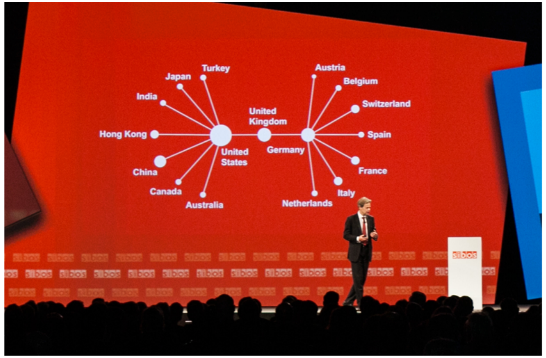
# FNA

## Monitoring FMIs & their Members

# Use Case: Understanding Interconnectedness


**R&D with SWIFT:** Mapping SWIFTs global payment network with FNA

**Background**

SWIFT message services are used by over 11,000 financial institutions in more than 200 countries. SWIFT was interested what insights could be drawn from the "Big Data" that it collects when transmitting messages between financial institutions.

**Objective**

Analyse the payment networks created by flows of SWIFT MT103 messages to draw insights about macroeconomic, geo-political and compliance topics.

**Insights**

Analysis of the SWIFT payment networks revealed a number of insights, including the phenomena of de-risking, payment country blocks relevant for sanctions analysis and how geopolitics shape them, and estimated the cost of the financial crisis at $5 Trillion. The outcome of the research was presented at Sibos 2014 by SWIFT CEO Gottfried Leibbrandt.

SWIFT Institute Research Paper: The global network of payment flows

Research Paper: The Impact of Anti-Money Laundering Regulation on Payment Flows

# It's all about data: using advanced analytics as an investigative tool

Kimmo Soramäki, FNA Analytics
Nam-Luc Tran, SWIFT

Link

# Use Case: Monitoring Liquidity and Solvency of FIs


"The FNA software platform has helped the bank improve its ongoing risk management processes [...] reducing the time it takes to run analysis from weeks to only a few minutes."

**Mr. Fabio Ortega**
Project Manager
Central Bank of Colombia

**Central Bank of Colombia** identifies early warning on liquidity and solvency of financial institutions

## Background

The Central Bank of Colombia has been using balance sheet and regulatory reporting data to understand the liquidity and solvency of participants in the Colombian financial system. However, the analysis is time consuming and the data comes months late.

## Objective

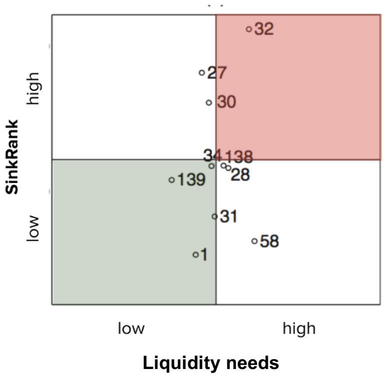
Using network analysis of data from the interbank payment system would allow the Bank to get early warning about risks substantially faster.

## Outcomes

Using the FNA Platform, the Bank is now able to monitor its banking system in near real time. Automatic alerts notify the bank of any abnormal behavior in the network. Furthermore, automated stress tests where they fail the two largest participants in the network help to understand the riskiness of the system.

Carlos León et al (2015). [Assessing Systemic Importance With a Fuzzy Logic Inference]

# Use Case: Monitoring Liquidity and Solvency of FIs




**Bank of Korea** and FNA develop methods for predicting intraday liquidity risk in payment systems

## Background

Bank of Korea, South Korea's central bank, was looking for ways to have early warning about intraday liquidity problems in its systemically important BoK-Wire+ interbank payment system.

## Objective

To develop methods to predict the liquidity position of each member in BoK-Wire+ in real-time, as well as measure the importance of member in terms of the liquidity and operational risk a liquidity shortage would cause.

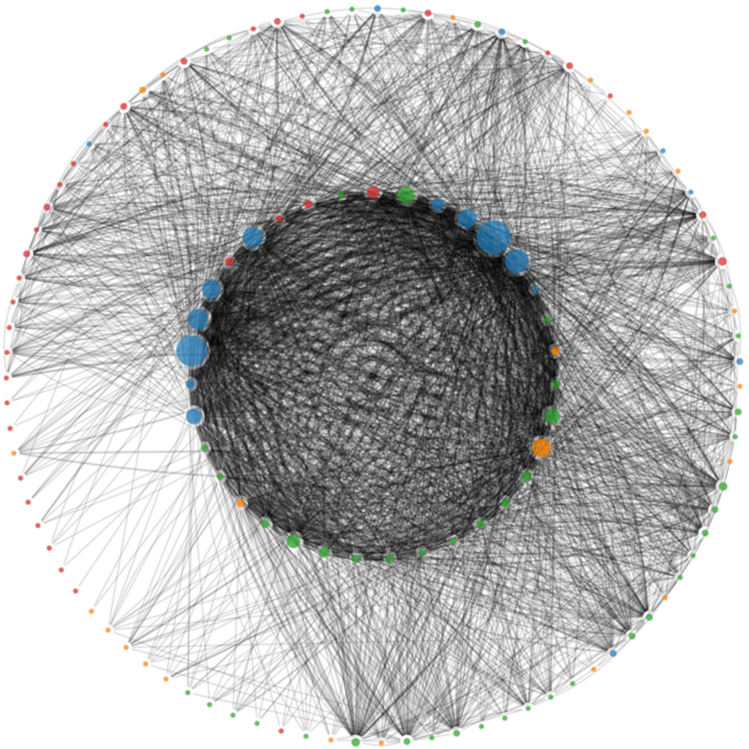
## Outcomes

Bank of Korea and FNA developed a framework for identifying bank's liquidity problems in real time and using FNA's SinkRank algorithm to identify most critical banks. The results were published as a research paper.

BoK Research paper: Network Indicators for Monitoring Intraday Liquidity in BOK-Wire+

Journal article: SinkRank: An Algorithm for Identifying Systemically Important Banks in Payment Systems

# Predicting Liquidity: Problem



Key issue in payment system is that each bank is dependent on incoming funds to make their own payments.

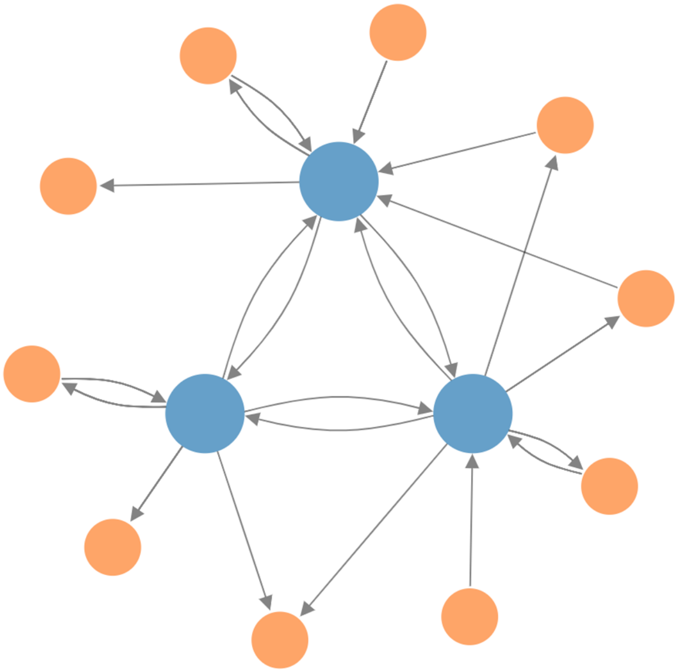
Objective of this work was to develop measures for ongoing monitoring of systemic risk in payment systems

Baek, Soramäki and Yoon (2014). Network Indicators for Monitoring Intraday Liquidity in BOK-Wire+. Journal of Financial Market Infrastructures 2:3.

# Core-Periphery Networks

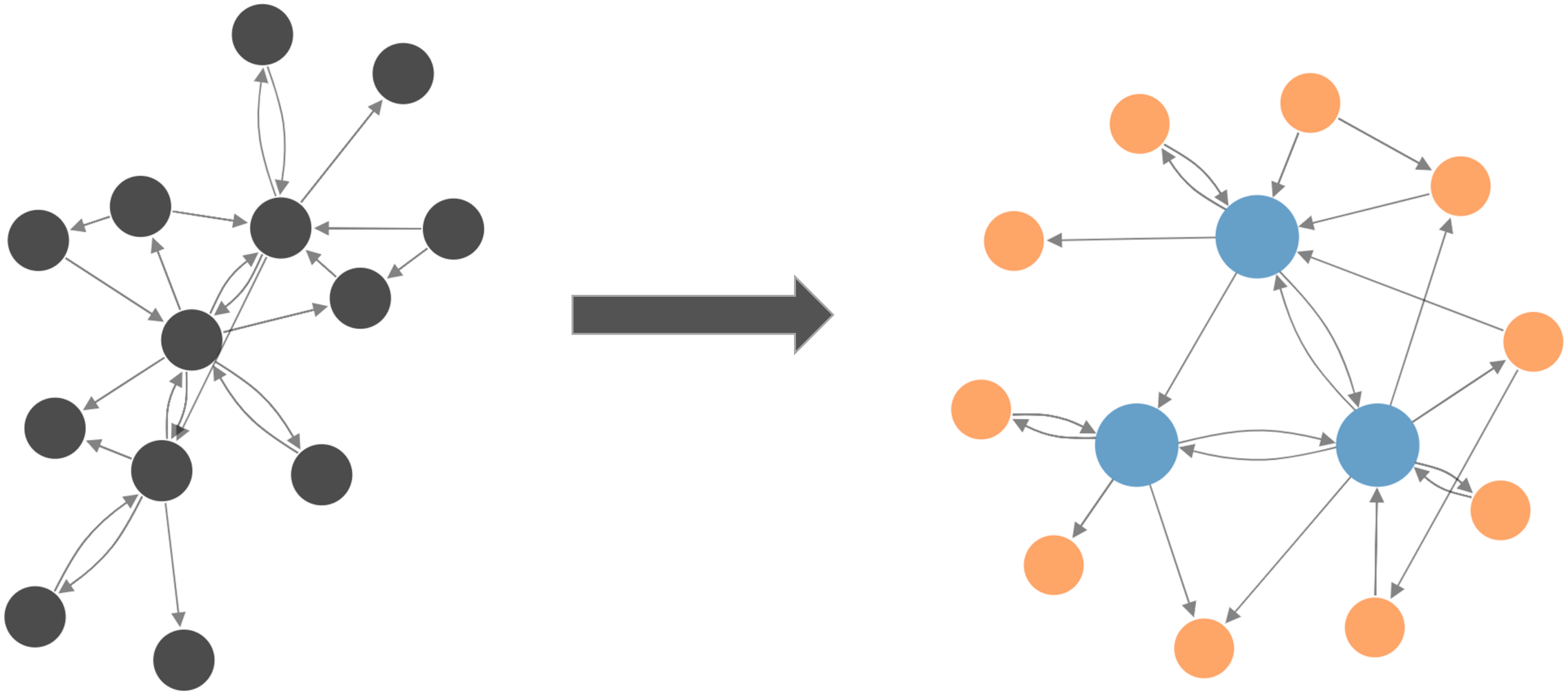
Craig and von Peter (2014) introduced the idea of a core-periphery or tiered structure in banking systems. A perfect core-periphery system has the following features:

- Core nodes are linked to all other core nodes
- All core nodes are linked to at least one periphery node
- Periphery nodes are not linked to any other periphery nodes



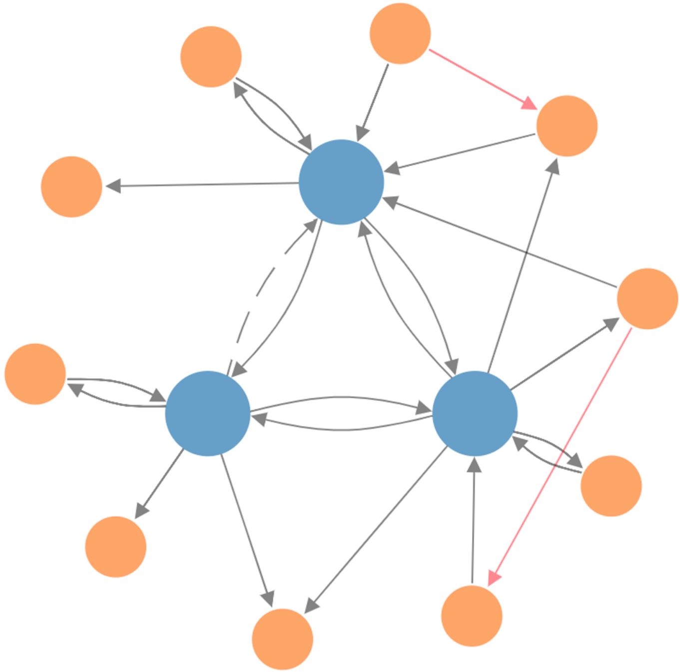
# Core-Periphery Networks

Real world network rarely follow a perfect core-periphery structure, but classification of institutions as core and periphery is often a useful generalization

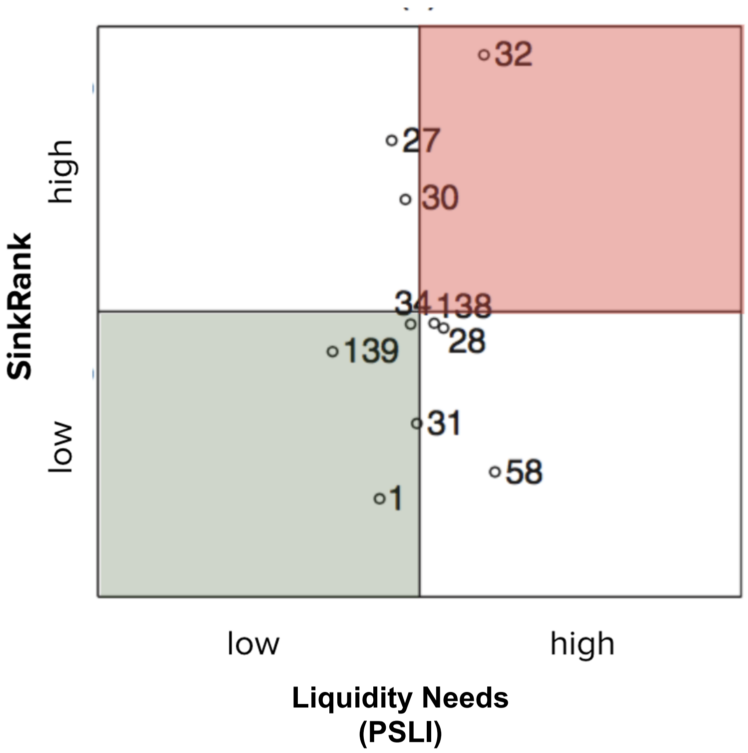


# Core-Periphery Networks

Classification of nodes as core or periphery minimizes the number of *errors*: Links between periphery nodes and missing links between core nodes



# Predicting Liquidity: Framework




Analytics need to be operationalized into a robust and repeatable decision making framework

# Predicting Liquidity: PSLI

PSLI (Payment System Liquidity Indicator) is the ratio of projected liquidity demands and projected liquidity supply:

Debits so far

Outgoing Payments Pending

Expected Debits

$$\mathrm{PSLI}_{ijt} = \frac{\mathrm{pending}_{ijt} + \mathrm{KRdebits}_{ijt} + \widehat{\mathrm{ERdebits}}_{ijt}}{\mathrm{balance}_{ijt} + \mathrm{limit}_{ijt} + \mathrm{KRcredits}_{ijt} + \widehat{\mathrm{ERcredits}}_{ijt}}$$

Balance now

Credits so far

Available overdraft facility

Expected Credits

>1 means liquidity problem

# Predicting Liquidity: PSLI

Expected credits and debits are estimated on the basis of a regression model.

The model takes into account the value already settled on the given day, effects related to reserve maintenance and to US holidays and the trade values of bonds and spot exchange.

The model has a good fit.

| Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|
| | Coefficient | $t$ | | Coefficient | $t$ |
| tue | −0.2939** | −3.09 | tue | −0.2692** | −3.49 |
| wed | −0.5075*** | −5.05 | wed | −0.4879*** | −5.67 |
| thu | 0.6049*** | 6.63 | thu | 0.6054*** | 7.93 |
| fri | −0.0128 | −0.14 | — | — | — |
| reserve_check | −5.2343*** | −35.43 | reserve_check | −5.2310*** | −35.50 |
| us_hol | −1.0795*** | −6.53 | us_hol | −1.0934*** | −6.82 |
| bond | 0.0037 | 0.87 | — | — | — |
| fx | 0.0001 | 0.04 | — | — | — |
| _Ireceiver_1 | 3.0615*** | 14.87 | _Ireceiver_1 | 3.1743*** | 31.34 |
| _Ireceiver_27 | 12.0550*** | 38.07 | _Ireceiver_27 | 12.1676*** | 130.47 |
| _Ireceiver_28 | 6.7873*** | 28.69 | _Ireceiver_28 | 6.9051*** | 80.15 |
| _Ireceiver_30 | 13.5095*** | 59.61 | _Ireceiver_30 | 13.6257*** | 87.87 |
| _Ireceiver_31 | 2.8790*** | 34.04 | _Ireceiver_31 | 2.9899*** | 32.92 |
| _Ireceiver_32 | 19.3134*** | 56.84 | _Ireceiver_32 | 19.4082*** | 89.10 |
| _Ireceiver_34 | 8.2016*** | 14.30 | _Ireceiver_34 | 8.3231*** | 118.77 |
| _Ireceiver_58 | 2.3454*** | 68.63 | _Ireceiver_58 | 2.4588*** | 26.63 |
| _Ireceiver_138 | 7.6201*** | 42.56 | _Ireceiver_138 | 7.7360*** | 87.08 |
| _Ireceiver_139 | 6.0048*** | 11.62 | _Ireceiver_139 | 6.1261*** | 56.87 |

| Model 1 | Model 2 |
|---|---|
| Number of obs = 2 480 | Number of obs = 2 490 |
| $F(18,2462) = 4\,159.70$ | $F(15,2475) = 5\,031.22$ |
| Prob > $F$ = 0.0000 | Prob > $F$ = 0.0000 |
| $R$-squared = 0.9682 | $R$-squared = 0.9682 |
| Adj $R$-squared = 0.9679 | Adj $R$-squared = 0.9681 |

*, ** and *** represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

# Measuring Importance: SinkRank

Payments move liquidity in the network.

Payments take place on links at some given frequency that can be measured (eg based on historical or projected flows).

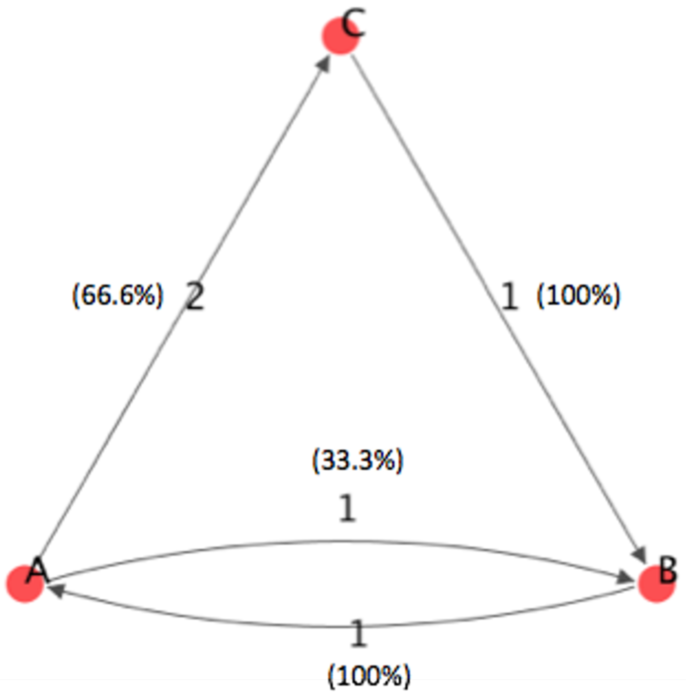
We are concerned on operational failures.The sink can receive payments but cannot send any.

**Example:**

Let's start by considering one unit of liquidity that is moved by payments in a simple system of three banks.

At the time of analysis, the unit of liquidity can be at either A, B or C.

What is the distance of the unit to the different 'sink nodes'

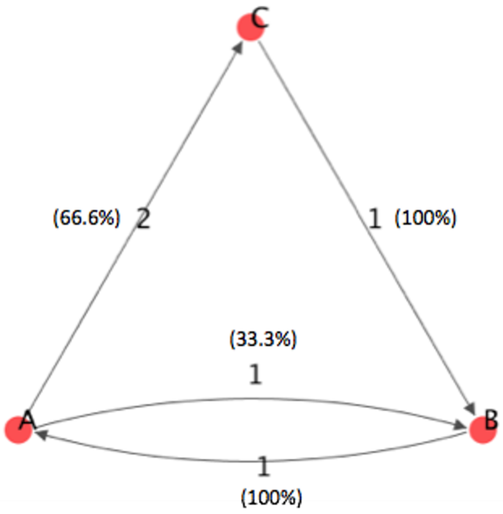



Research: [SinkRank: An Algorithm for Identifying Systemically Important Banks in Payment Systems]()

# Measuring Importance: SinkRank

SinkRank can also incorporate node weights

In that case, SinkRank is the inverse of the *weighted* average of SinkDistances




| | | SinkDistances (same as before) | SinkRank |
|---|---|---|---|
| To A | From B | 1 | = 1/(1+2)/2 = 0.66 |
| | From C | 2 | |
| To B | From A | $\frac{2}{3}\cdot 2+\frac{1}{3}\cdot 1=\frac{5}{3}$ | = 1/((5/3+1)/2) = 0.75 |
| | From C | 1 | |
| To C | From A | $\sum_{i=1}^{\infty}(2i-i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=2$ | = 1/((2+3)/2) = 0.4 |
| | From B | $\sum_{i=1}^{\infty}(2i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=3$ | |

# Measuring Importance: SinkRank

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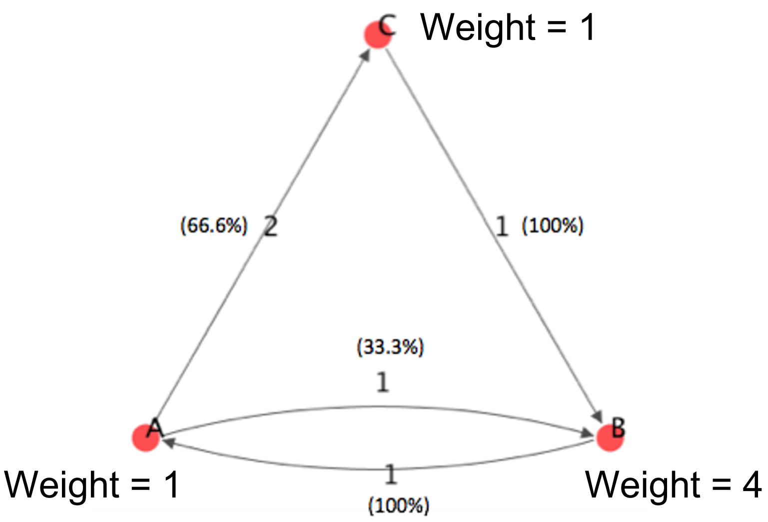



SinkDistances (same as before)

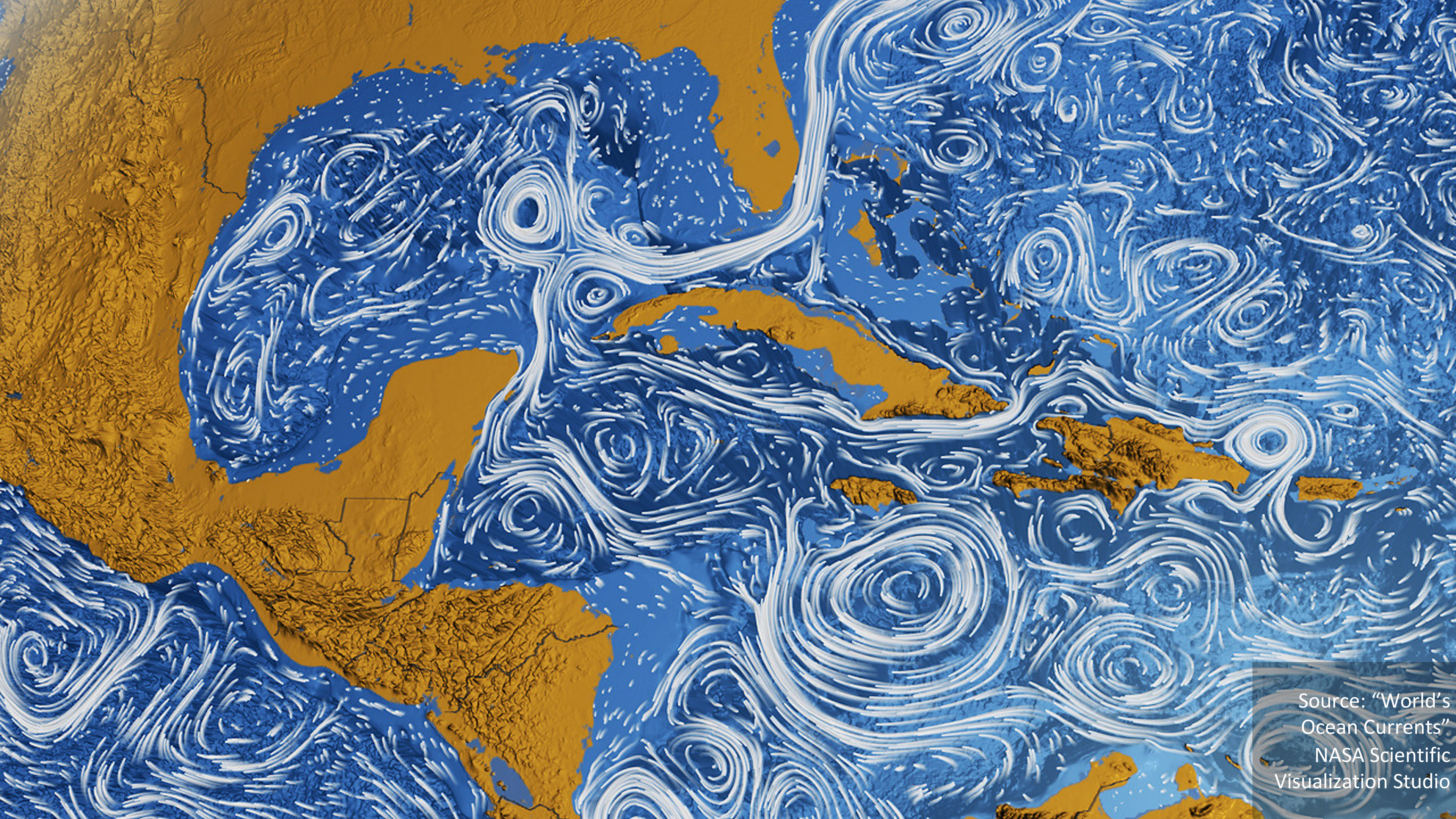
| | | |
|---|---|---|
| To A | From B | 1 |
| | From C | 2 |
| To B | From A | $\frac{2}{3}\cdot 2+\frac{1}{3}\cdot 1=\frac{5}{3}$ |
| | From C | 1 |
| To C | From A | $\sum_{i=1}^{\infty}(2i-i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=2$ |
| | From B | $\sum_{i=1}^{\infty}(2i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=3$ |

SinkRank

$$\frac{1}{\frac{(1)(4)+(2)(1)}{4+1}}=\frac{1}{\frac{6}{5}}=\frac{5}{6}=0.833$$

$$\frac{1}{\frac{\left(\frac{5}{3}\right)(1)+(1)(1)}{1+1}}=\frac{1}{\frac{8/3}{2}}=\frac{6}{8}=0.75$$

$$\frac{1}{\frac{(2)(1)+(3)(4)}{1+4}}=\frac{1}{\frac{14}{5}}=\frac{5}{14}=0.357$$



Source: “World’s Ocean Currents” NASA Scientific Visualization Studio

# Measuring Importance: SinkRank

SinkRank is suited for Predictive Modeling

Given an observed distribution of liquidity, and a historical pattern of payment flows

- What is the distribution if bank A has an operational disruption at noon?
- Who is affected first?
- Who is affected most?
- How is Bank C affected in an hour?

Valuable information for decision making

- Crisis management
- Participant behavior

FNA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