Network Analysis in R of Derivatives Trade Repository Data

An Application of the `igraph` Package

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The opinions expressed here are our own, and do not reflect the views of the Board of Governors or its staff.

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Objectives

Our objective is to build tools for monitoring systemic risk in OTC derivative markets. Two forms of systemic risk:

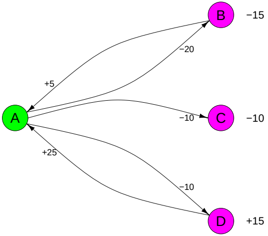
- Default cascades due to counterparty credit risk
  - AIG as poster child.
  - Monitoring to identify largest net positions.
- Interconnectedness
  - More difficult to quantify, but no less a concern.
  - If a firm plays a key role in intermediation, its default may disrupt the normal functioning of the market.
  - Network methods characterize and quantify patterns of interconnectedness.

Data

- DTCC Trade Information Warehouse (TIW) is a trade repository of nearly all of credit default swap (CDS) transactions worldwide.
- We have position data (i.e., stock, not flow of transactions).
- Two snapshots from June and September, 2010. Each contains
  - Single-name CDS on corporates, sovereigns, munis.
    2879 unique reference entities.
  - CDS Index trades. 50 unique indices.
  - 1135 market participants, of which 20 are dealers, 2 are CCP.
- Our snapshots exclude trades on non-domestic reference entities between two non-domestic institutions.
- Repository data not useful for assessing current market-valued exposures.
  - TIW provides notional size of each position, not current value.
  - No data on netting sets or collateral exchange.

Net positions and bilateral exposures

- Three levels of aggregation of the CDS market:
  - Single-name reference entities and CDS indices
  - Sectors (e.g., Financials, Consumer Services)
  - Aggregate CDS market (reference entities as interchangeable)
- For each underlying under each market aggregation, tally
  - Gross protection sold by each firm to each counterparty.
  - Bilateral exposure between each pair of firms
    - net notional amount of protection sold by firm A to firm B on the underlying.
  - Net position of each firm
    - notional dollars of protection bought less protection sold
    - in example at right, net position is $-15 - 10 + 15 = -10$ (net seller).



Network analysis

- Objectives
  - to characterize and quantify patterns of interconnectedness.
  - to identify firms crucial to the transfer of risk.
  - to assess the resilience of the network to the disabling of crucial vertices.
- Terminology
  - Vertex: a firm engaged in trading.
  - Edge: link between two nodes.
    - Directed from seller to buyer.
    - Weighted by dollar notional.
  - Sub-networks: Interdealer, Customer-facing.

Network methods in finance

Caveat! Application to financial markets still nascent.

- Network methods were developed for physical systems where meaning of a connection (edge) between vertices is unambiguous.
- Allen and Gale (2000) and Allen and Babus (2007) study contagion in interbank market.
- Game theoretic approach: Cohen-Cole, Patacchini & Zenou (2011).
- Agent-based approach: Tedeschi *et al.* (2011).
- Network topology: Adamic *et al.* (2011).
- Link between topological properties of network and economic performance of market not yet clearly understood.

Define the graph

We build these inputs from a dataframe:

- $\mathrm{Agross}[i, j]$ is the total protection sold by i to j.
- $\mathrm{isdealer}[i]$ is true if firm i is a dealer.
- $\mathrm{isccp}[i]$ is true if firm i is a CCP.

Create the graph object

```r
Anet <- pmax(Agross-t(Agross),0) # net protection sold
mkt <- graph.adjacency(adjmatrix=Anet, mode="directed",
                                  diag=FALSE, weighted=TRUE)
# Assign vertex attributes, noting V(mkt) preserves order
V(mkt)$isdealer <- isdealer
V(mkt)$isccp <- isccp
```

Plotting the network

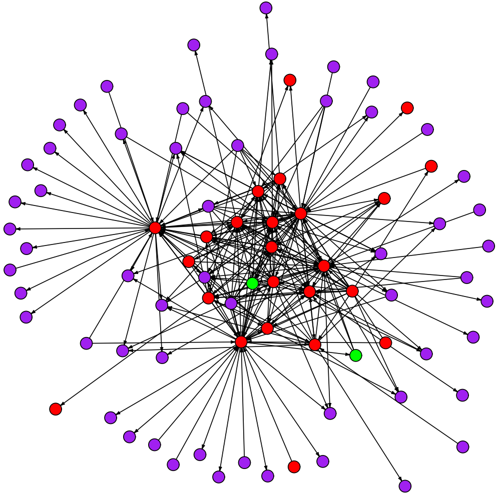
Color firms according to firm type

```
V(mkt)$color <- "purple"
V(mkt)[isdealer]$color <- "red"
V(mkt)[isccp]$color <- "green"
```

Subgraph of the largest edges

```
alpha <- 1050  # smallest net position to retain in USD mm.
mkt.alpha <- delete.edges(mkt, edges=E(mkt)[weight < alpha])
mkt.alpha <- delete.vertices(mkt.alpha,
      v=V(mkt.alpha)[degree(mkt.alpha, mode="total")==0])
```

CDS market as a network



Dealers CCP Buyside

Centrality

Centrality measures the contribution of each firm to risk-transfer in the network. It is an attribute of the vertex.

Vertex attribute wcentrality

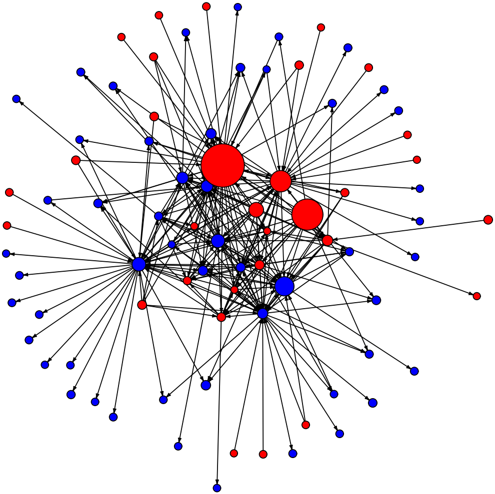
```
V(mkt)$windeg <- graph.strength(mkt, mode="in")
V(mkt)$woutdeg <- graph.strength(mkt, mode="out")
V(mkt)$wcentrality <-
      (V(mkt)$windeg-V(mkt)$woutdeg)/sum(V(mkt)$windeg)
```

When weighted centrality large and negative, the vertex is a major seller of protection.

Plot centrality for subgraph of large edges

```
V(mkt.alpha)$color <- "red"
V(mkt.alpha)[wcentrality >= 0]$color <- "blue"
# Plot vertex size as some function of abs(weighted centrality)
V(mkt.alpha)$size <- vertexsize(abs(V(mkt.alpha)$wcentrality)
```

Centrality in CDS market



Positive Negative

Size proportional to abs(V(mkt)$wcentrality).

Centralization

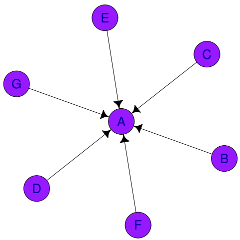
Gini centralization gauges the relative concentration between the protection buying and protection selling sides of the market.

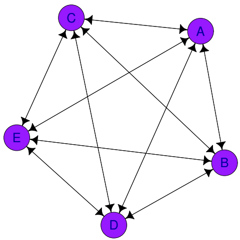
- Measure concentration on each side of market by Gini coefficient, then take difference.
- Equals 1 when market has one buyer facing many sellers, and equals -1 in opposite extreme.
- Weight by notional dollars.

Assume we have function **gini**

```
centralization <- gini(V(mkt)$windeg)- gini(V(mkt)$woutdeg)
```

Illustration of network metrics





Centralization $= 0.714$
Clustering Coeff $= 0$

Centralization $= 0$
Clustering Coeff $= 1$

Centralization by sector

Government	-0.077
Basic Materials	-0.071
Industrials	-0.069
Consumer Services	-0.067
Telecommunications	-0.064
Consumer Goods	-0.063
Technology	-0.056
Financials	-0.056
Oil & Gas	-0.042
Health Care	-0.040
Utilities	-0.016

Clustering coefficient

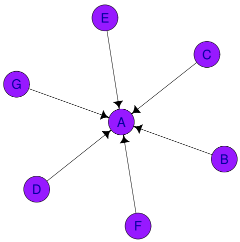
Clustering coefficient (CC) is a measure of market intermediation.

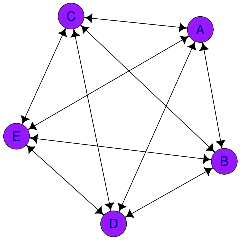
- High CC when everyone in market trades with everyone else.
- CC is zero when there is a single central counterparty.
- Low CC may be indicative of network fragility, especially if intermediating vertices are not central counterparties.
- CC is unweighted, but can examine how CC changes when smallest edges are truncated.

Function **transitivity** calculates clustering coefficient

```
CC <- rep(0, length(alpha)) # alpha sorted smallest to largest
for (j in 1:length(alpha)) {
   mkt <- delete.edges(mkt, edges=E(mkt)[weight < alpha[j]])
   mkt <- delete.vertices(mkt,
             v=V(mkt)[degree(mkt, mode="total")==0])
   CC[j] <- transitivity(mkt, type="global")
}
```

Illustration of network metrics





Centralization = 0.714
Clustering Coeff = 0

Centralization = 0
Clustering Coeff = 1

Clustering Coefficient in truncated networks