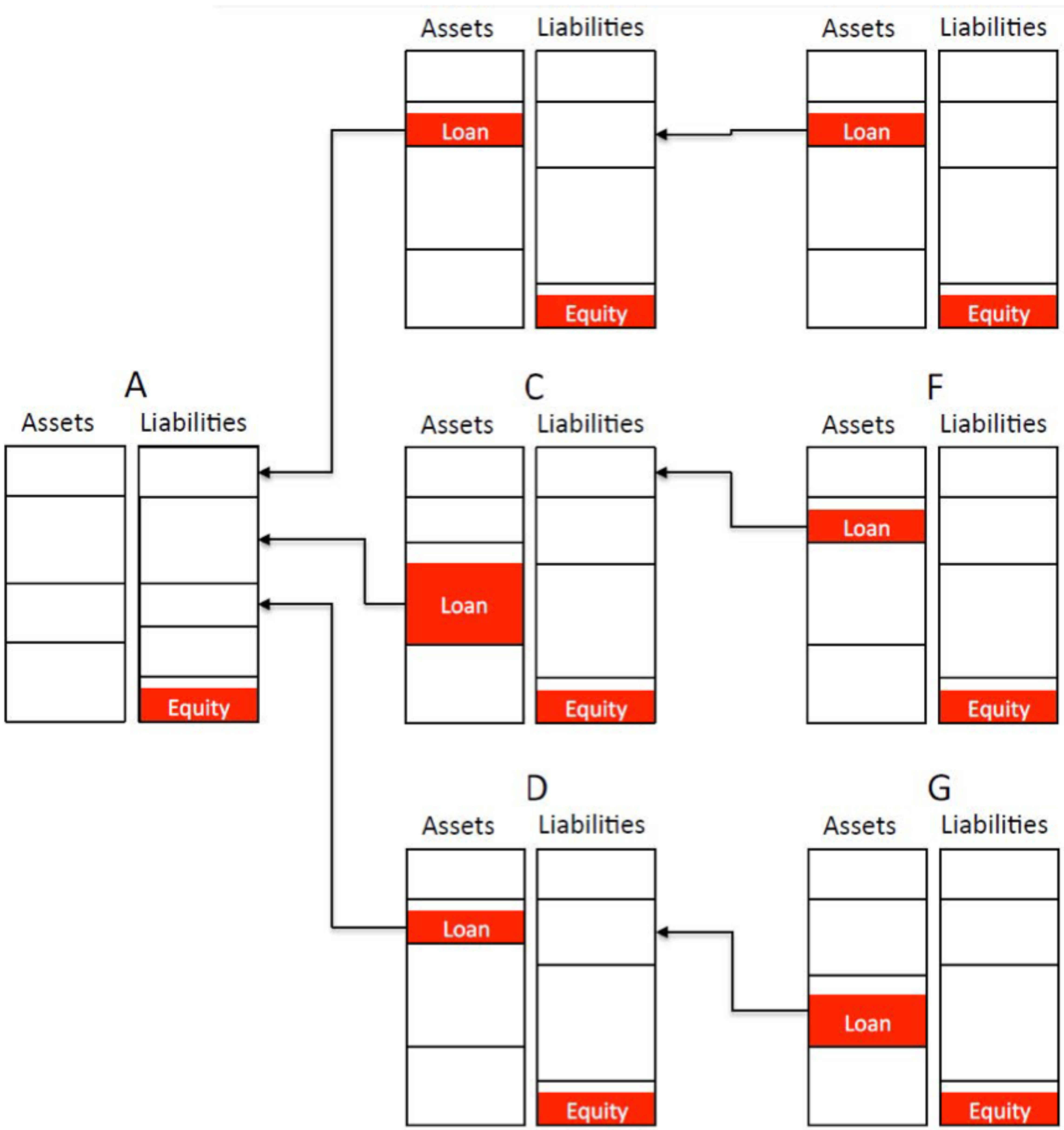

(a)
deri
(b)
secu
(c)
FX
(d)
DL
(e)
comb
$R_i \geq .02$
$R_i < .2$
$R_i < .15$
$R_i < .1$
$R_i < .05$
$R_i < .01$
$R_i < .005$
$R_i < .0025$


(b)
$J_{\alpha\beta}$
$\rho^{exp}_{\alpha,\beta}$
$\rho^{liab}_{\alpha,\beta}$
$\rho^{R}_{\alpha,\beta}$
$J_{\alpha\beta}, \rho^{exp}_{\alpha,\beta}, \rho^{liab}_{\alpha,\beta}, \rho^{R}_{\alpha,\beta}$
1
0.8
0.6
0.4
0.2
0
DL:Deri
DL:Secu
DL:FX
Deri:Secu
Deri:FX
Secu:FX

DebtRank

- Recursive method suggested by Battiston et al. (2012) to quantify the systemic importance of nodes in terms of losses
- Measures the fraction of the total economic value in the financial system that is potentially lost by the default of a single bank.
- $\hat{R}_i^{\alpha}$ is the DebtRank of bank i in layer α.

DebtRank


Assets
Liabilities
Loan
Equity
Assets
Liabilities
Loan
Equity
A
Assets
Liabilities
Equity
C
Assets
Liabilities
Loan
Equity
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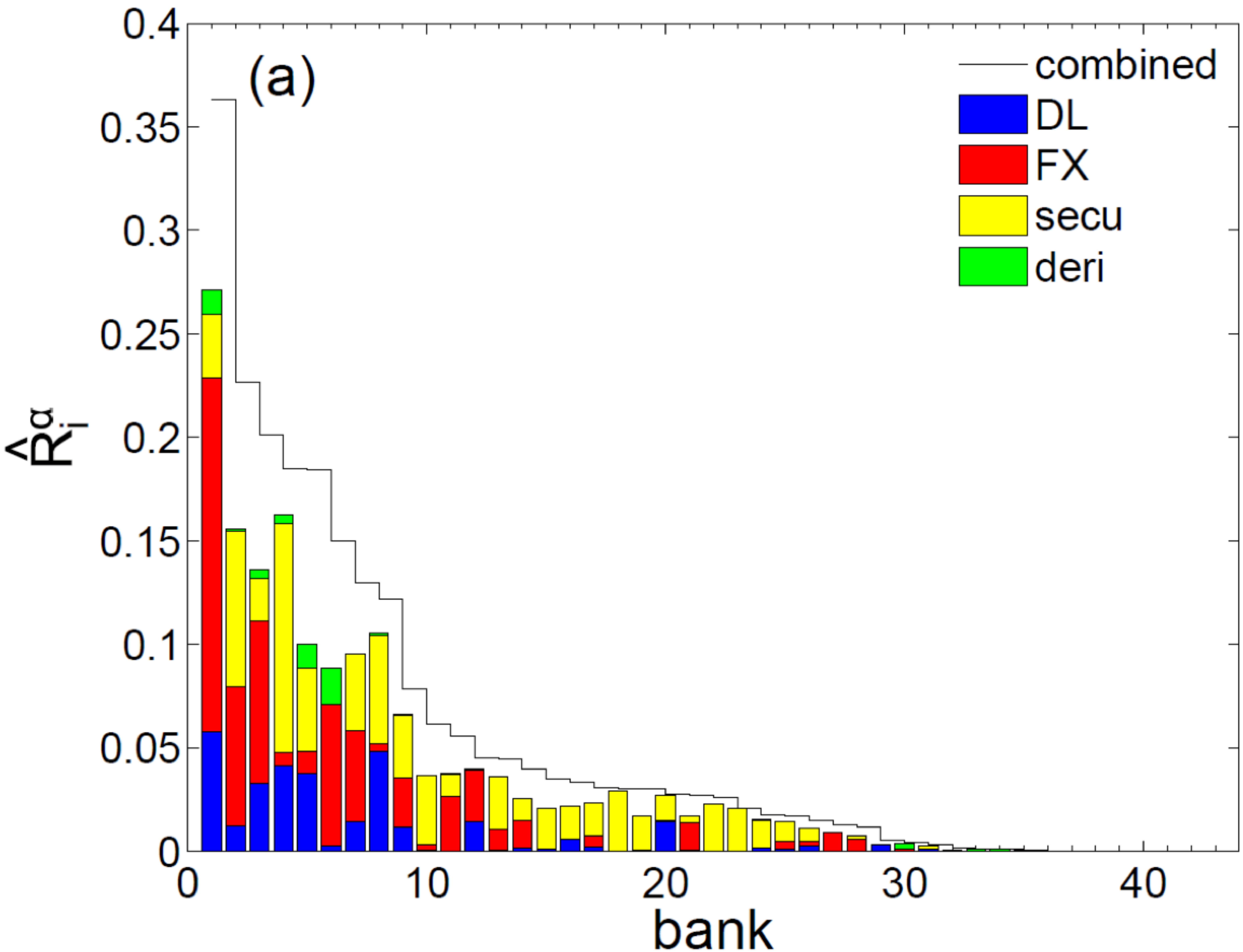
G
Assets
Liabilities
Loan
Equity


(a)
combined
DL
FX
secu
deri
$\hat{R}_i^\alpha$
bank
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
10
20
30
40

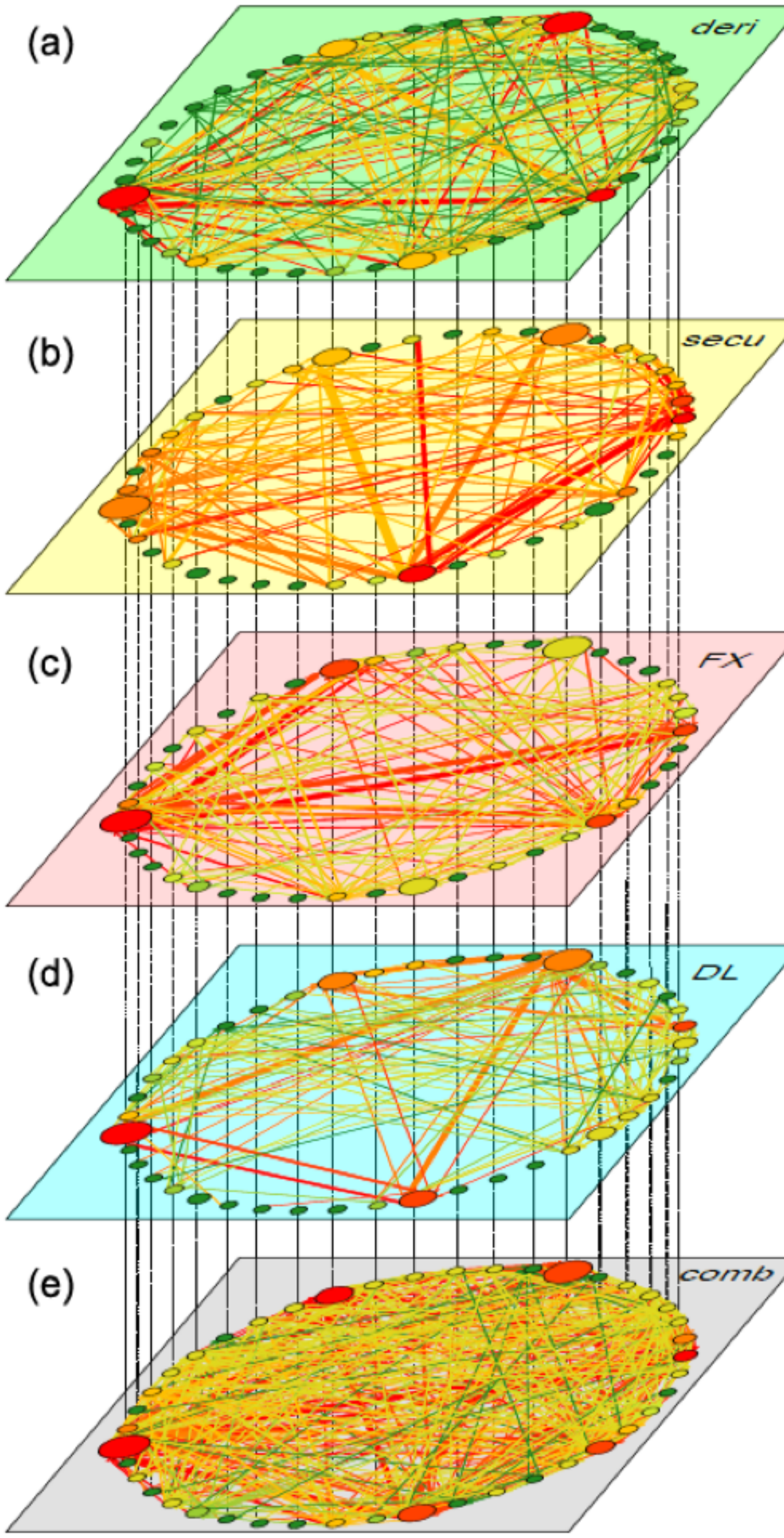
Layers matter and may increase systemic risk

A

B

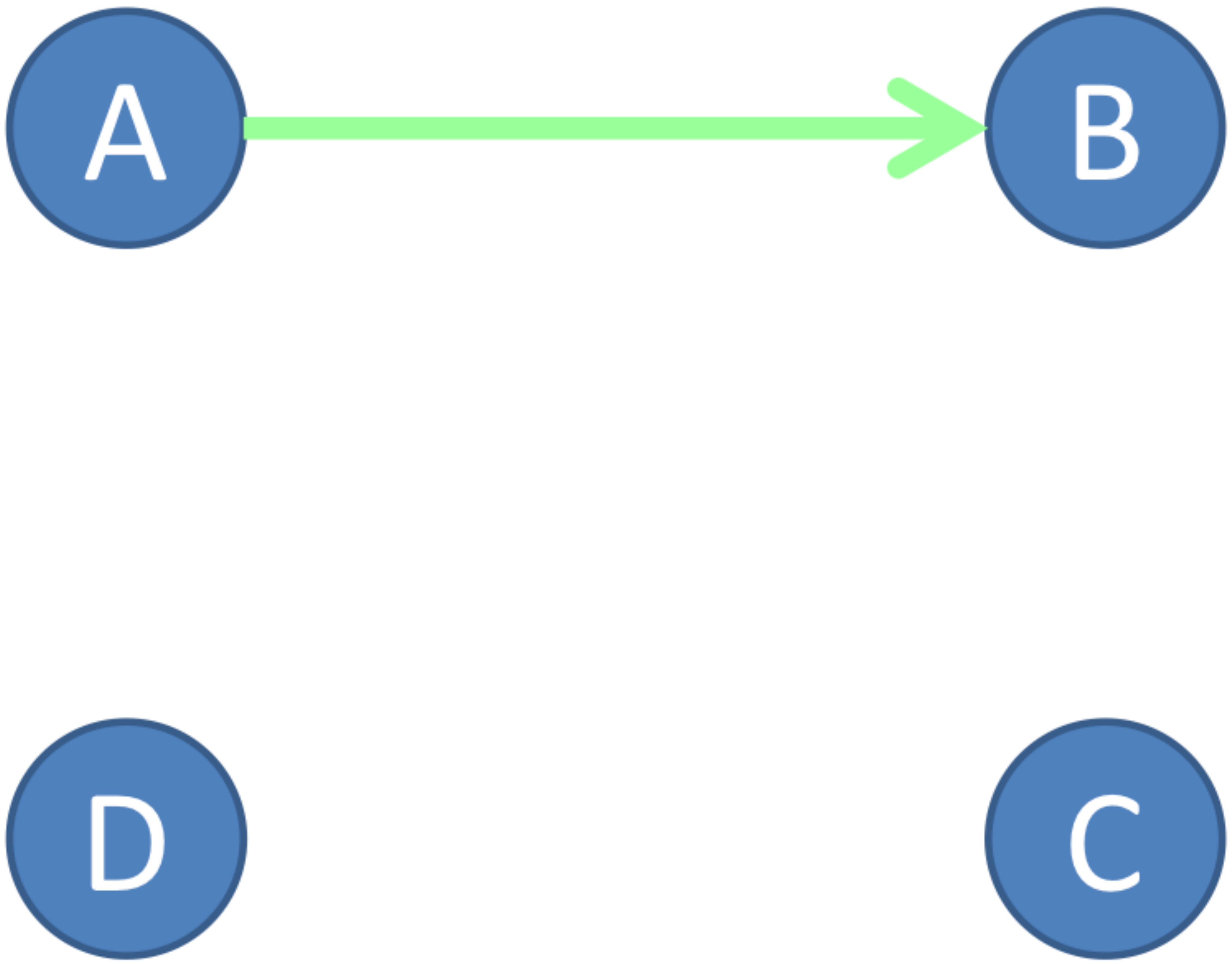
D

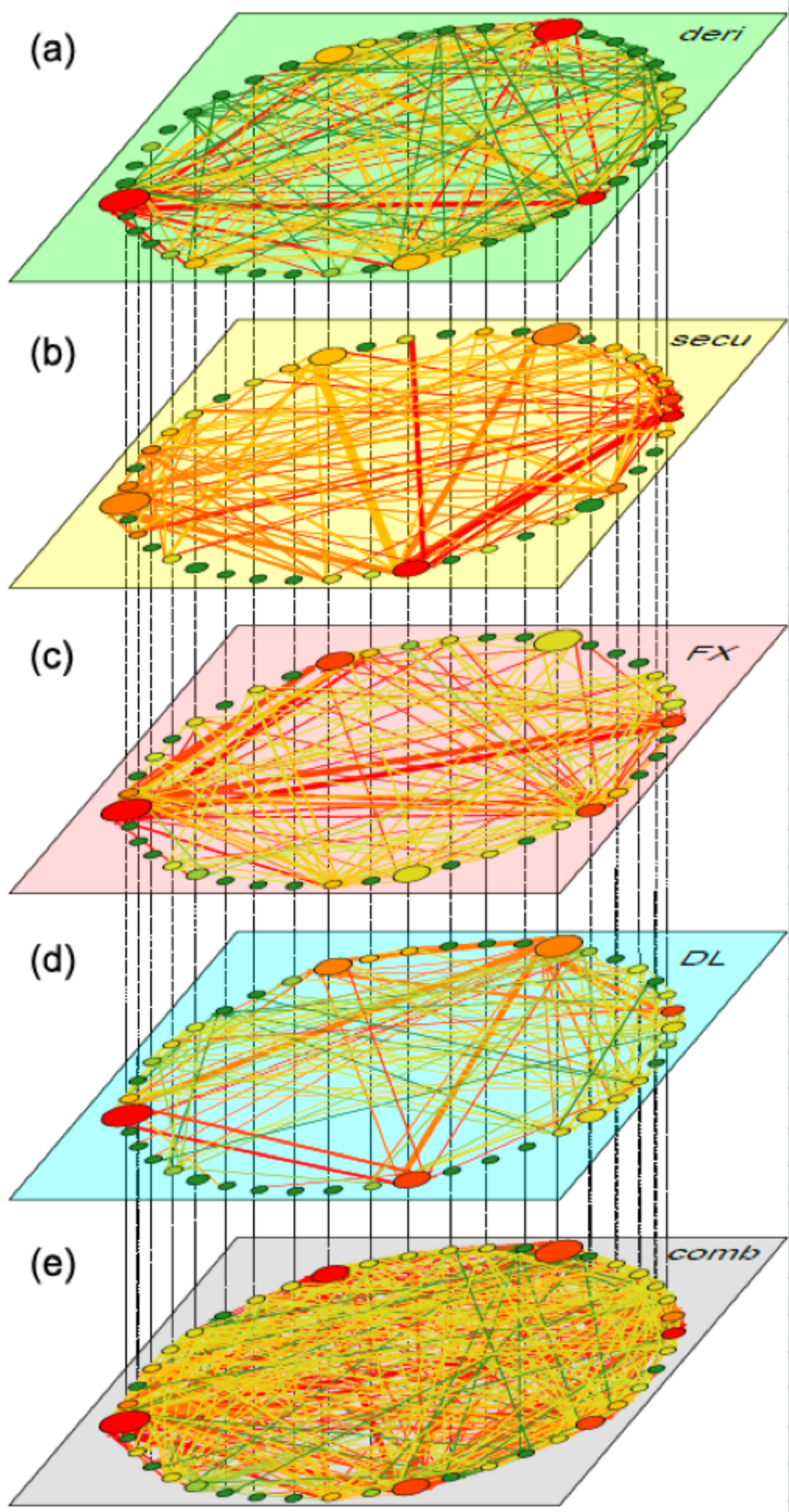
C



Comments by Andre Lucas

Layers matter and may increase systemic risk





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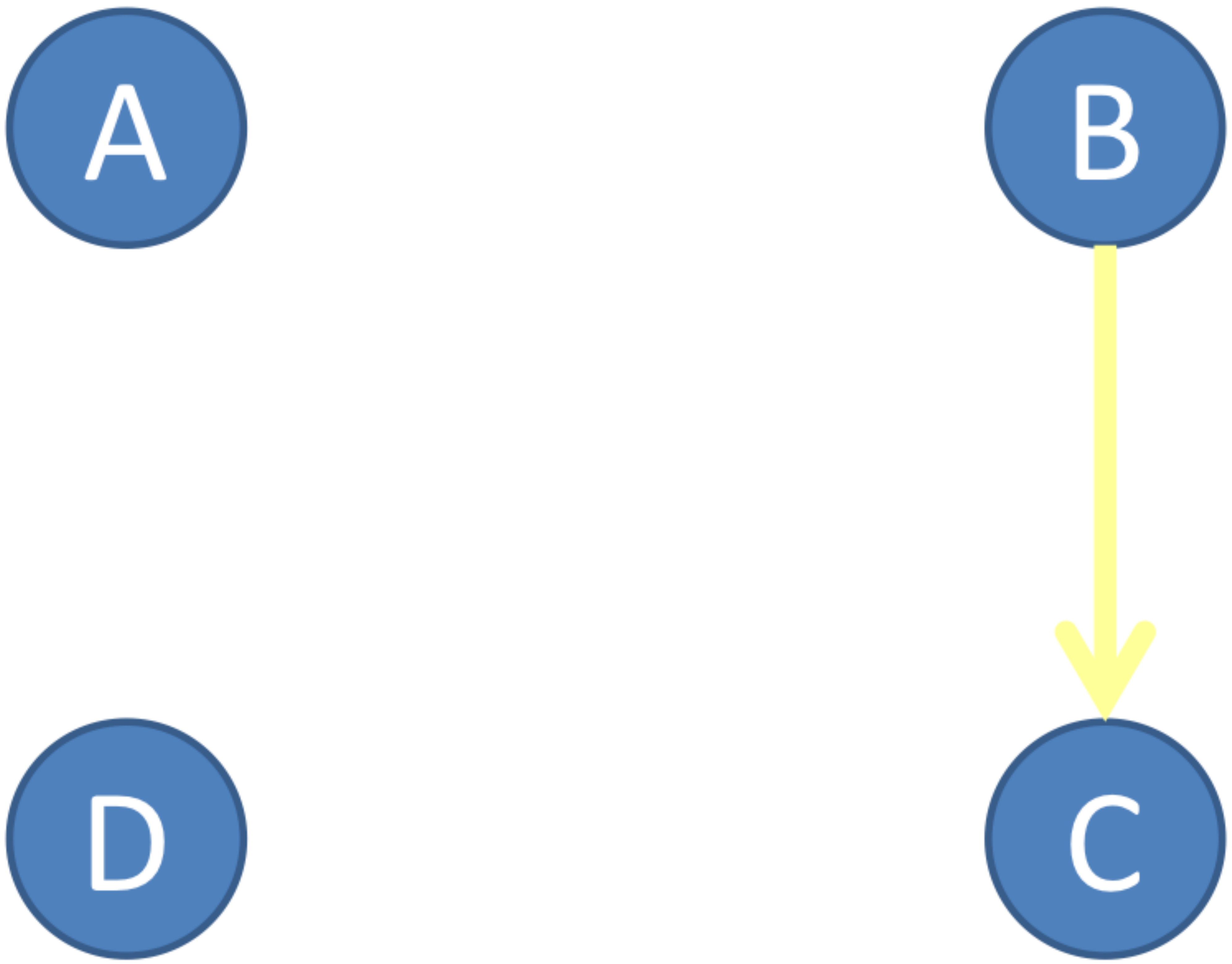

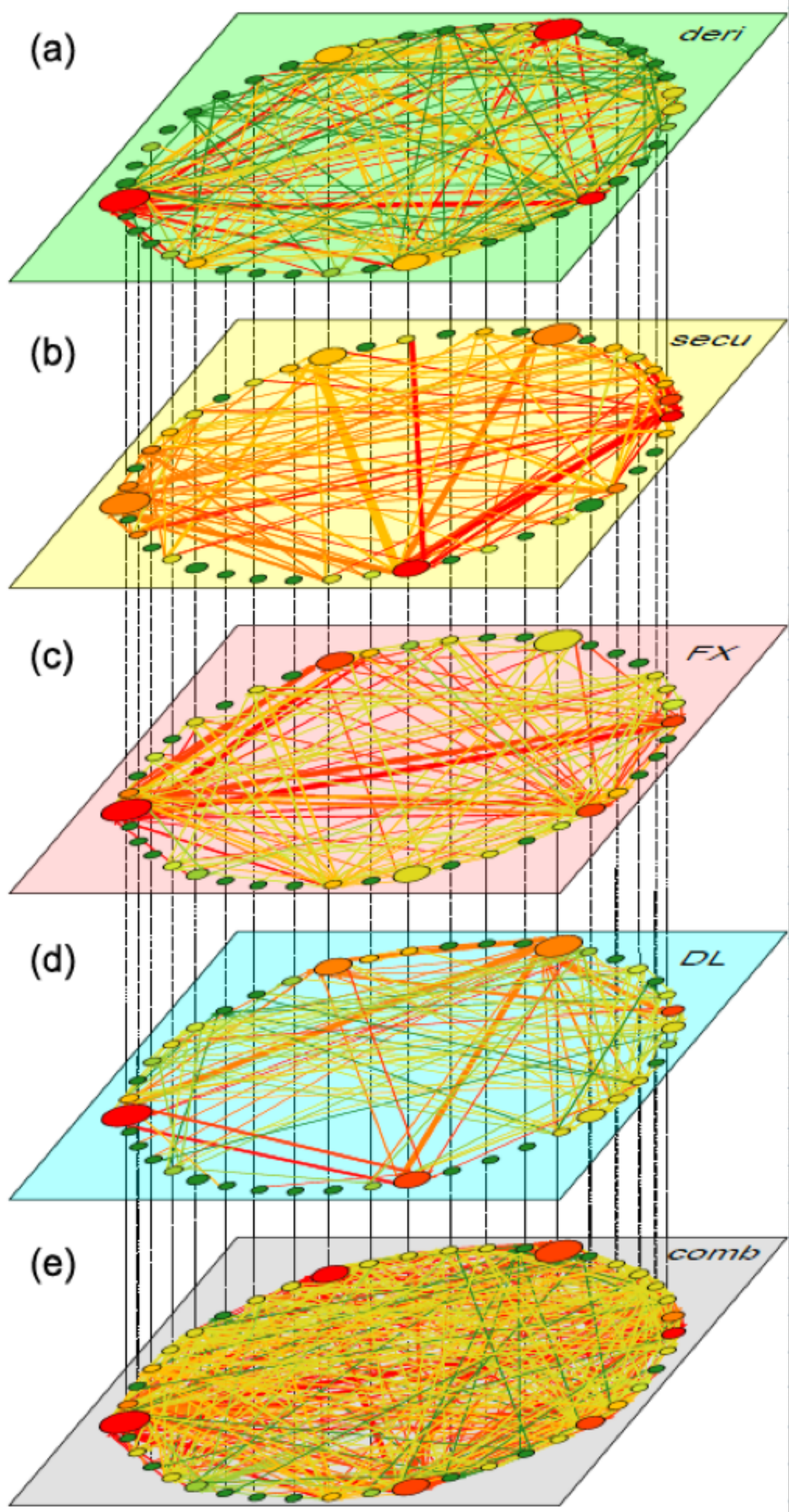

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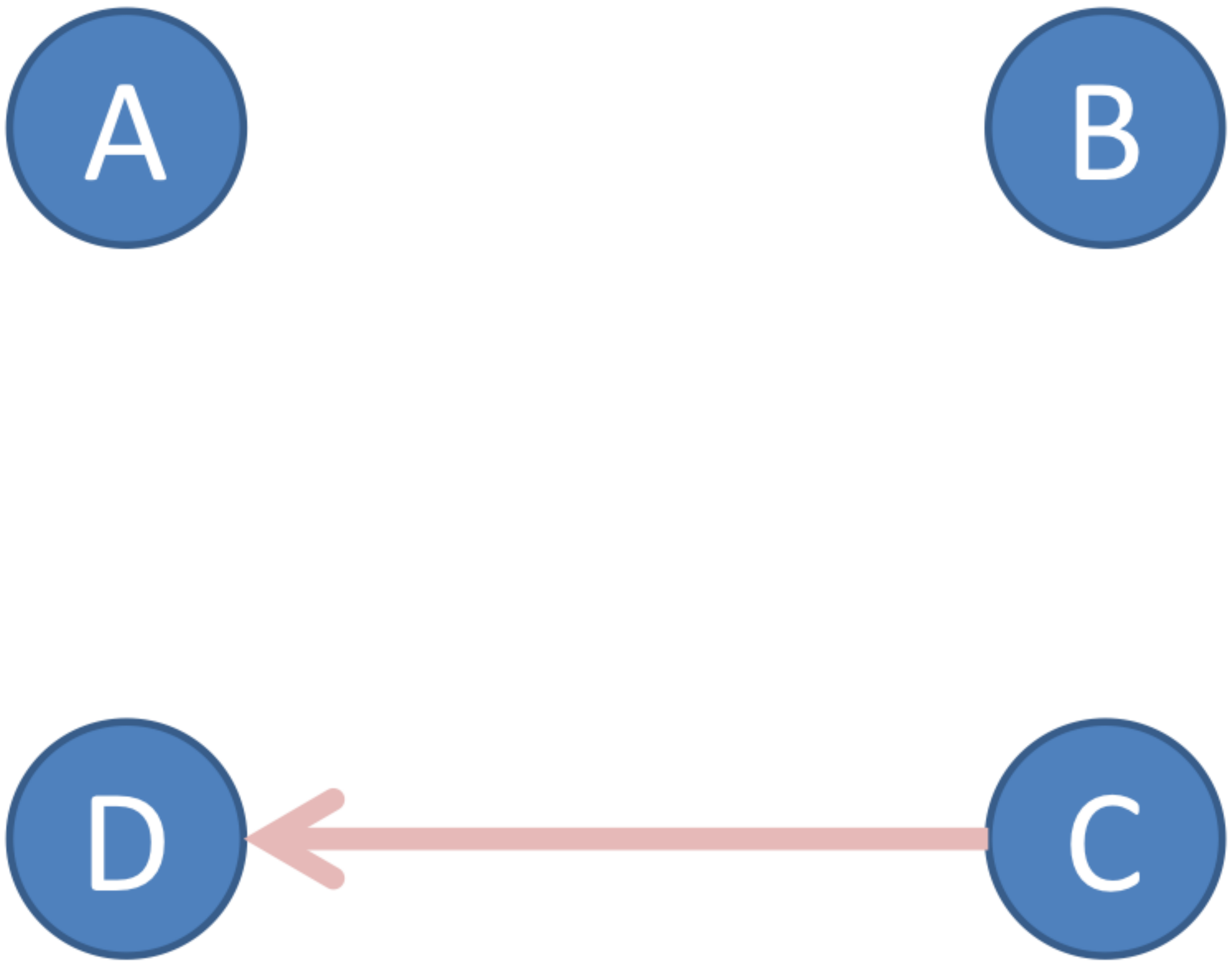

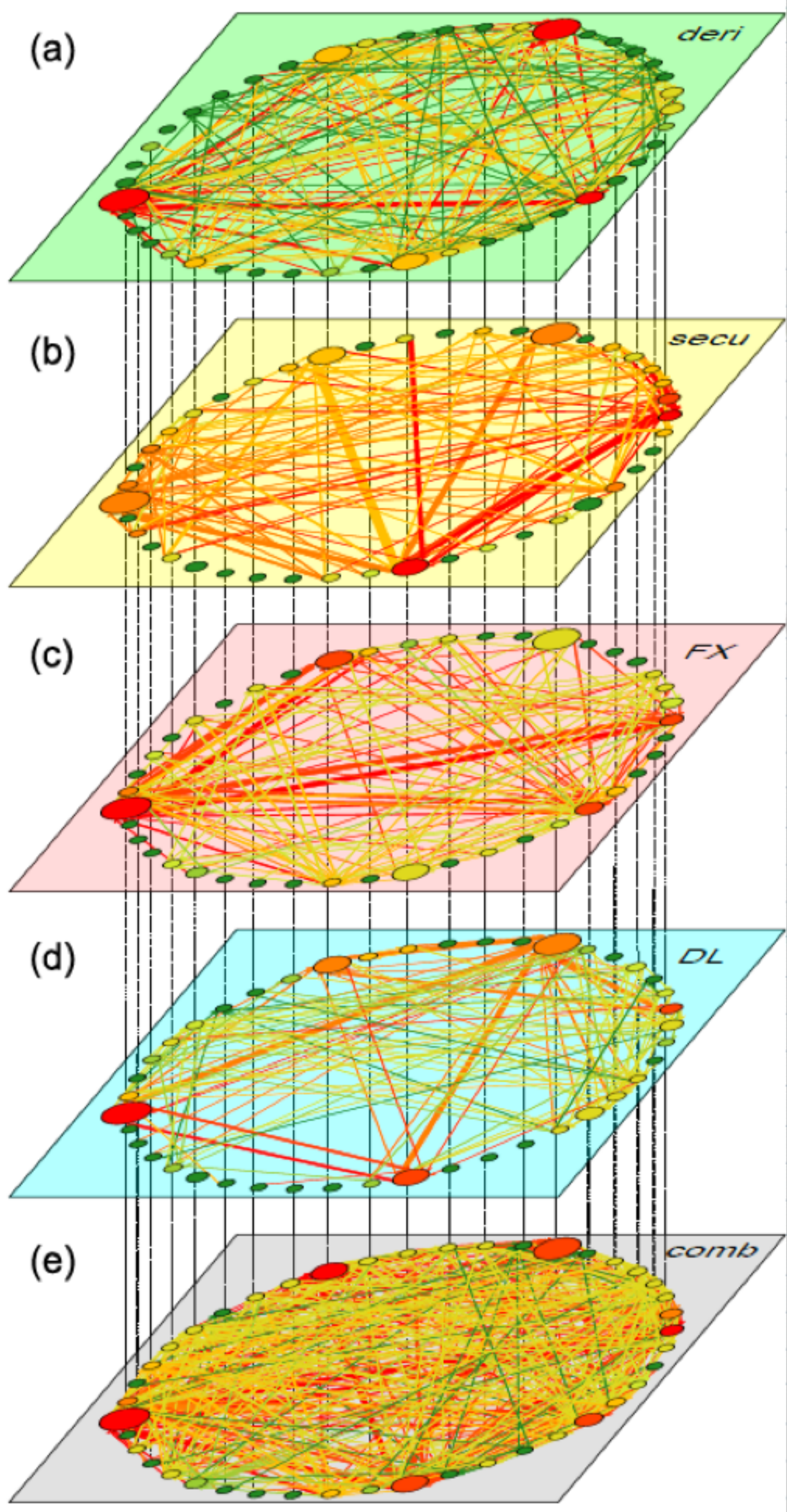

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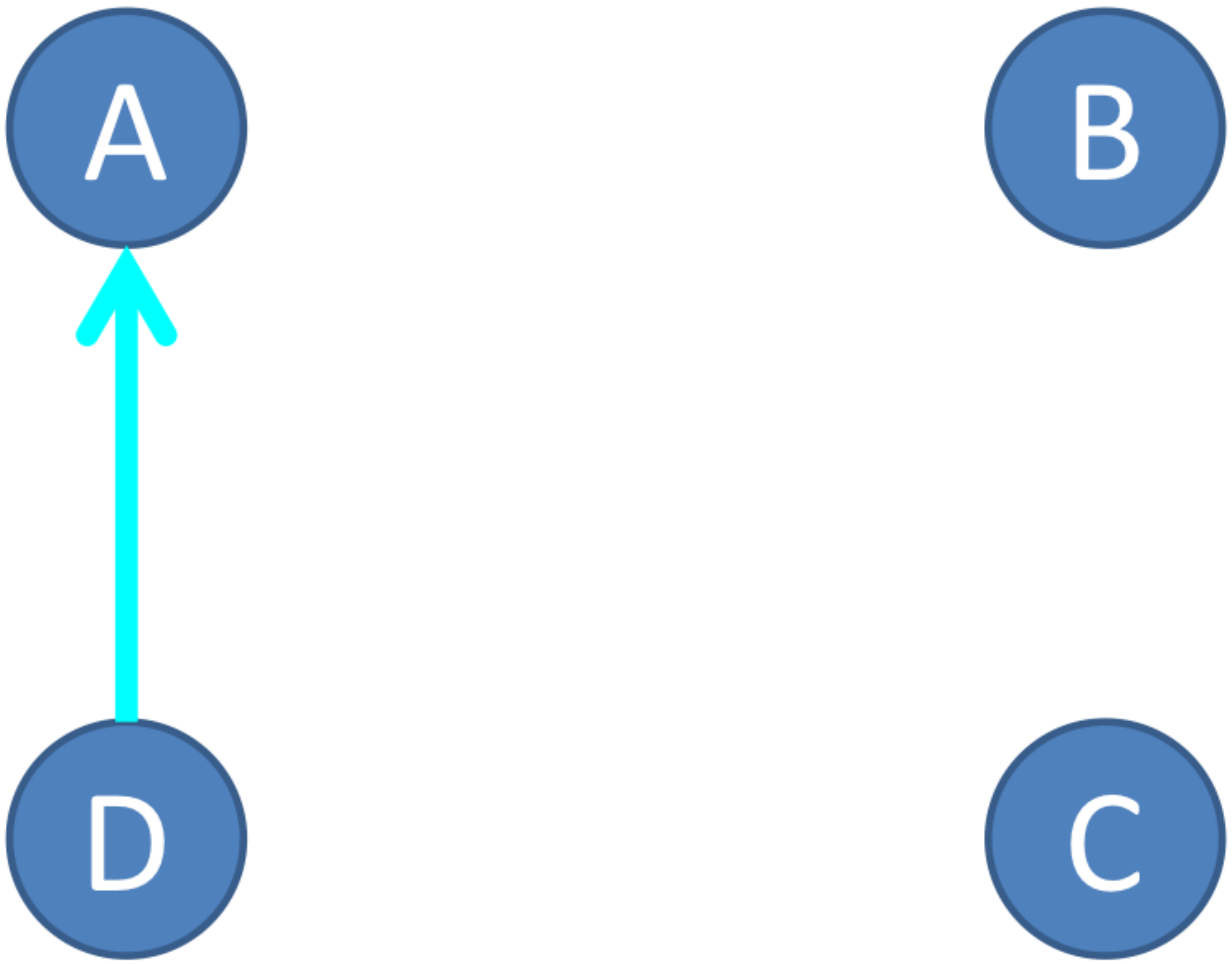

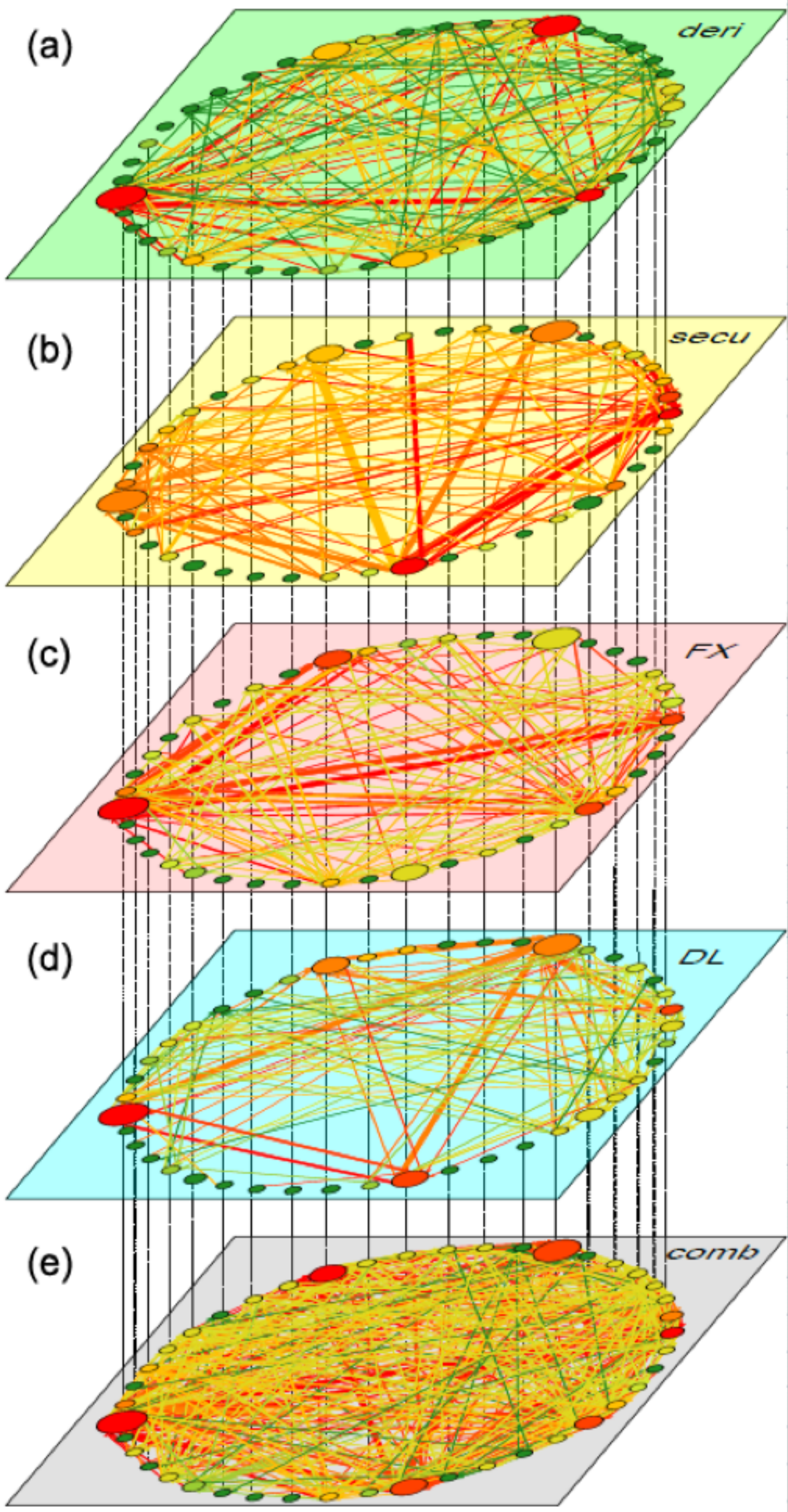

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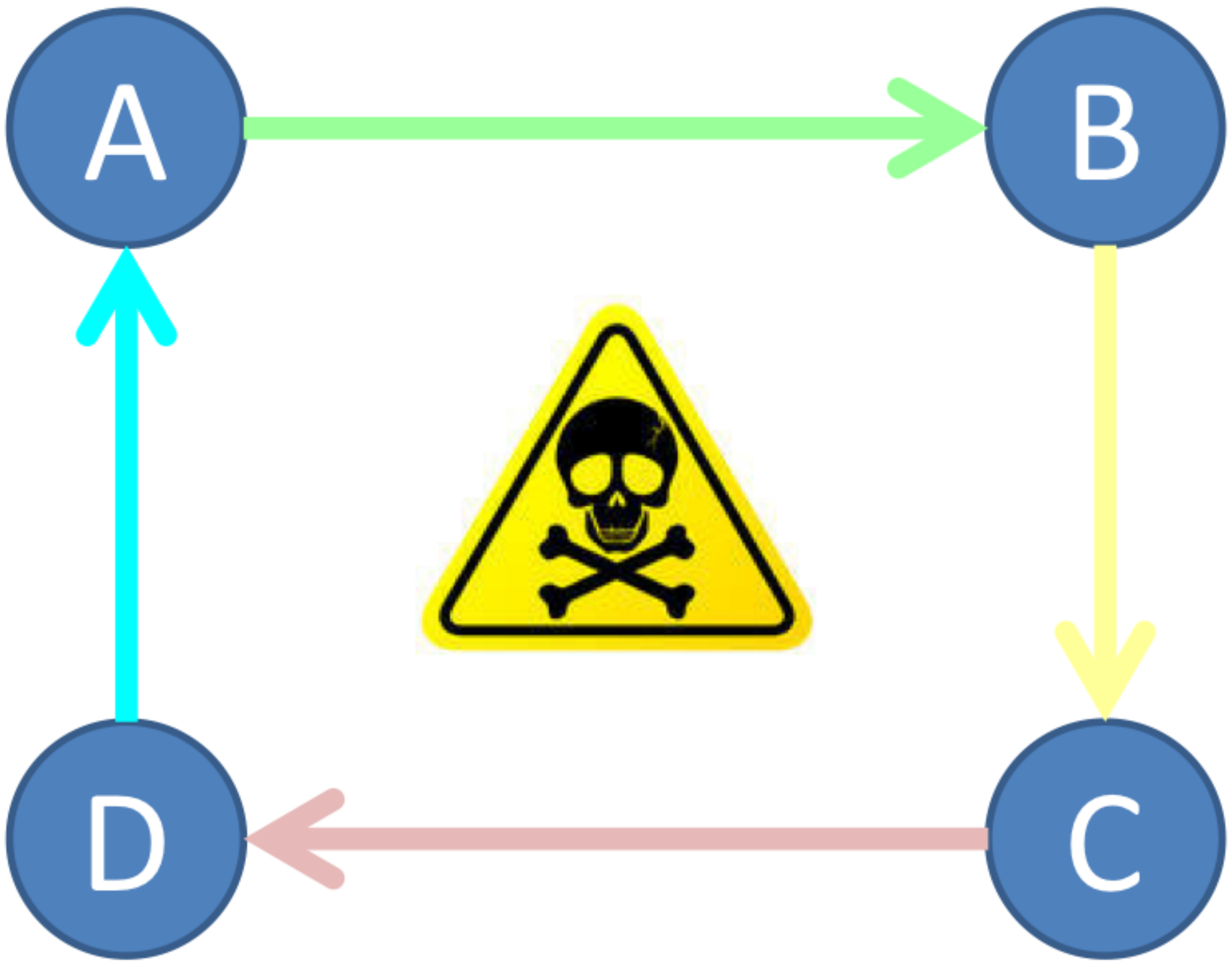
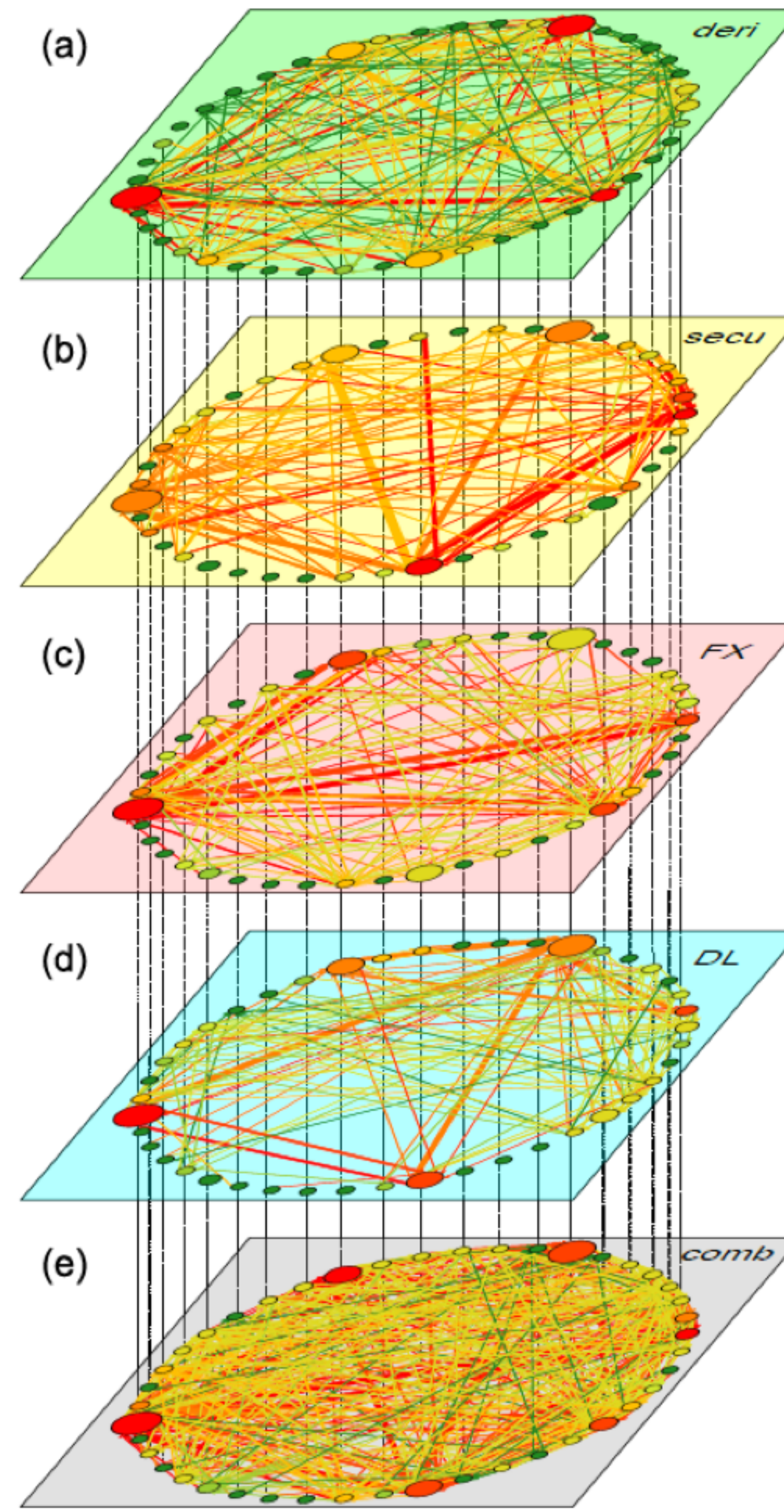
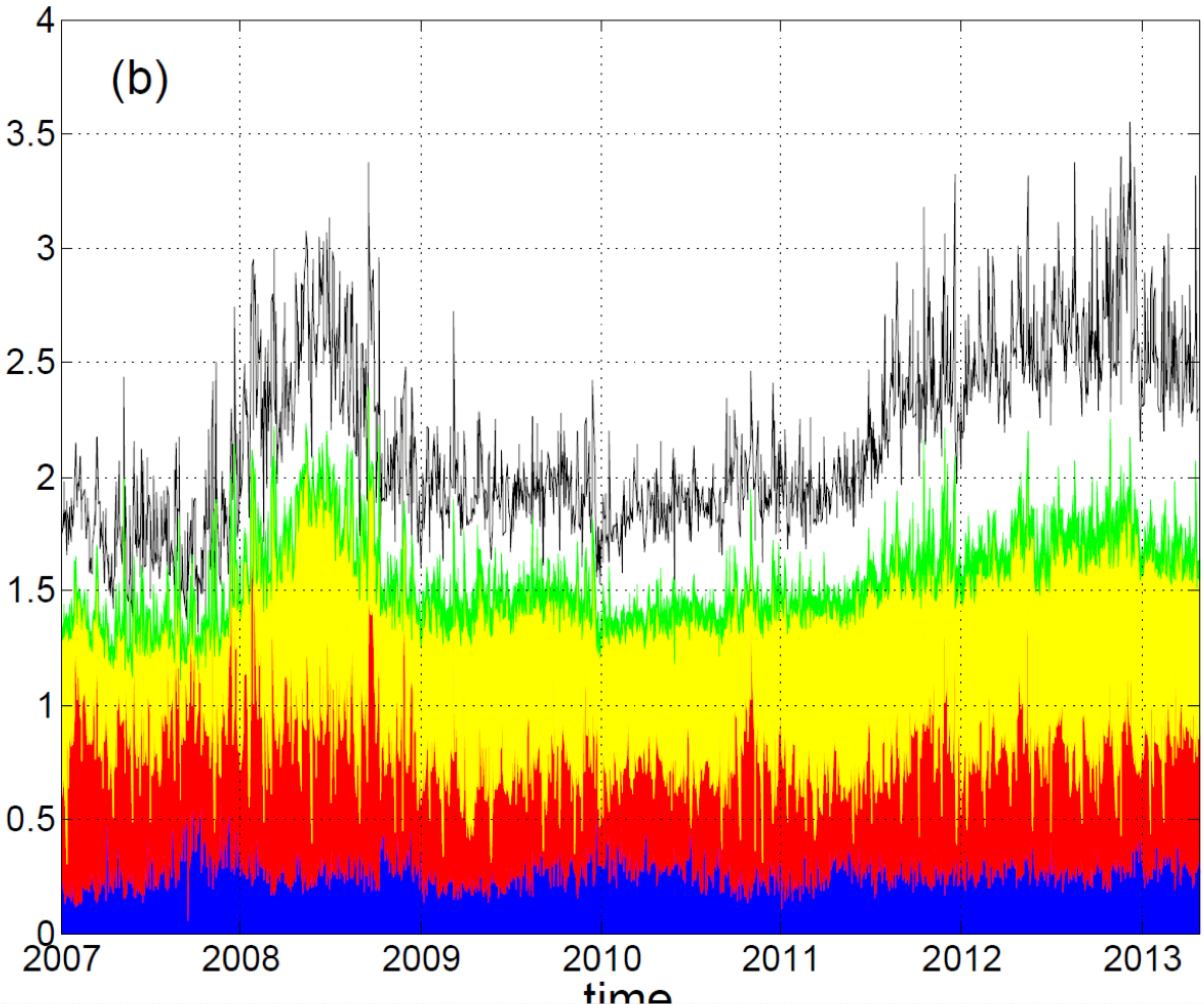




Comments by Andre Lucas

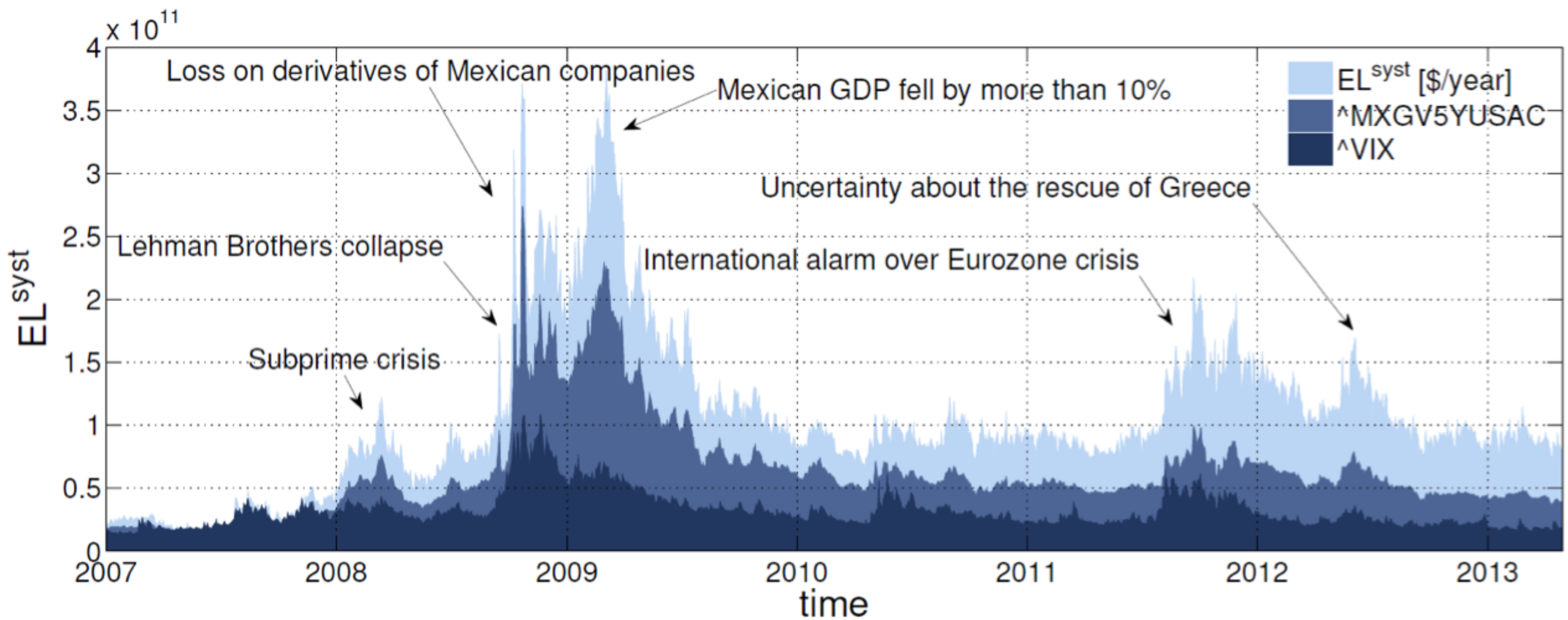
Systemic Risk for the Entire System

Define an SR index for the entire system: $SRI^{\alpha}(t) = \sum_{i=1}^{B} \hat{R}_i^{\alpha}(t)$.



Expected Systemic Losses

- Calculated as $EL^{syst} = V^{comb} \sum_{i=1}^{B} p_i^{def} R_i^{comb}$.
- Combines SR contributions from networks and default rates.
- Compare to measure of CDS spread on 5-year Mexican government bond, and VIX volatility index



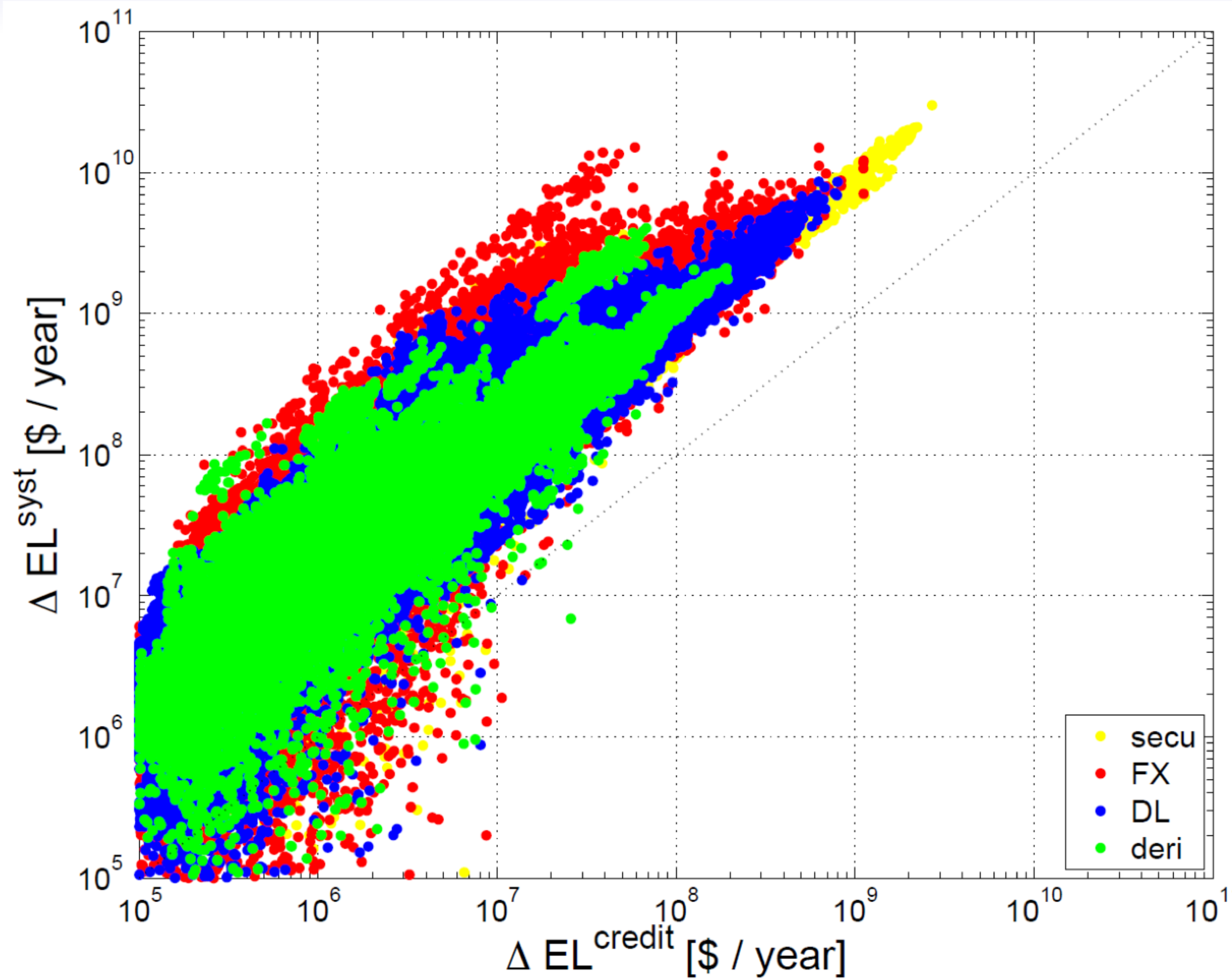
Marginal contribution of individual transactions

Consider an individual loan between bank i and j:

- Marginal contribution to systemic risk: ΔEL^{syst}

Compare to

- Marginal contribution to idiosyncratic credit risk: ΔEL^{credit}



10^{5} 10^{6} 10^{7} 10^{8} 10^{9} 10^{10} 10^{11}
$\Delta\, EL^{syst}$ [$ / year]
$\Delta\, EL^{credit}$ [$ / year]
secu
FX
DL
deri

Conclusion

In this paper we

- consider a data set of different exposures between banks in Mexico
- analyze individual layers and the combined multilayer network
- using systemic risk measures based on DebtRank

Conclusion

We find that

- Using only interbank loans underestimates systemic risk by 90%
- Systemic risk of the combined exposure network is higher than the sum of the 4 layers: non-linear effect of combining layers
- Financial markets underestimates current systemic risk
- The contribution of a credit transaction to expected systemic loss is up to a hundred times higher than the corresponding credit risk

Learning goals

Part 1

- Explain 3 main channels of financial contagion:
  - Default cascades,
  - Funding contagion / liquidity hoarding
  - Fire sales externality
- Compute by hand:
  - Fictitious default algorithm of Eisenberg & Noe (2001)
  - DebtRank algorithm of Bardoscia, Battiston, Caccioli et Cardarelli (2015)

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Learning goals

Part 2

- Give typical characteristics of large networks
- Construct financial network data from balance sheet data and large exposures
- Compute measures of financial contagion:
  - System level: systemic risk, expected systemic loss
  - Bank level: systemic importance, vulnerability
- Explain what is a multilayer network and why it is important for assessing systemic risk
  - Poledna et al. (JFS, 2015)

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