

# Stock Market Volatility Networks

Creating fear spillover networks

# What is Spillover?

Crisis -> High stock market volatility & decreasing stock prices

Global connectedness -> Contagion

1. Who are the **leading players** in stock markets?
2. Are there any special connections between **particular stock markets**?



# But first! What is stock market volatility?

Volatility is latent

Therefore, it has to be estimated!

$$\sigma^2 = \frac{\sum (x - \mu)^2}{N}$$

Best to use 5 minute returns: >100 / day!  
(and extremely hard to get...)



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Garman-Klass (1980)'s range based volatility estimator:

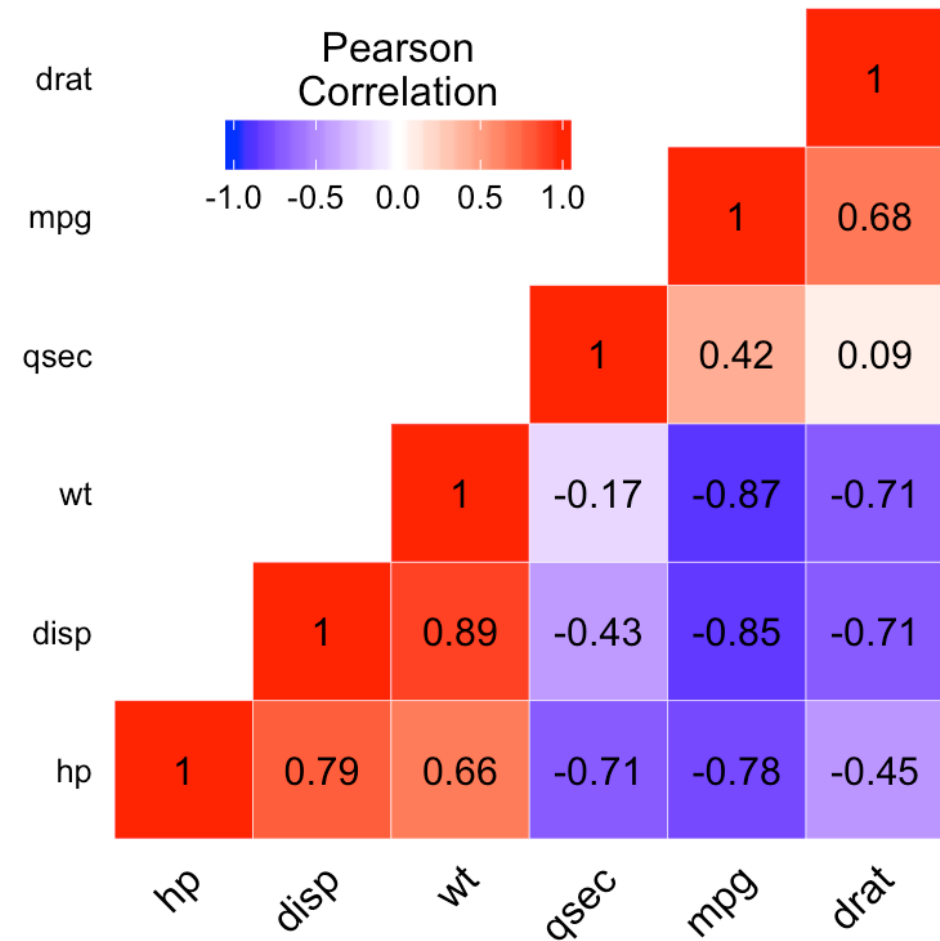
$$(1) \quad \sigma^2 = 0.5 * (h - l)^2 - (2 * \ln(2) - 1) * c^2$$

Open, Close, High, Low price: 4 / day!

Now we have volatility time series!

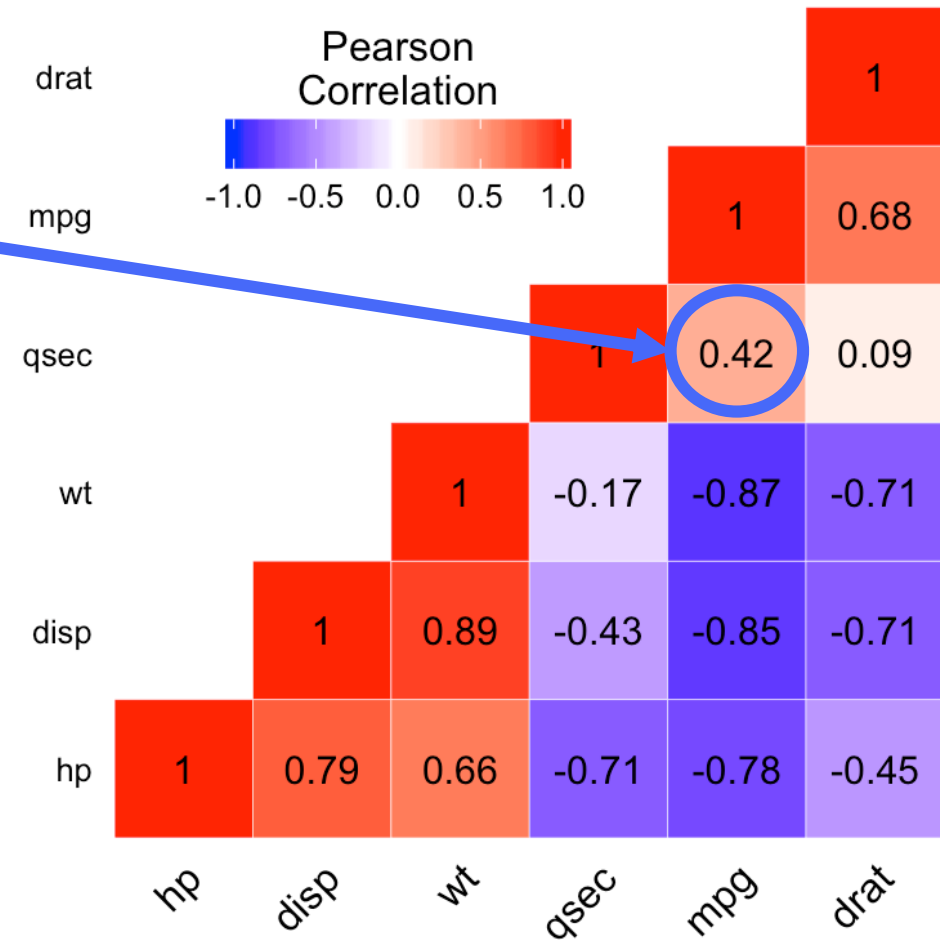


# OK. Why not correlation?



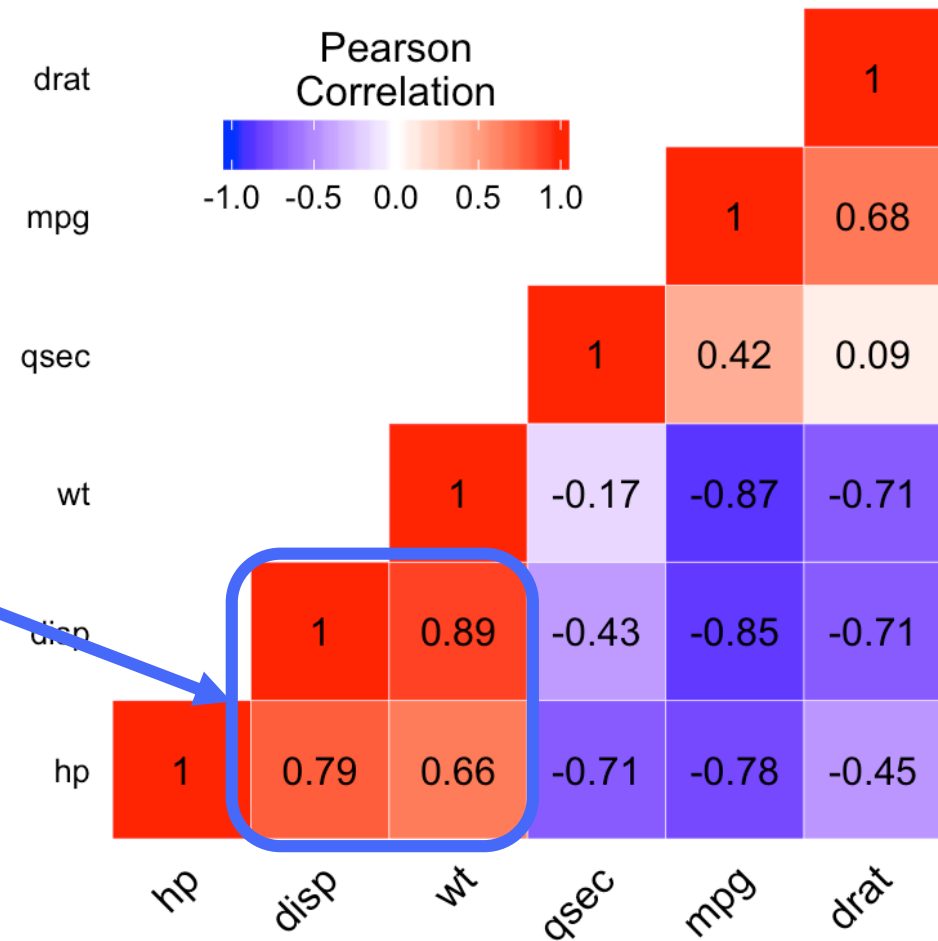
# OK. Why not correlation?

1. We aim to have **directed** effects.



# OK. Why not correlation?

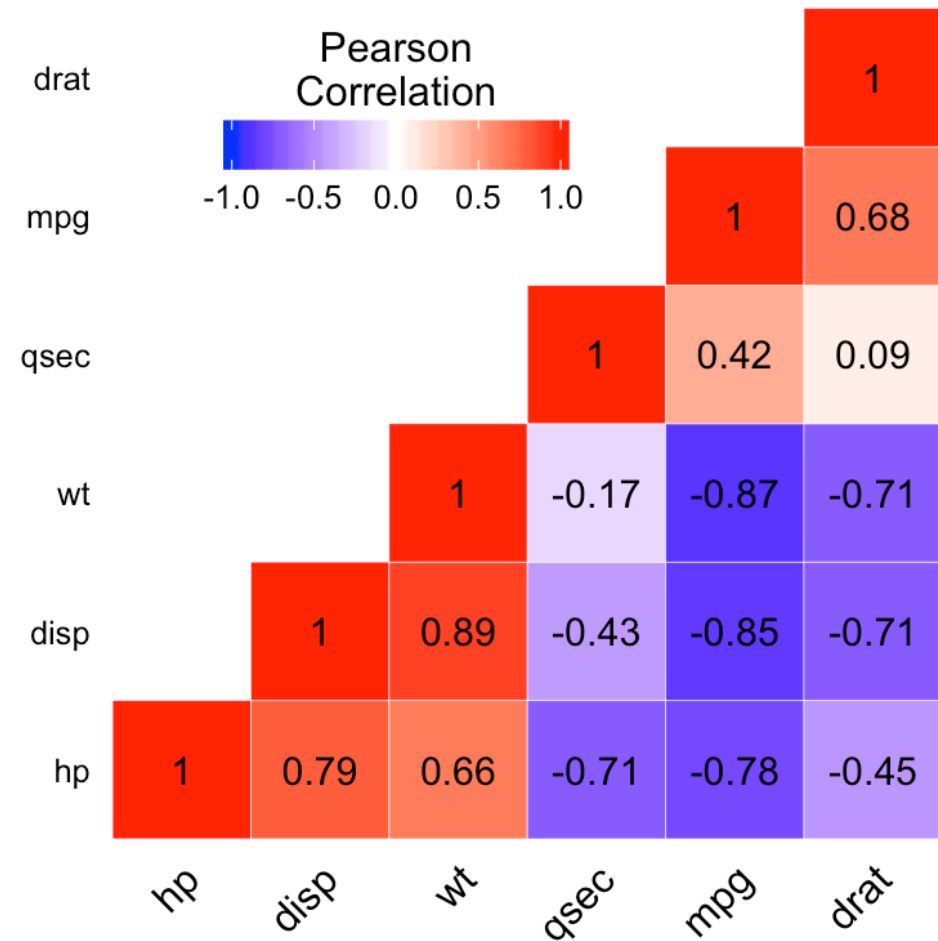
1. We aim to have **directed** effects.
2. We aim to have **conditional** effects.



# OK. Why not correlation?

1. We aim to have **directed** effects.
2. We aim to have **conditional** effects.

We need a better method!





# Diebold-Yilmaz (2009) Spillover Framework

Let's fit a VAR model on the time series of volatilities!

16 leading stock market index (4-4 from Europe, Asia, North and South America), for a 10 year period

$$(12) \quad X_{t+1} = \theta * X_t + \epsilon_{t+1,t}; \quad X_{t+1,t} = \theta * X_t$$

A vector of volatilities in time t.

$$\mathbf{e}_{t+1,t} = \mathbf{x}_{t+1} - \mathbf{x}_{t+1,t} = \mathbf{A}_0 \mathbf{u}_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},$$

Forecast error

Spillover table

Diagonals: effect of own shocks

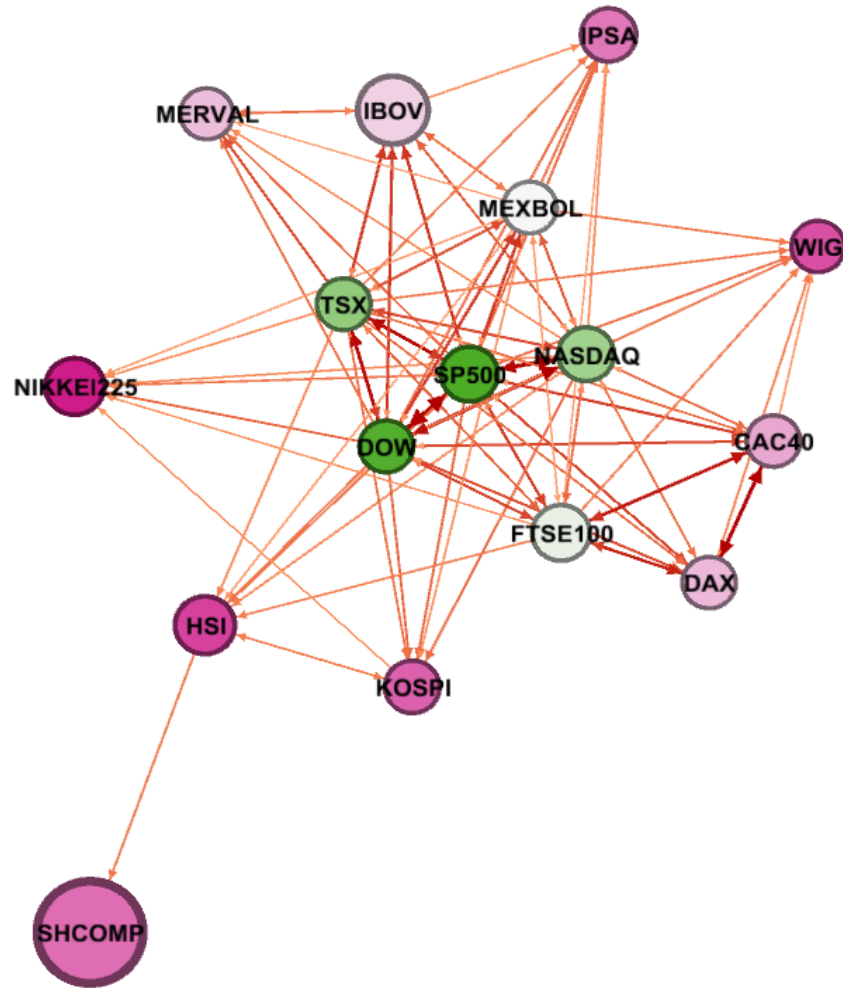
Non-diagonals: Spillover

Daily volatility changes

# A Spillover Table

SPILOVER	SP500	NASDAQ	DOW	TSX	IBOV	MERVAL	IPSA	MEXBOL	FTSE100	DAX	CAC40	WIG	SHCOMP	KOSPI	HSI	NIKKEI225	FROM
SP500	0,17	0,13	0,16	0,10	0,06	0,04	0,03	0,06	0,07	0,05	0,05	0,03	0,00	0,02	0,02	0,01	0,83
NASDAQ	0,15	0,17	0,14	0,09	0,05	0,04	0,03	0,06	0,06	0,05	0,05	0,03	0,01	0,03	0,02	0,01	0,83
DOW	0,16	0,12	0,17	0,10	0,06	0,04	0,03	0,06	0,07	0,05	0,05	0,03	0,01	0,02	0,02	0,02	0,83
TSX	0,12	0,09	0,12	0,20	0,06	0,05	0,04	0,06	0,07	0,05	0,05	0,03	0,01	0,03	0,02	0,01	0,80
IBOV	0,10	0,08	0,10	0,10	0,24	0,07	0,04	0,08	0,05	0,03	0,03	0,02	0,00	0,02	0,01	0,02	0,76
MERVAL	0,07	0,06	0,07	0,09	0,08	0,40	0,03	0,05	0,03	0,03	0,03	0,01	0,00	0,01	0,01	0,01	0,60
IPSA	0,08	0,06	0,08	0,07	0,06	0,04	0,31	0,08	0,05	0,03	0,03	0,03	0,01	0,02	0,02	0,02	0,69
MEXBOL	0,10	0,08	0,10	0,09	0,07	0,04	0,04	0,22	0,06	0,03	0,03	0,04	0,01	0,03	0,02	0,02	0,78
FTSE100	0,10	0,08	0,09	0,08	0,04	0,03	0,03	0,05	0,17	0,10	0,10	0,04	0,01	0,03	0,03	0,02	0,83
DAX	0,09	0,07	0,09	0,08	0,04	0,03	0,03	0,04	0,11	0,17	0,13	0,04	0,00	0,02	0,02	0,01	0,83
CAC40	0,10	0,08	0,09	0,07	0,04	0,03	0,03	0,04	0,12	0,14	0,18	0,04	0,00	0,02	0,02	0,01	0,82
WIG	0,08	0,07	0,07	0,07	0,05	0,03	0,03	0,07	0,07	0,07	0,06	0,27	0,01	0,04	0,02	0,01	0,73
SHCOMP	0,03	0,03	0,04	0,03	0,02	0,01	0,02	0,03	0,02	0,01	0,01	0,01	0,64	0,03	0,07	0,01	0,36
KOSPI	0,08	0,08	0,08	0,07	0,04	0,03	0,02	0,06	0,05	0,04	0,02	0,03	0,01	0,28	0,07	0,03	0,72
HSI	0,07	0,07	0,07	0,07	0,04	0,03	0,03	0,06	0,07	0,04	0,03	0,03	0,03	0,07	0,26	0,03	0,74
NIKKEI225	0,07	0,06	0,08	0,06	0,04	0,04	0,03	0,06	0,06	0,03	0,03	0,02	0,01	0,06	0,04	0,30	0,70
TO	1,42	1,16	1,40	1,18	0,74	0,55	0,47	0,86	0,95	0,76	0,72	0,42	0,11	0,45	0,39	0,26	Total connectedness
NET	0,59	0,33	0,57	0,38	-0,01	-0,05	-0,22	0,08	0,12	-0,07	-0,11	-0,31	-0,24	-0,27	-0,35	-0,43	0,74

# Spillover Network - Volatilities



**Arrows:** volatility spillover (directed)

**Edge thickness & color:** strength of spillover

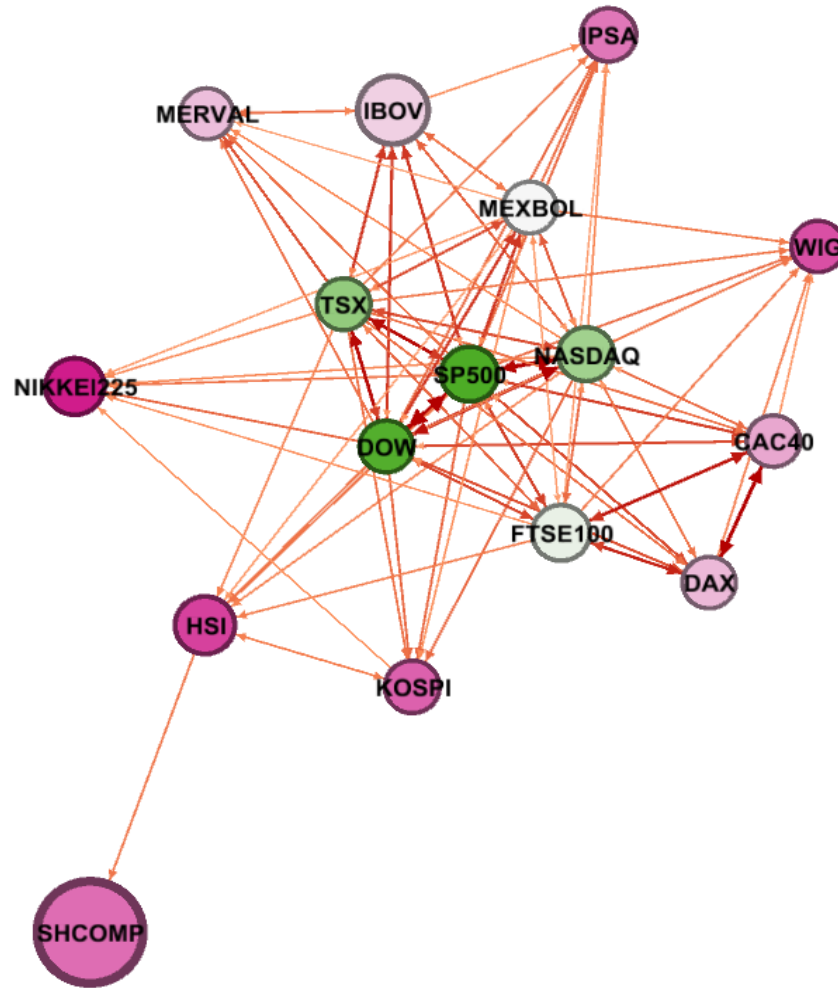
**Node size:** average daily trade volume of the index

**Node color:** Net spillover (green-positive; purple-negative)

**Visualization algorithm:** Force Atlas 2  
(node closeness shows edge strength as well)

**Visualization program:** Gephi

# Spillover Network - Volatilities



Weights: 1 - spillover

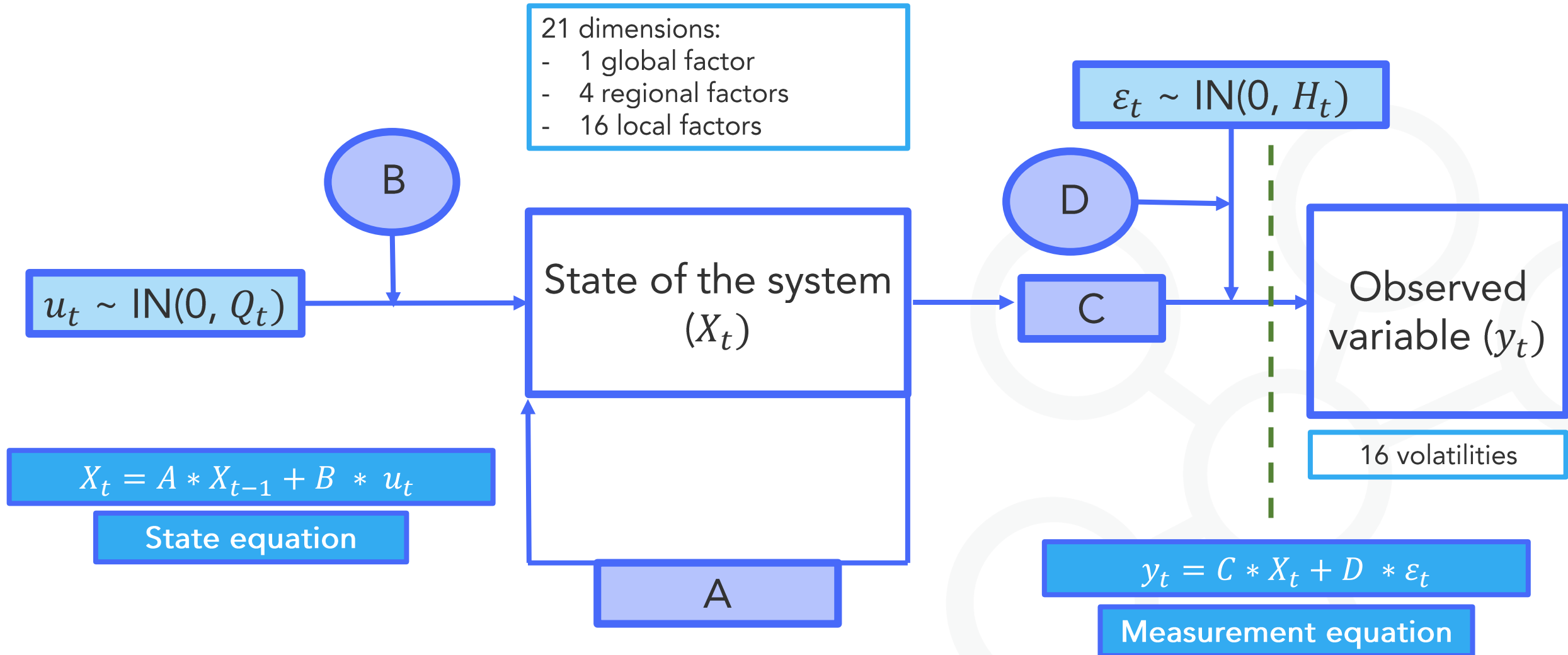
	d closeness	eigenvector	katz	betweenness	pagerank
SP500	0.59	0.37	0.36	0.08	0.12
NASDAQ	0.59	0.38	0.37	0.00	0.12
DOW	0.59	0.37	0.36	0.01	0.12
NIKKEI225	0.57	0.00	0.08	0.00	0.01
IPSA	0.55	0.00	0.08	0.00	0.01
WIG	0.55	0.00	0.08	0.00	0.01
HSI	0.54	0.00	0.10	0.05	0.02
KOSPI	0.51	0.00	0.10	0.00	0.01
TSX	0.49	0.38	0.37	0.03	0.12
IBOV	0.49	0.28	0.27	0.07	0.08
FTSE100	0.49	0.35	0.33	0.05	0.11
MEXBOL	0.49	0.33	0.33	0.01	0.10
Merval	0.48	0.04	0.11	0.00	0.02
CAC40	0.46	0.25	0.25	0.00	0.07
DAX	0.45	0.25	0.25	0.00	0.07
SHCOMP	0.37	0.00	0.08	0.00	0.01

# We found the key players!

Let's dig for special relationships between particular subsets of indices!

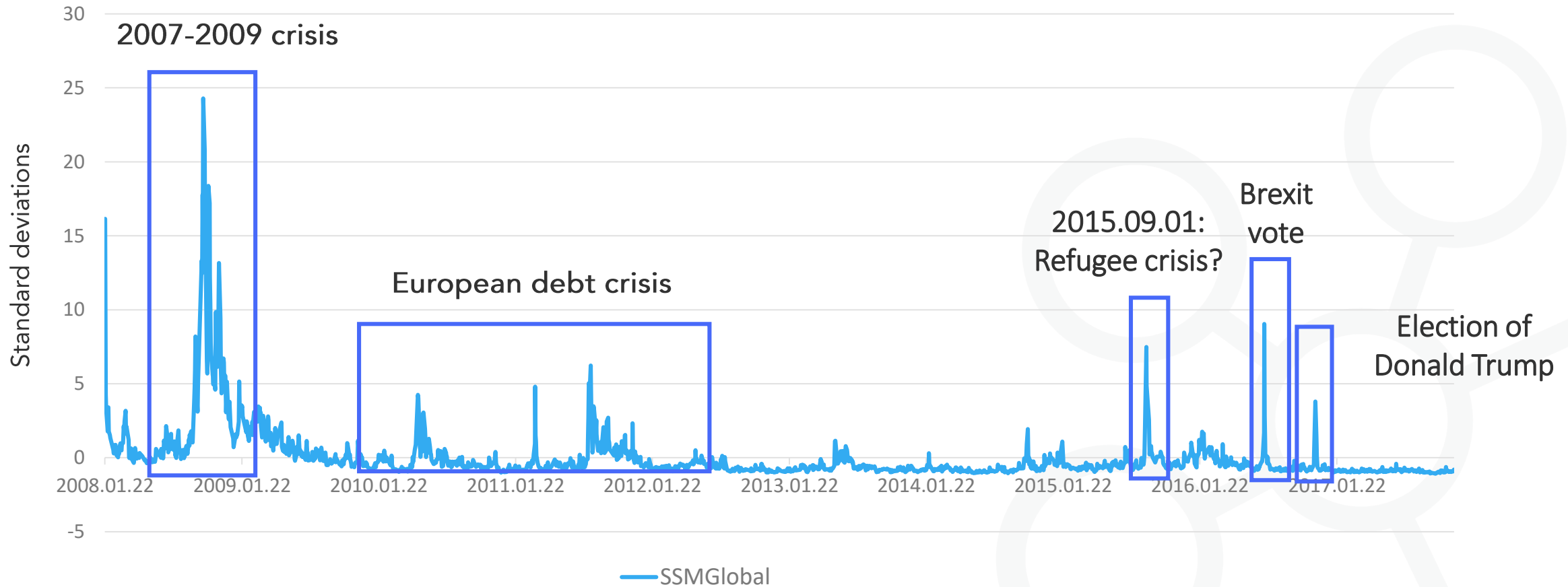


# A State-Space model - Commandeur & Koopman (2007)



# The global volatility factor

The Global factor has some notable spikes at globally relevant events



# Variance decomposition

## North America

VARIANCE SHARES	SP500	NASDAQ	DOW	TSX
Global factor	80,69%	76,87%	77,12%	73,73%
North American factor	18,87%	11,07%	21,20%	1,94%
Local factor	0,44%	12,07%	1,68%	24,33%

## Europe

VARIANCE SHARES	FTSE100	DAX	CAC40	WIG
Global factor	75,33%	70,17%	66,35%	46,80%
European factor	11,75%	24,18%	28,28%	2,82%
Local factor	12,92%	5,65%	5,37%	50,38%

## South (Latin) America

VARIANCE SHARES	IBOV	MERVAL	IPSA	MEXBOL
Global factor	51,12%	27,73%	35,71%	58,93%
South American factor	30,68%	24,44%	21,65%	7,96%
Local factor	18,20%	47,83%	42,63%	33,11%

## Asia

VARIANCE SHARES	SHCOMP	KOSPI	HSI	NIKKEI225
Global factor	12,70%	51,13%	46,92%	37,95%
Asian factor	20,66%	20,03%	38,22%	10,88%
Local factor	66,64%	28,84%	14,86%	51,16%



# Variance decomposition

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North American factor	18,87%	11,07%	21,20%	1,94%
Local factor	0,44%	12,07%	1,68%	24,33%

There is nothing local for SP500

## Europe

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Global factor	75,33%	70,17%	66,35%	46,80%
European factor	11,75%	24,18%	28,28%	2,82%
Local factor	12,92%	5,65%	5,37%	50,38%

Western Europe is much like North America  
Poland has a strong local factor

## South (Latin) America

VARIANCE SHARES	IBOV	MERVAL	IPSA	MEXBOL
Global factor	51,12%	27,73%	35,71%	58,93%
South American factor	30,68%	24,44%	21,65%	7,96%
Local factor	18,20%	47,83%	42,63%	33,11%

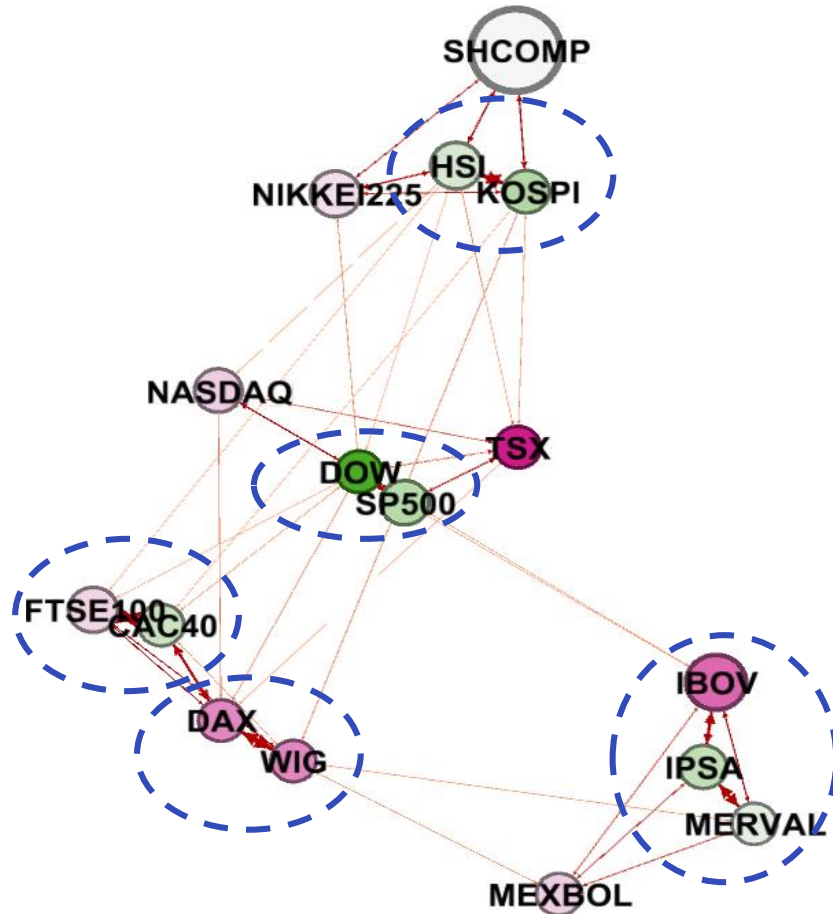
Maybe Mexico is in the wrong group...

## Asia

VARIANCE SHARES	SHCOMP	KOSPI	HSI	NIKKEI225
Global factor	12,70%	51,13%	46,92%	37,95%
Asian factor	20,66%	20,03%	38,22%	10,88%
Local factor	66,64%	28,84%	14,86%	51,16%

South Korea & Hong-Kong globalized  
Japan is unique  
China is even more unique

# Spillover Network – Local components



**Arrows:** volatility spillover (directed)

**Edge thickness & color:** strength of spillover

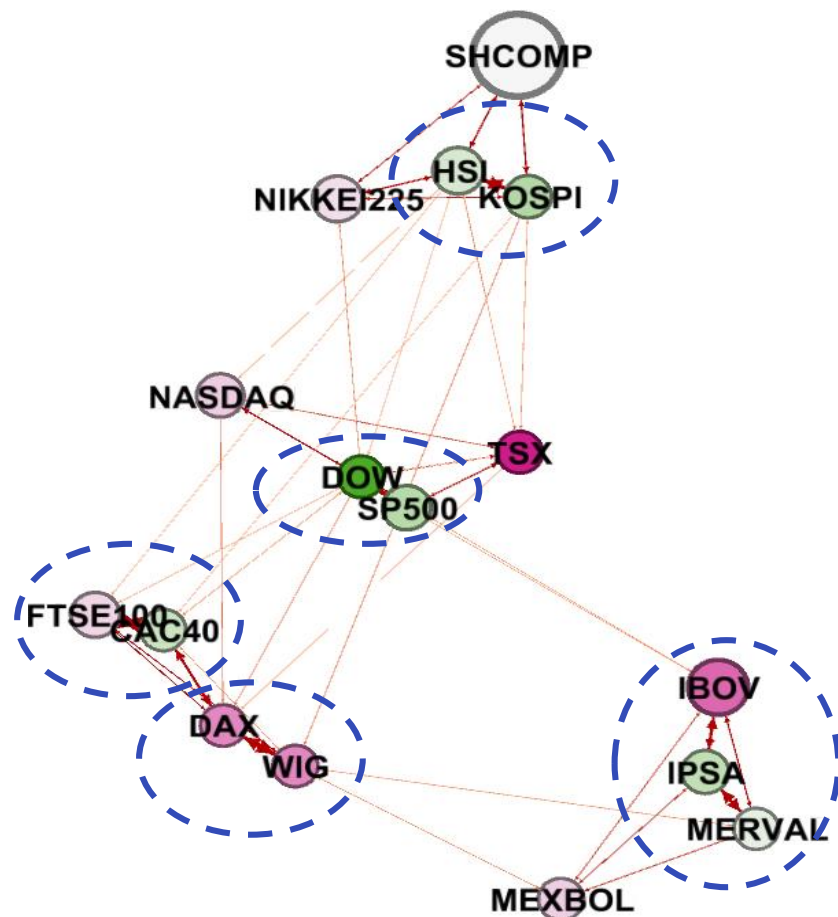
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	d closeness	eigenvector	katz	betweenness	pagerank
HSI	0.24	0.61	0.29	0.02	0.10
DAX	0.20	0.00	0.27	0.02	0.09
CAC40	0.20	0.00	0.26	0.02	0.09
KOSPI	0.19	0.50	0.27	0.00	0.06
SHCOMP	0.17	0.54	0.28	0.00	0.07
IPSA	0.17	0.00	0.27	0.01	0.09
IBOV	0.16	0.00	0.25	0.00	0.05
NIKKEI225	0.14	0.30	0.25	0.00	0.04
FTSE100	0.14	0.00	0.24	0.00	0.04
WIG	0.14	0.00	0.24	0.00	0.05
SP500	0.12	0.00	0.26	0.01	0.12
DOW	0.12	0.00	0.26	0.01	0.12
NASDAQ	0.12	0.00	0.22	0.00	0.01
TSX	0.12	0.00	0.22	0.00	0.01
Merval	0.11	0.00	0.27	0.00	0.07

- Commandeur, J. J. F., & Koopman, S. J. (2007): An Introduction to State Space Time Series Analysis. Oxford University Press, New York.
- Diebold, F. X. & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), pp. 158-171.
- Garman, M. B., & Klass, M. J. (1980): On the estimation of security price volatilities from historical data. *The Journal of Business*, 53, pp. 67–78.

Thank you for your attention!