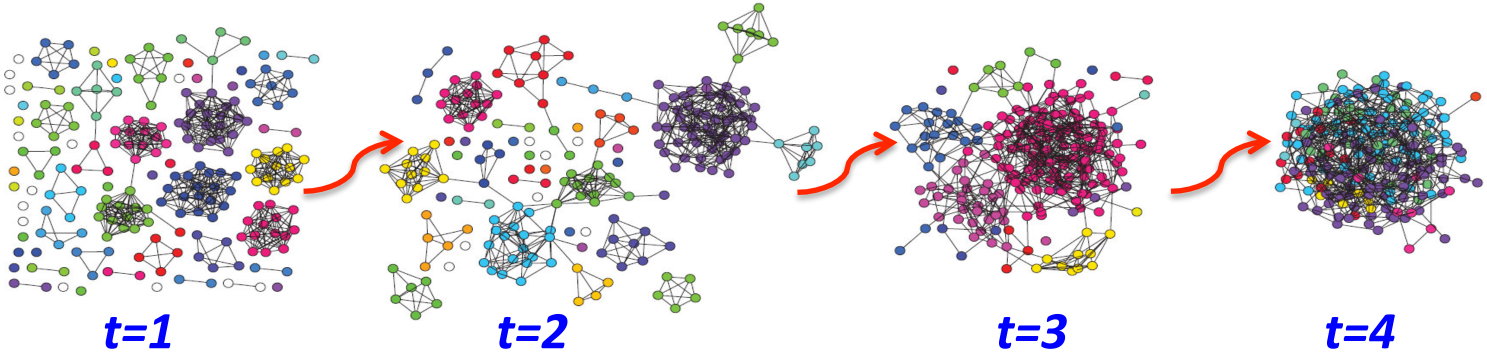
4322 North Quad, 105 S. State St.
Ann Arbor, MI 48109-1285

Social Network Under Stress

Daniel M. Romero
School of Information
University of Michigan

In collaboration with Jon Kleinberg, Toby Stuart, and Brian Uzzi

Social Network Temporal Dynamics



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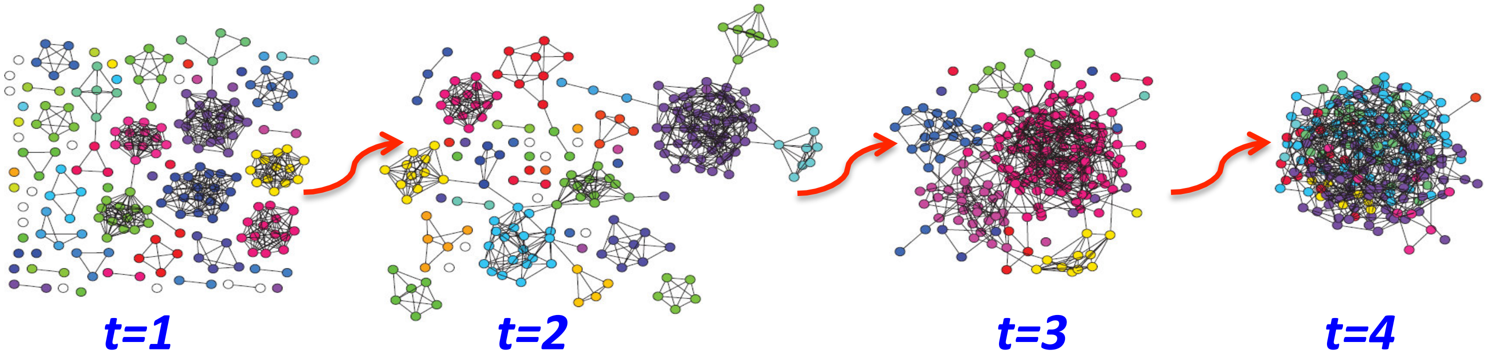

Temporal dynamics of networks:

Short diameter, densification, clustering, heavy tail degree distribution, … [Leskovec et al. 2007, Barabasi et al. 1999, Kossinets et al. 2009, …]

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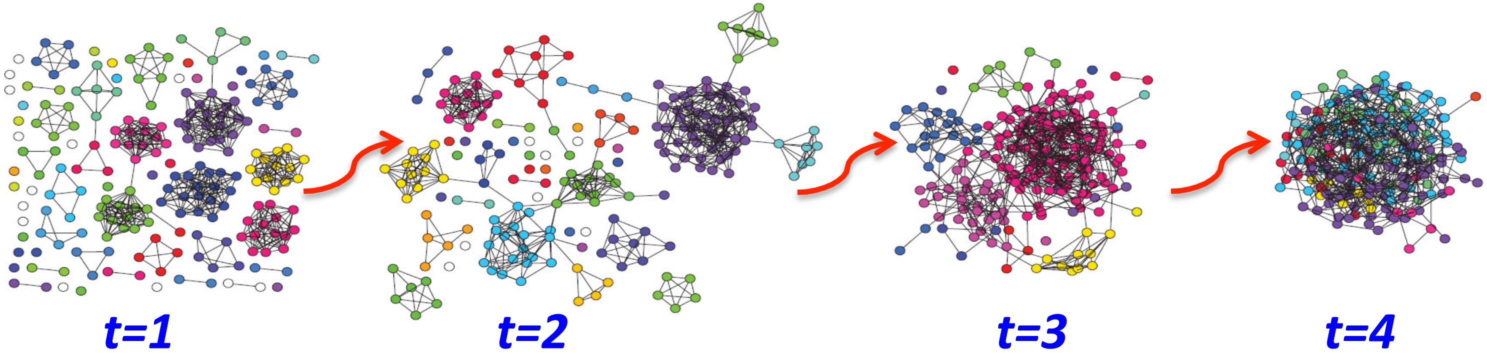

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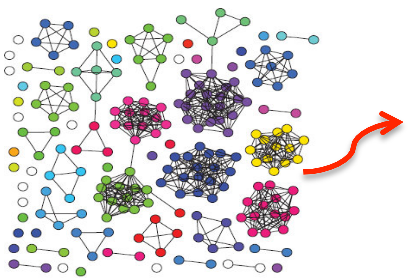
Useful for:

- Link prediction
- Detecting influential nodes
- Finding communities

Social Network Temporal Dynamics



t=1

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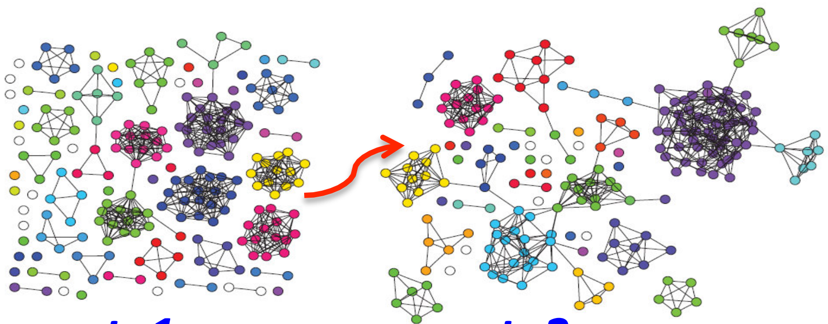

t=1 *t=2*

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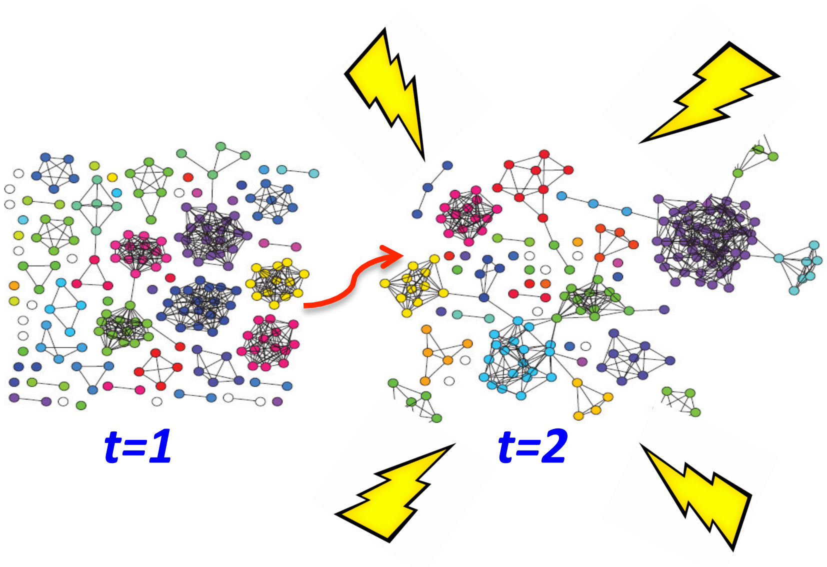

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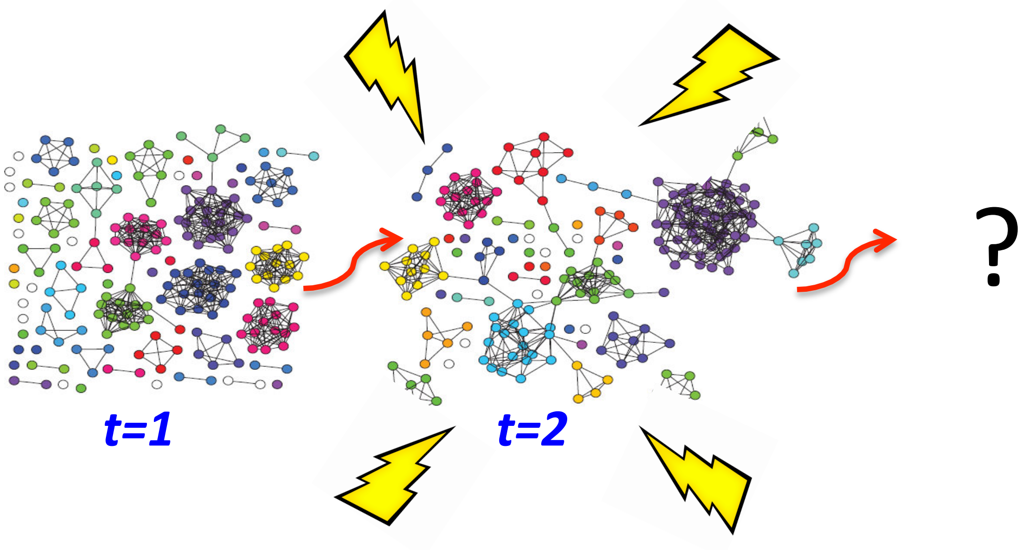

Hedge Fund Data

Instant Messages (IM):

- Full record of IMs: content, sender, recipient, timestamp
- 182 internal decision makers, 8646 outside contacts
- 22 Million IMs

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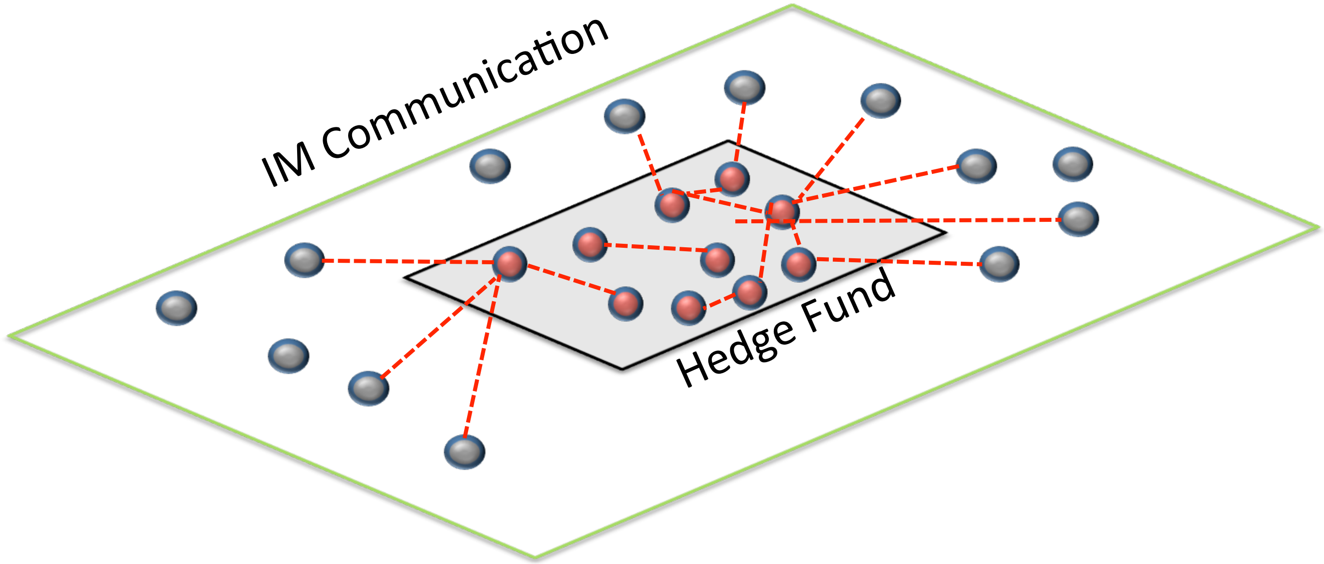
Stock Trading:

- Full record of all transactions: stock, price, number of stocks, type of transaction (Buy, Sell), timestamp
- 600K trades
- 2008 – 2012

Hedge Fund Organizational Structure



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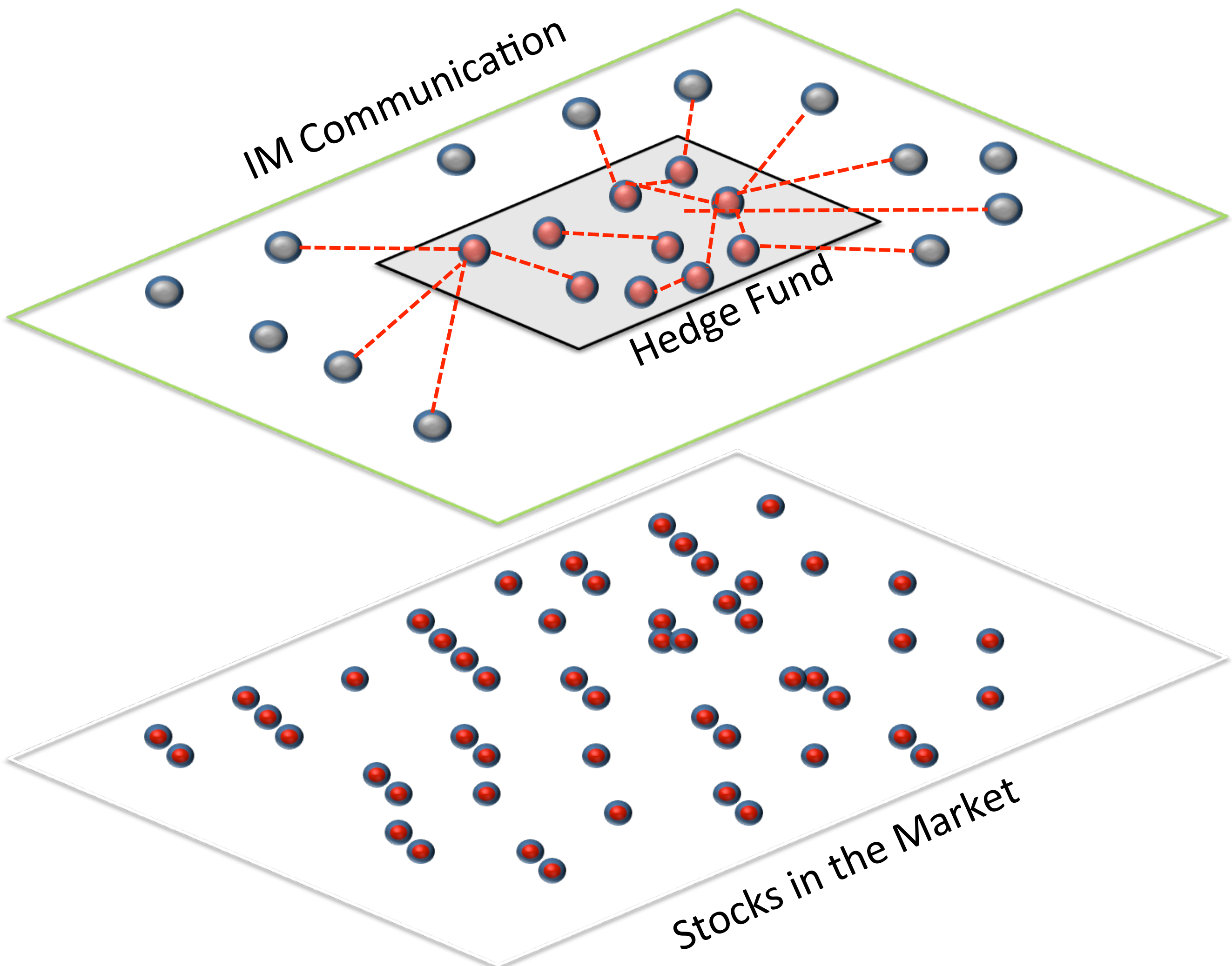

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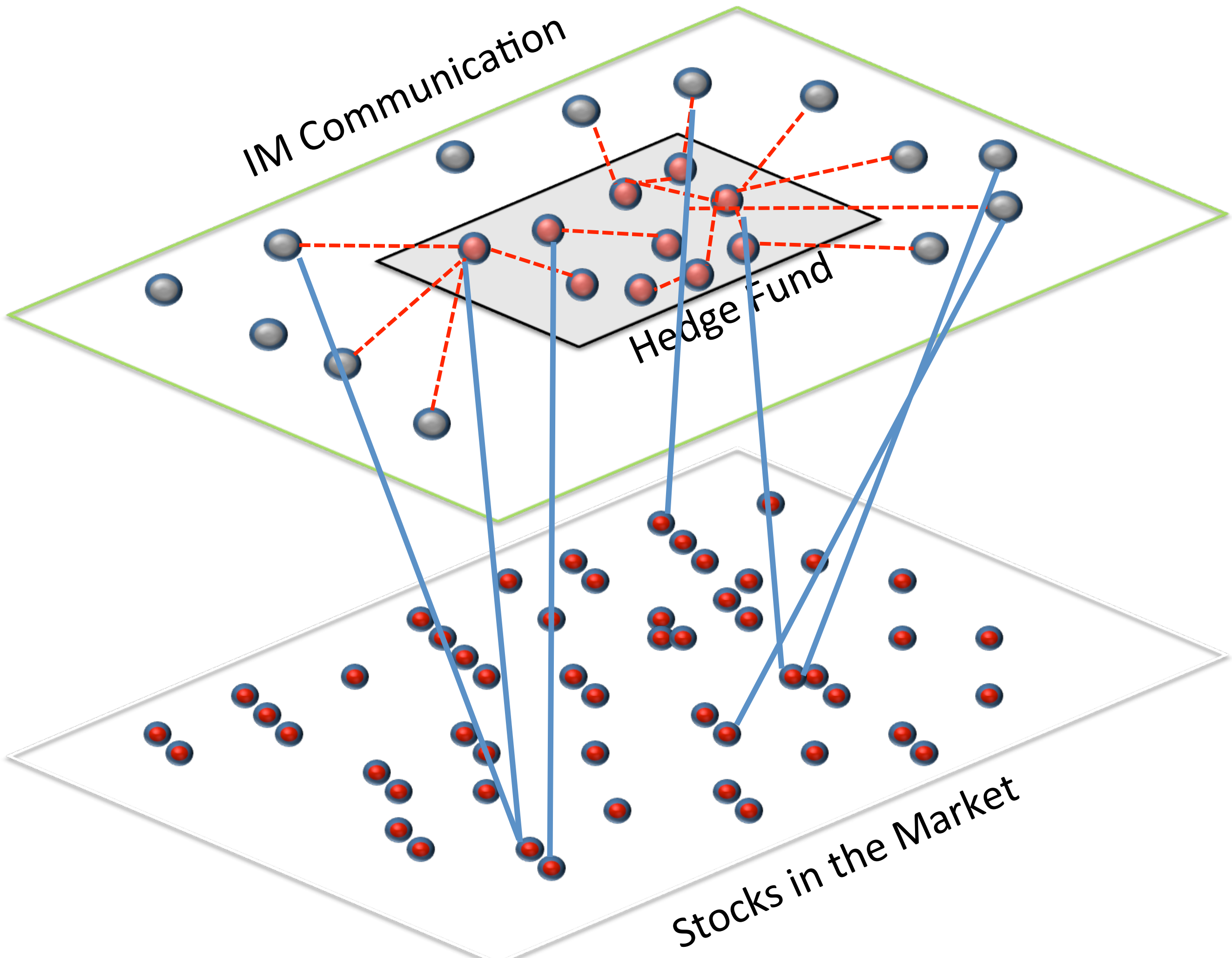

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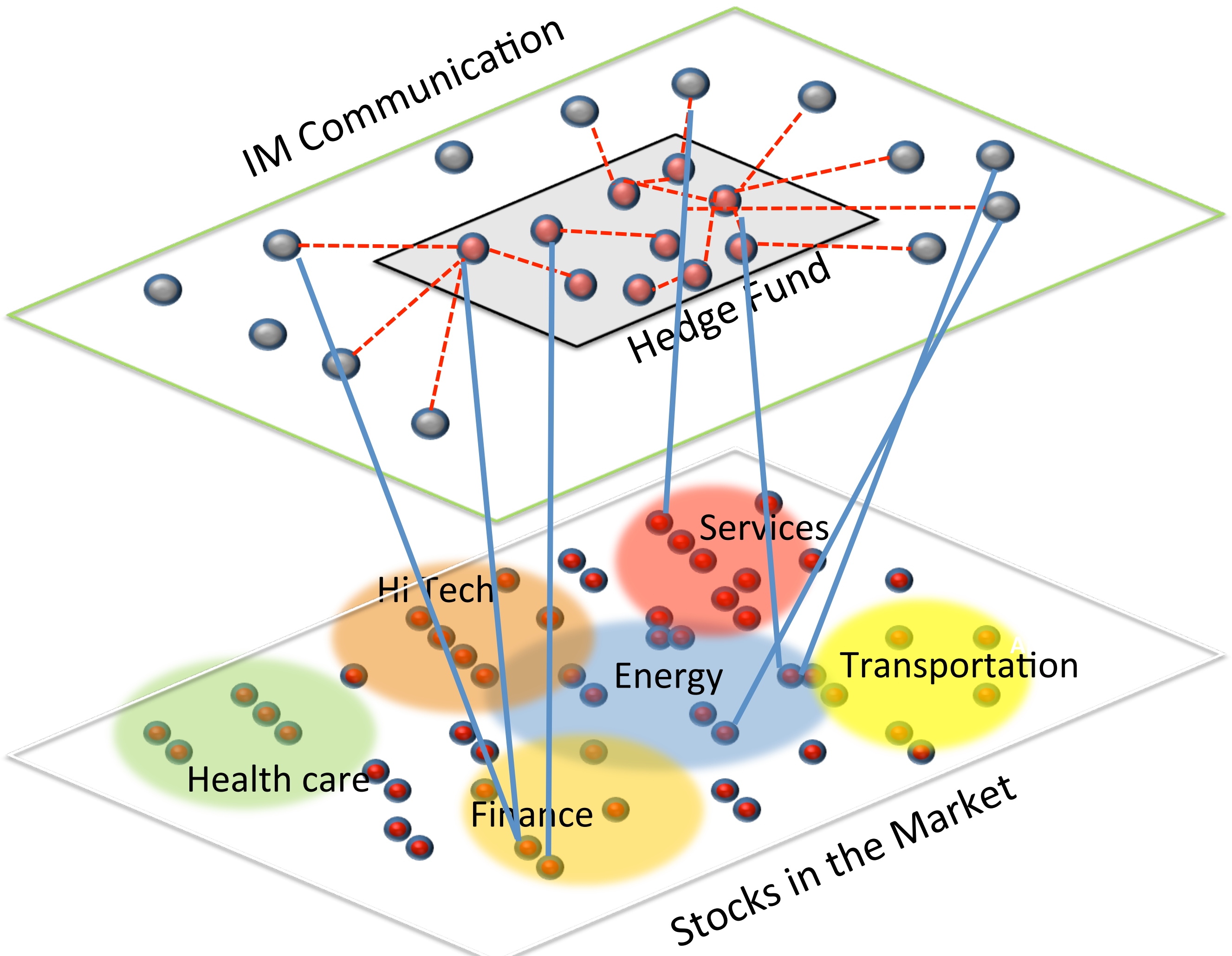

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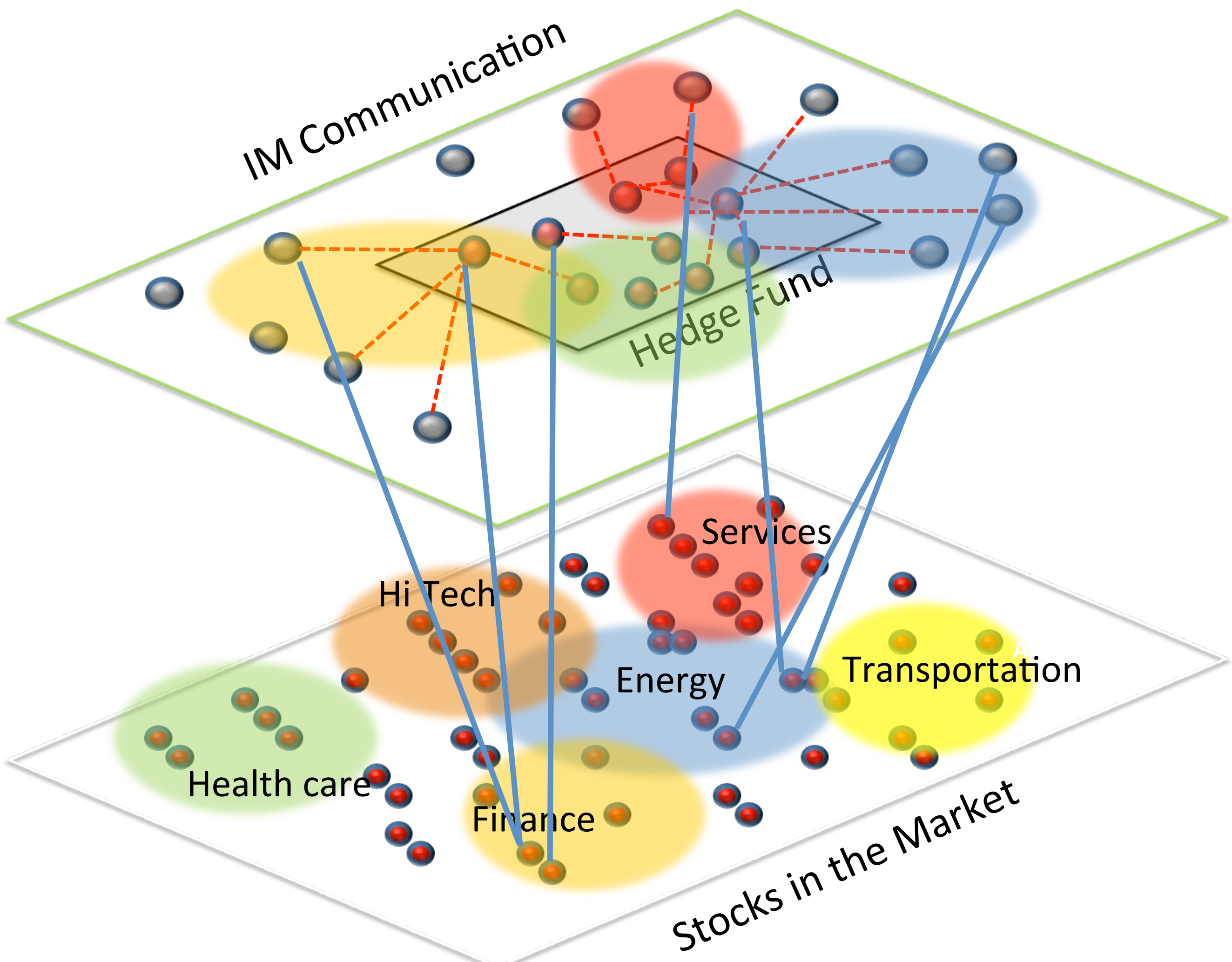

Organizations and Individuals Under Threat

Ego-networks:
Individuals under threat activate different contacts in their network depending on the subject's power, status, and identity consistency (*Menon & Smith 2014, Smith, Thompson, Menon 2012*).

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Organization theory: Reactions to threat:
- Threat rigidity effect [*Staw et al. 1981*].

In This Talk

Market Movements
(Shocks)

Social Network

In This Talk

Trading

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Social Network

In This Talk

Trading

Market Movements
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Social Network

Performance

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Trading

Market Movements
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Performance

Emotional and
Cognitive Content

In This Talk

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% change: (closing – opening) / opening

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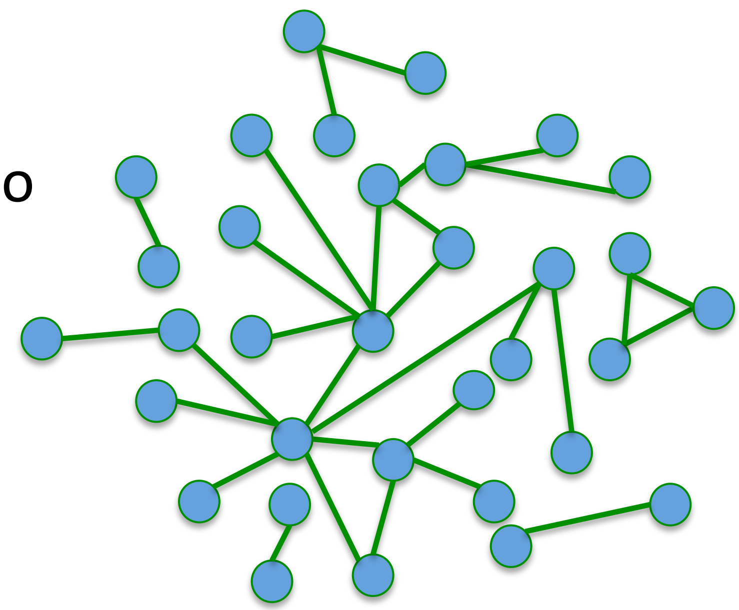

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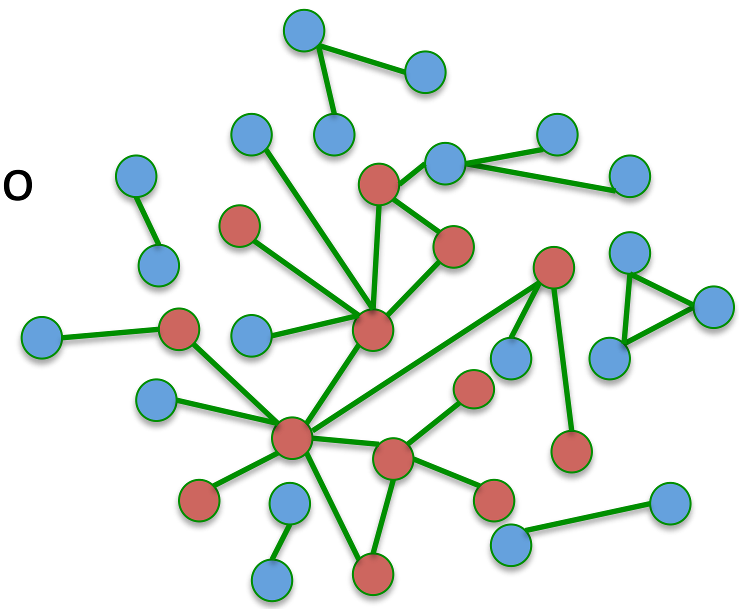

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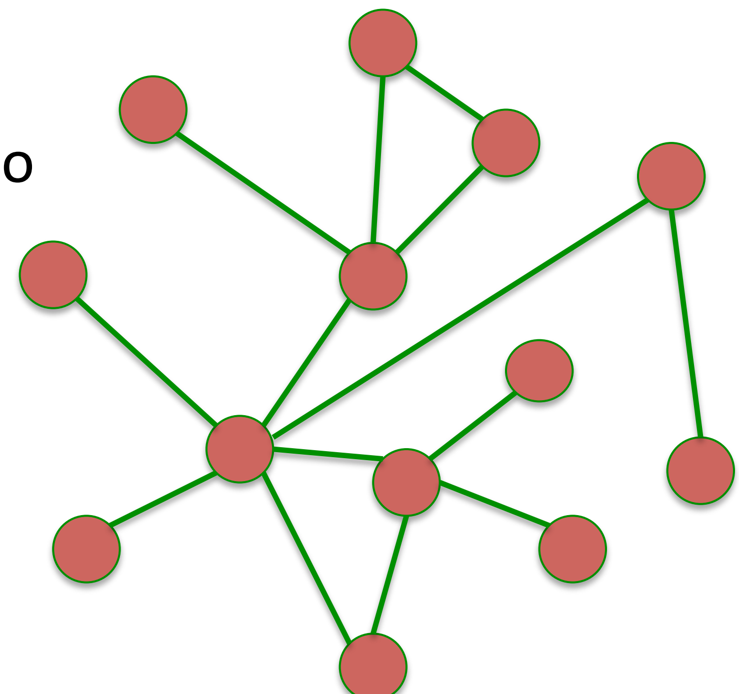

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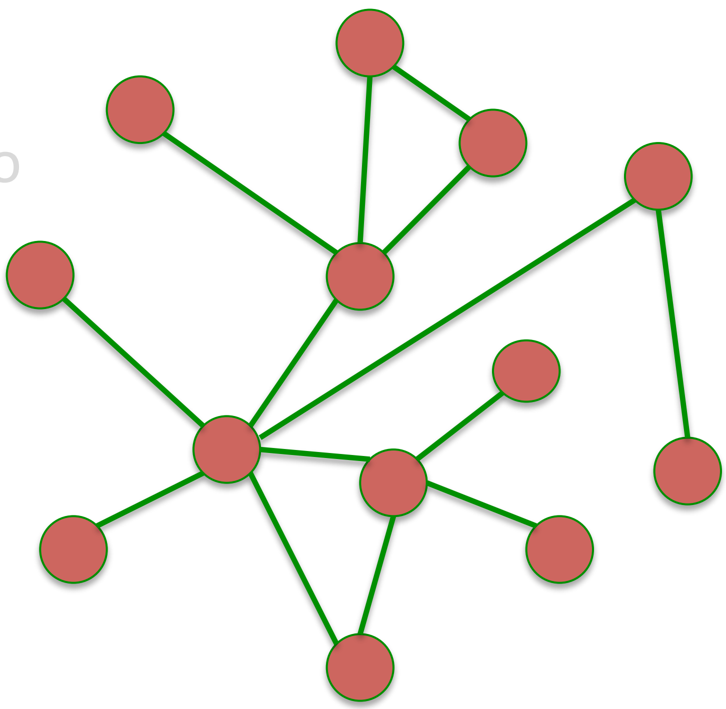

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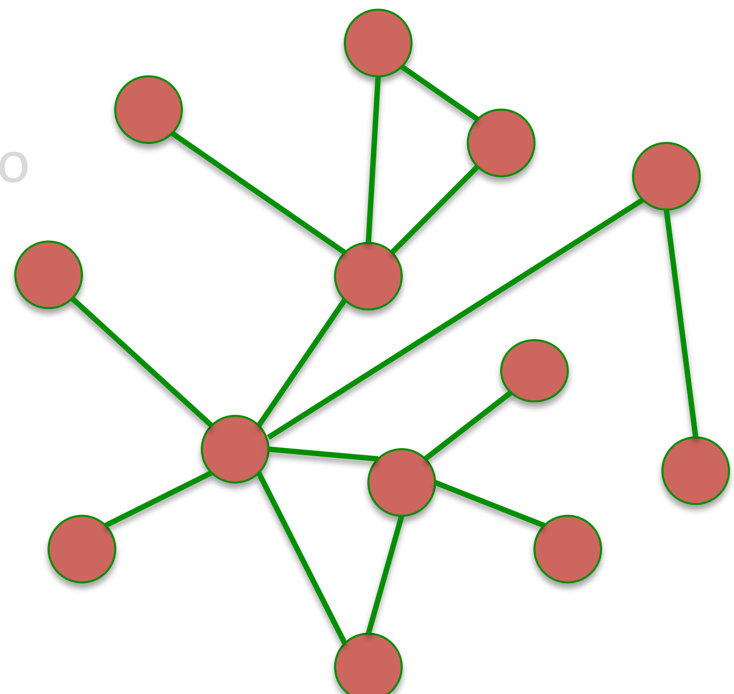

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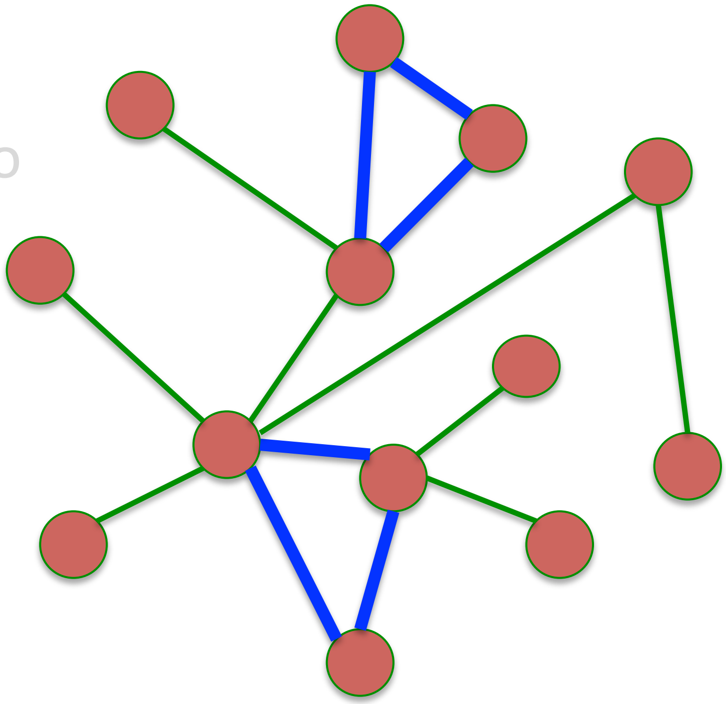

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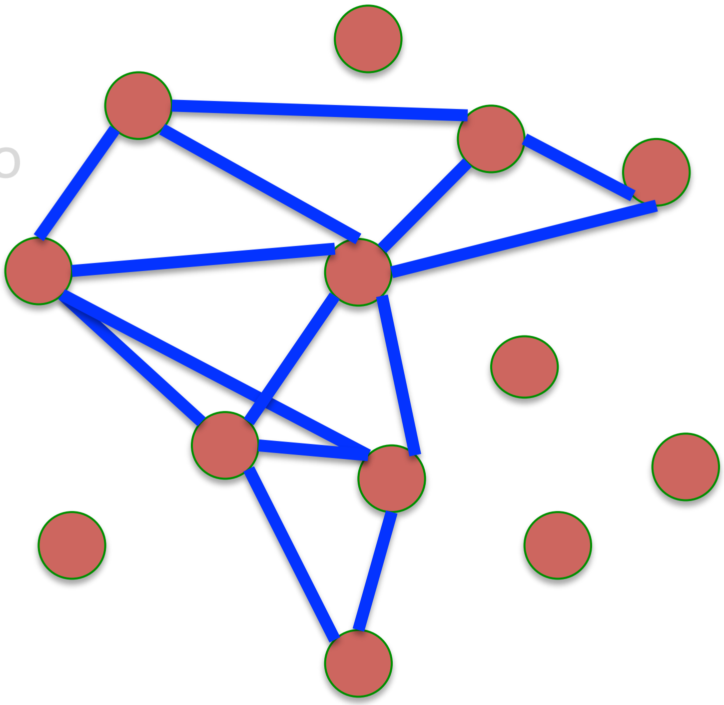

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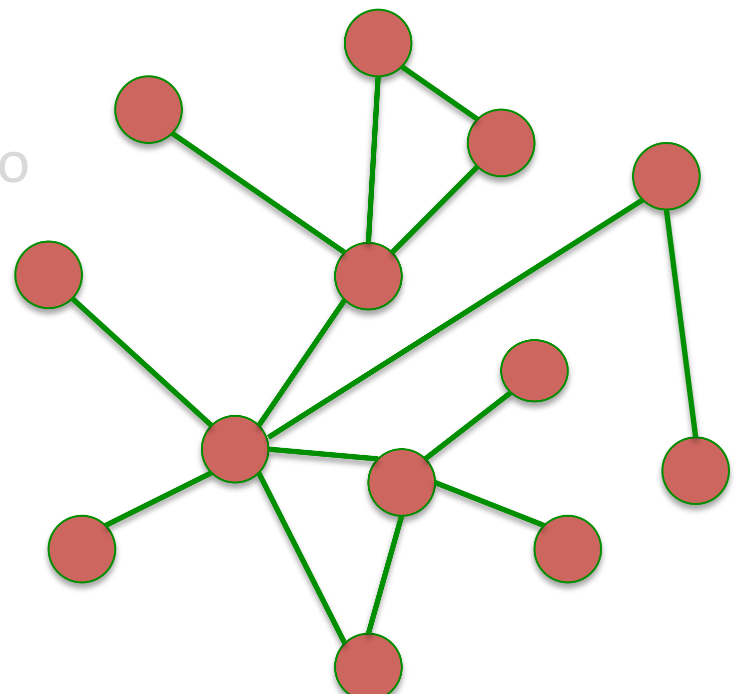

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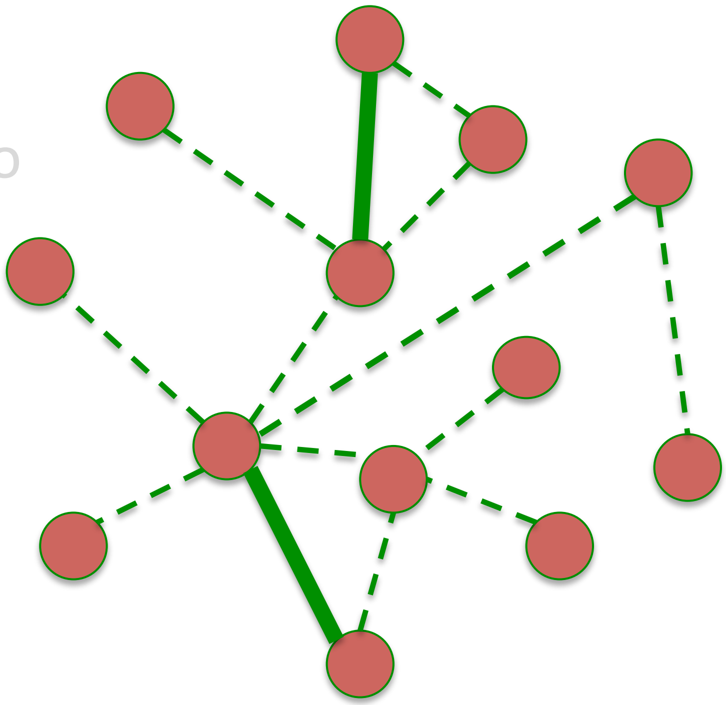

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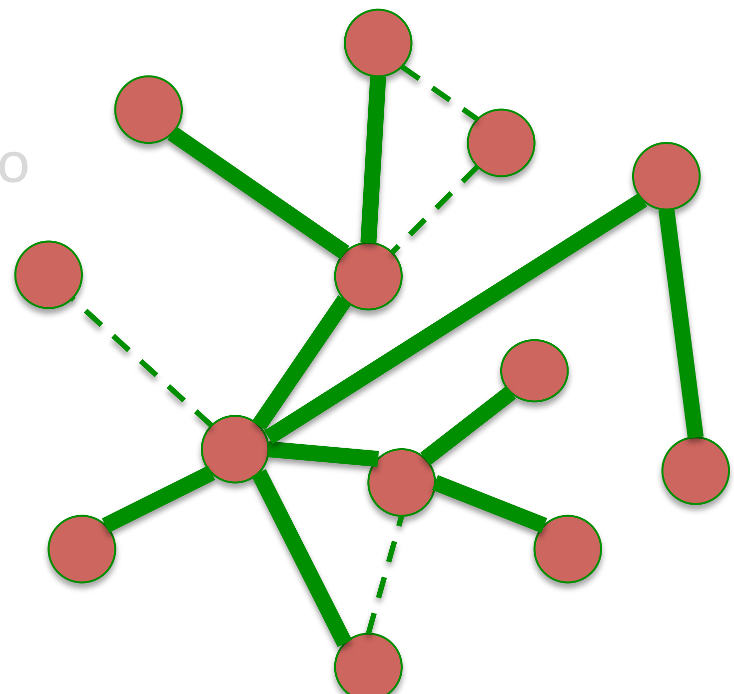

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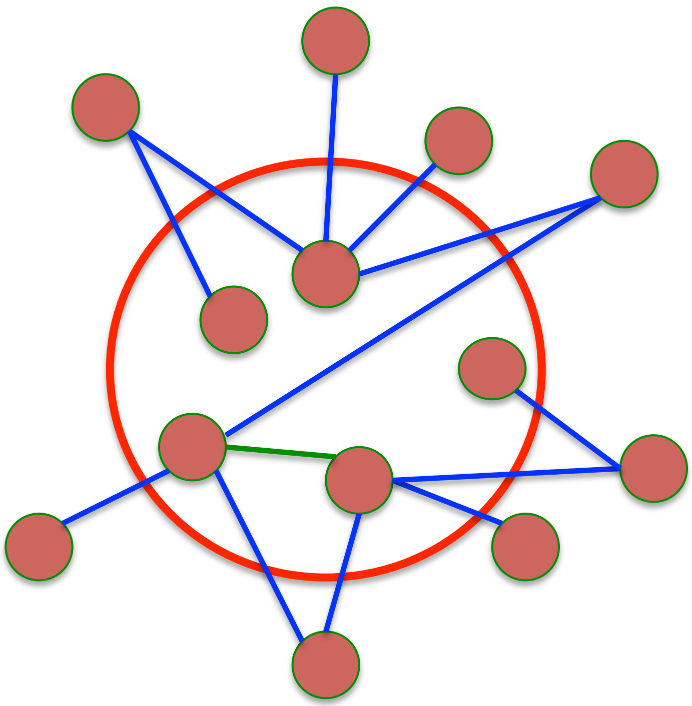

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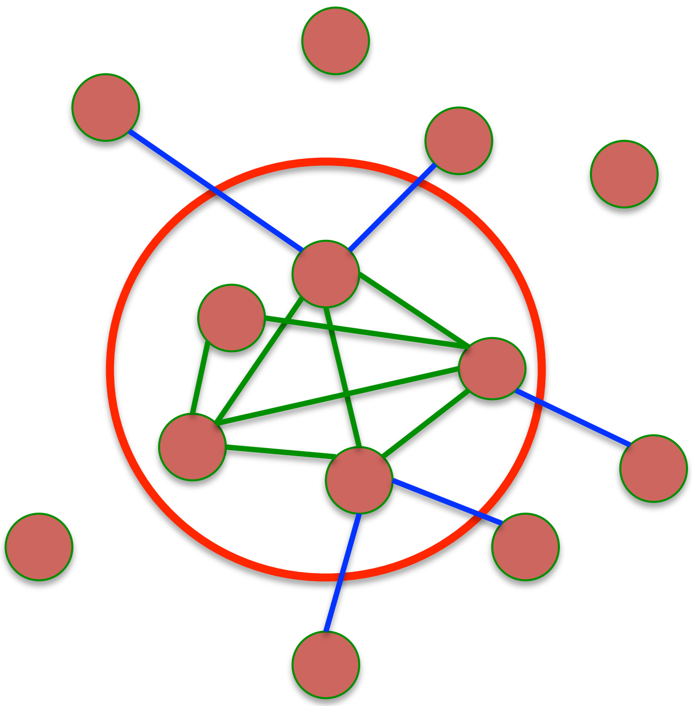

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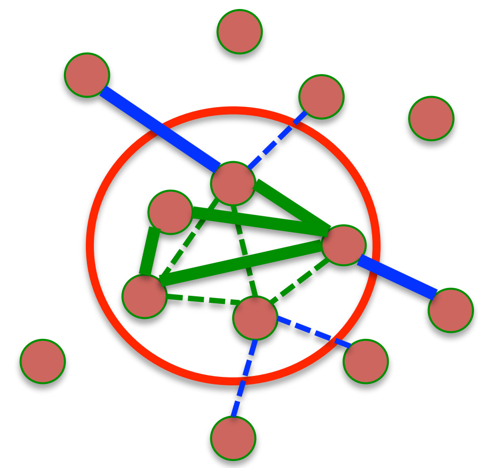
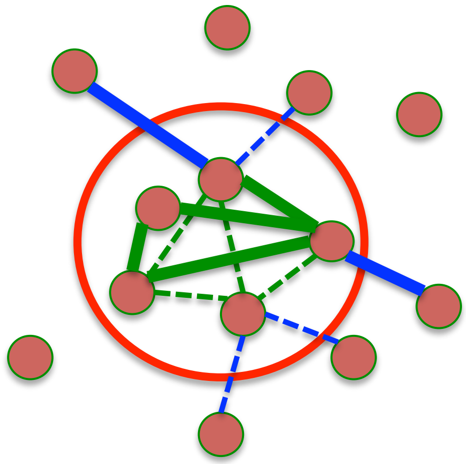


Turtled-up network



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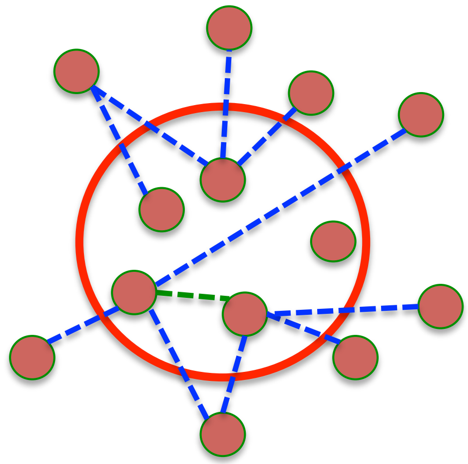
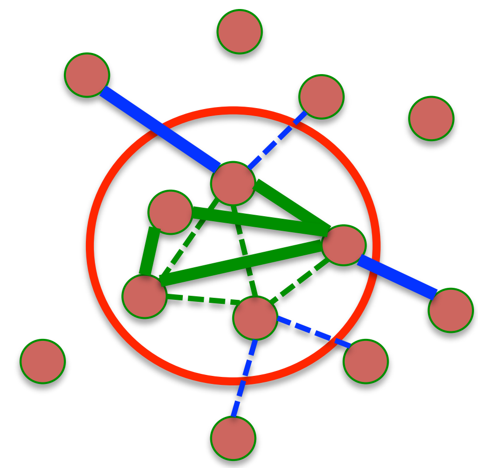


Open network

Theoretical Expectations

Networks may turtle-up during shocks:

- Trust (Granovetter 1985, Coleman 1988)
- Expertise knowledge, repeated information channels (Coleman 1990)
- Threat rigidity (*Staw 1981*)



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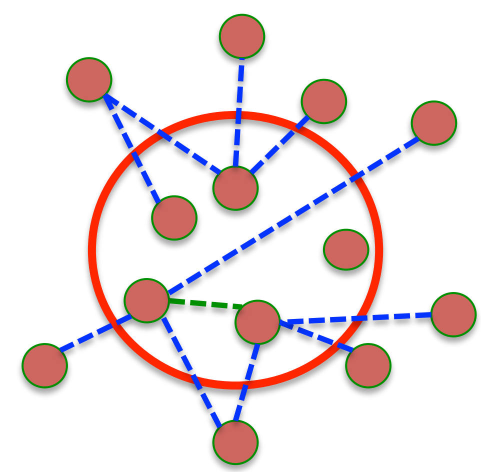

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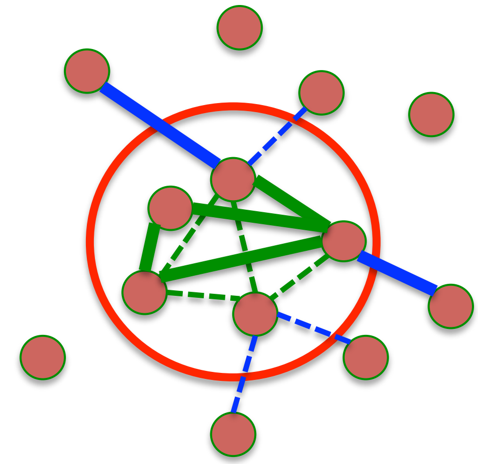
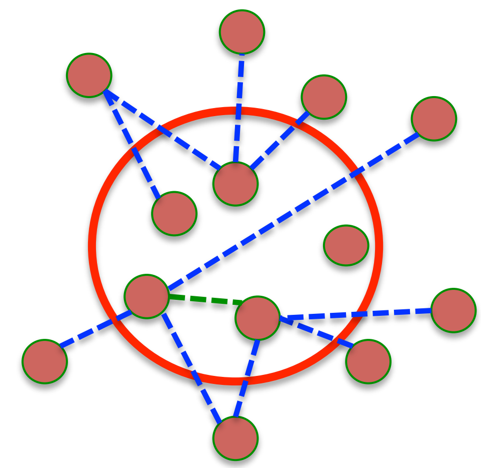
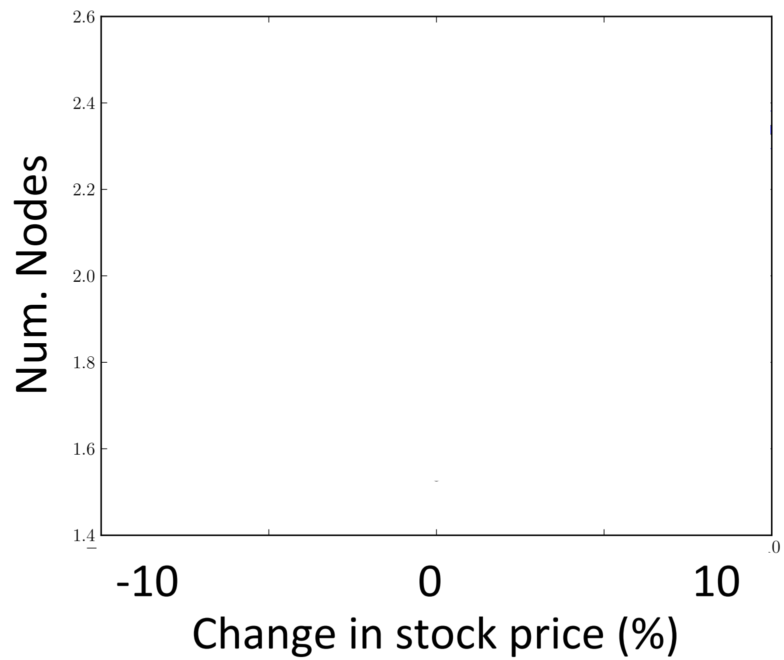


Networks may open-up during shocks:

- New information through weak ties [Granovetter 1973]
- Diverse information from different groups (structural holes) [Burt 92]



Findings: Size



Num of nodes | Past: Ratio of num. nodes in *G(s,d)* and mean num. nodes in *G(s,d')* for *d' < d*.

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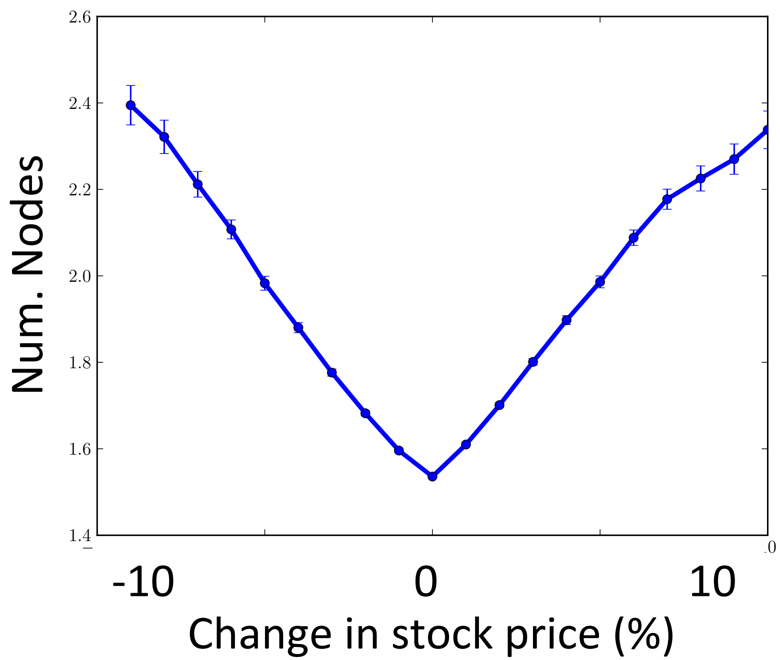

Shocks → **More nodes and edges**

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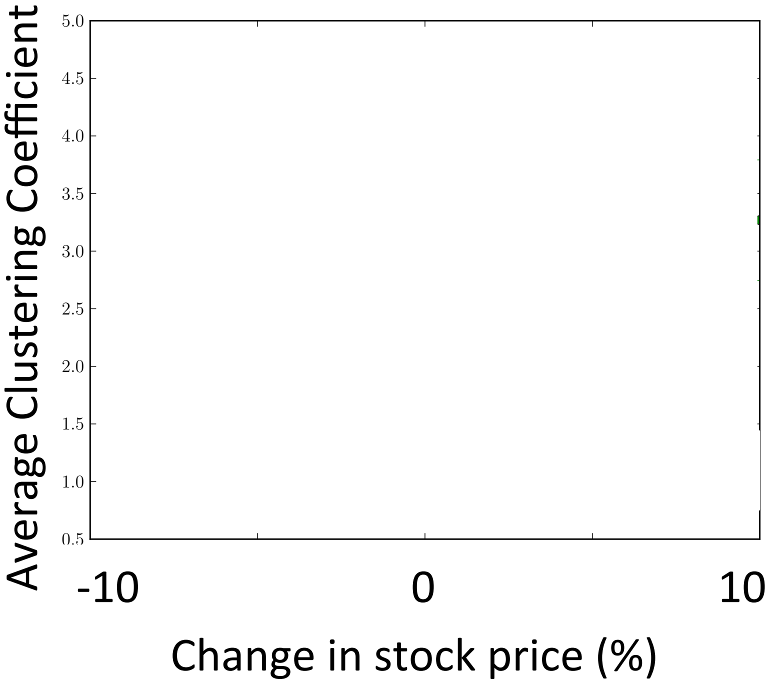
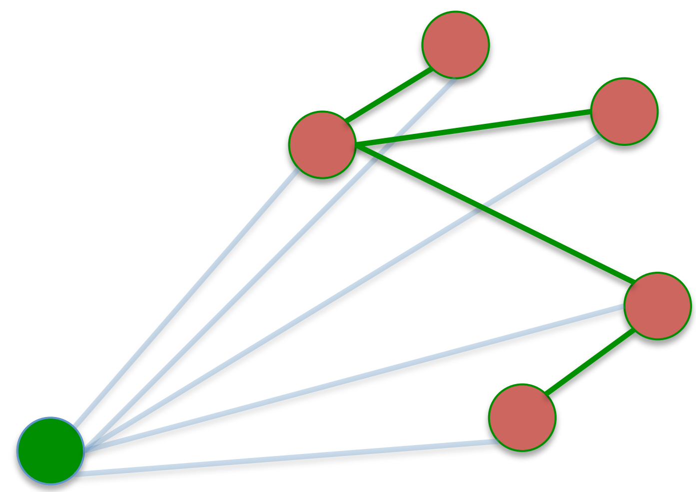
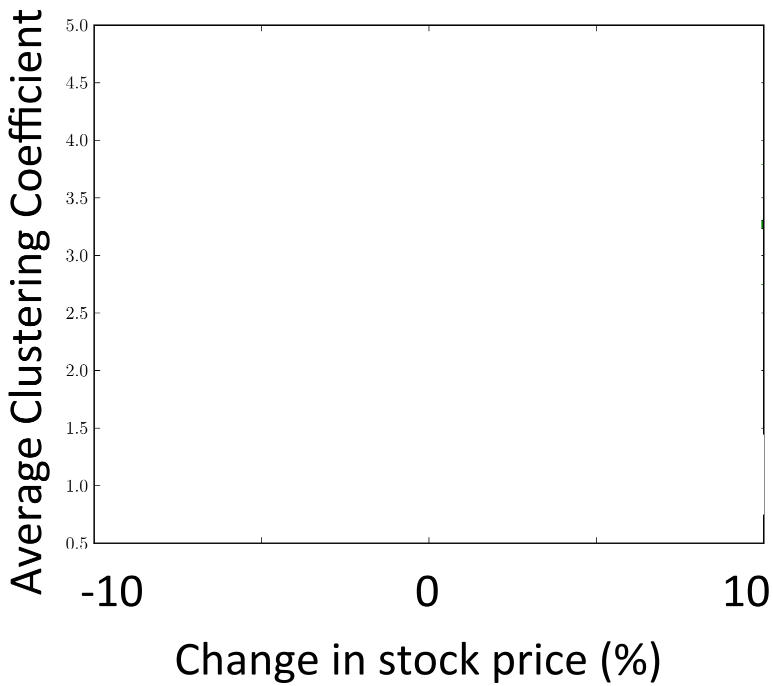
Findings: Clustering Coefficient

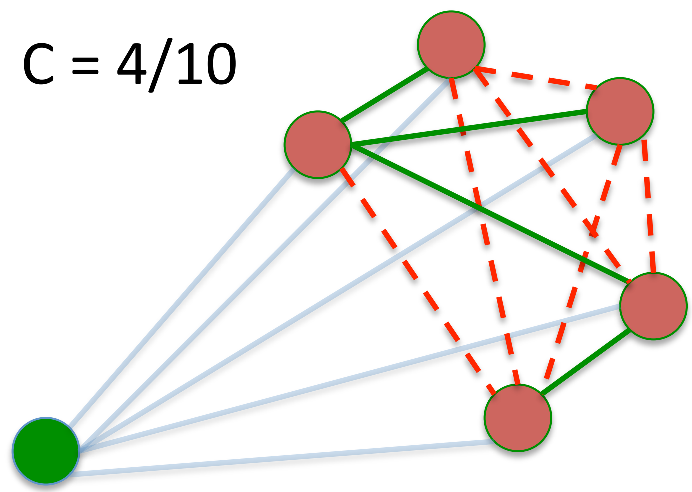




Clustering coefficient of a node *n*: the ratio of the existing and possible number of edges among the neighbors of *n*.

Findings: Clustering Coefficient





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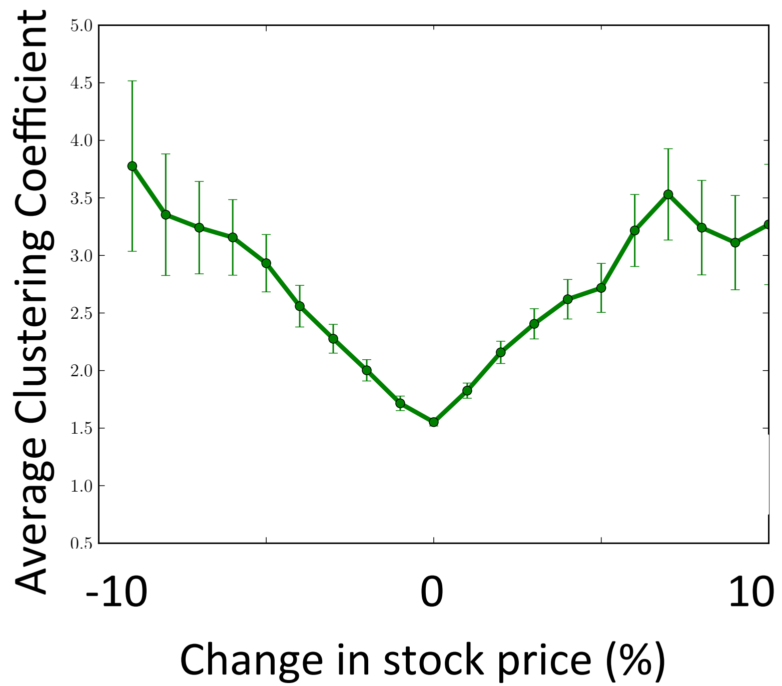

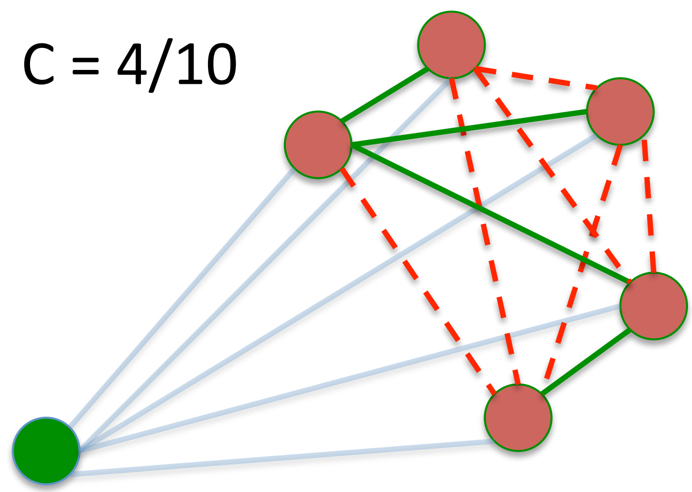

Shocks → **Higher Clustering coefficient**

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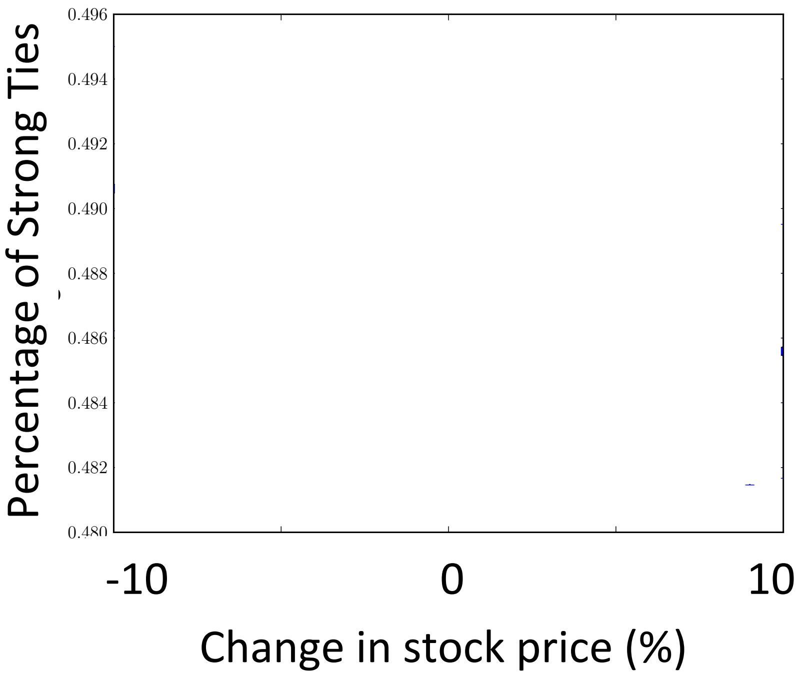
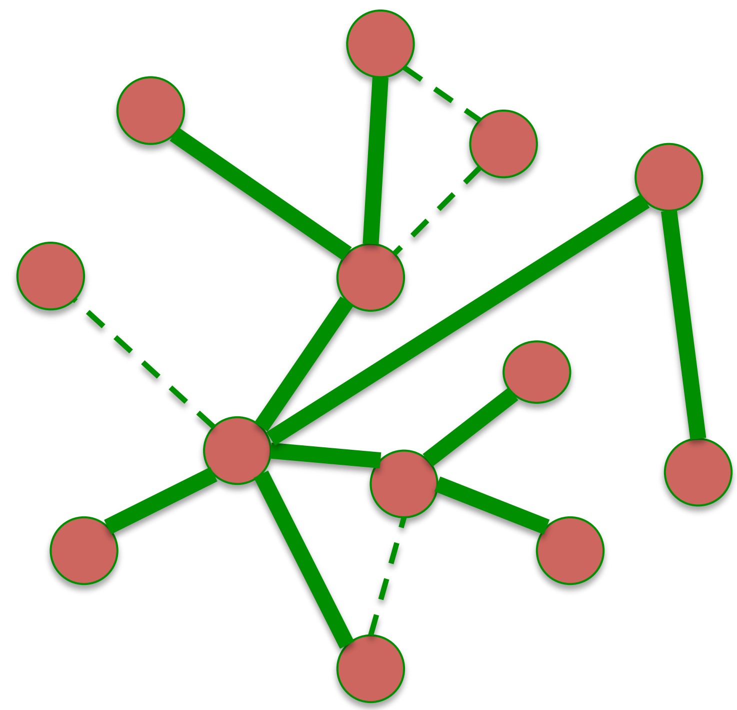
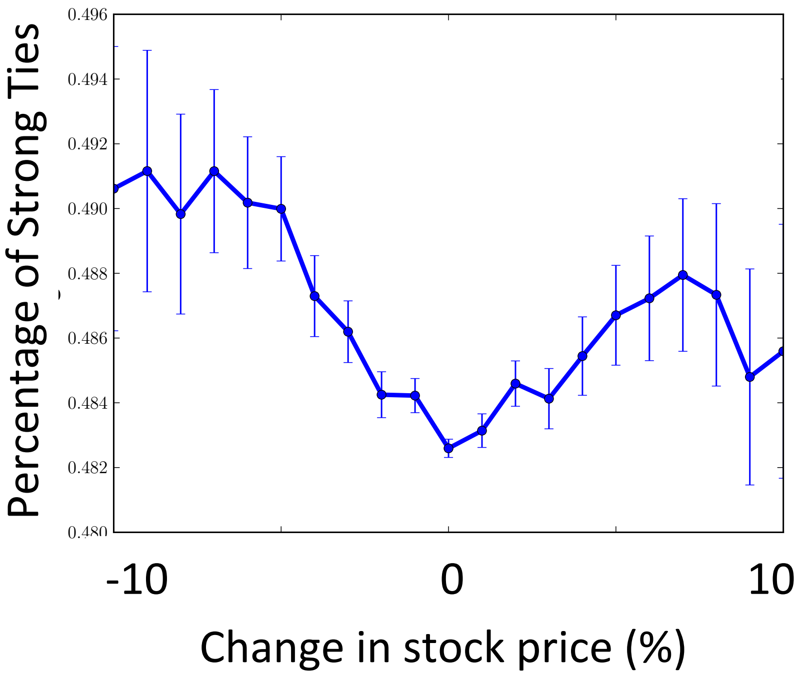
Findings: Tie Strength

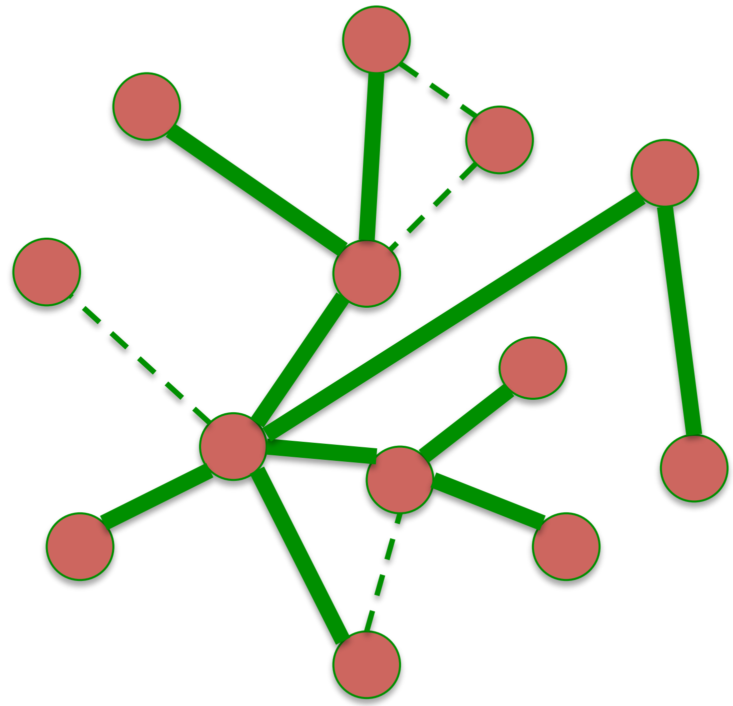




Tie strength: *(x,y)* is *k-strong*, if *y* is among the top *k%* most frequent connections of *x*

Findings: Tie Strength





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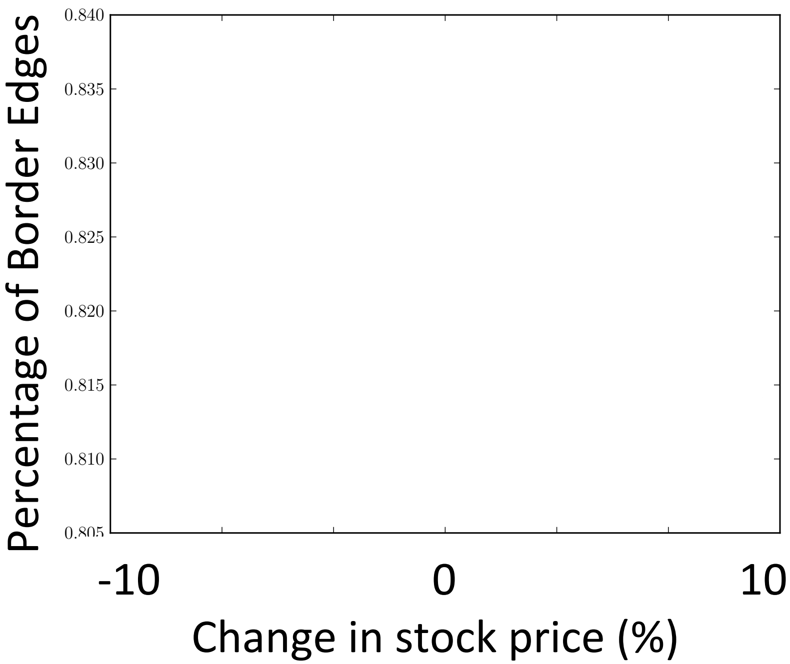
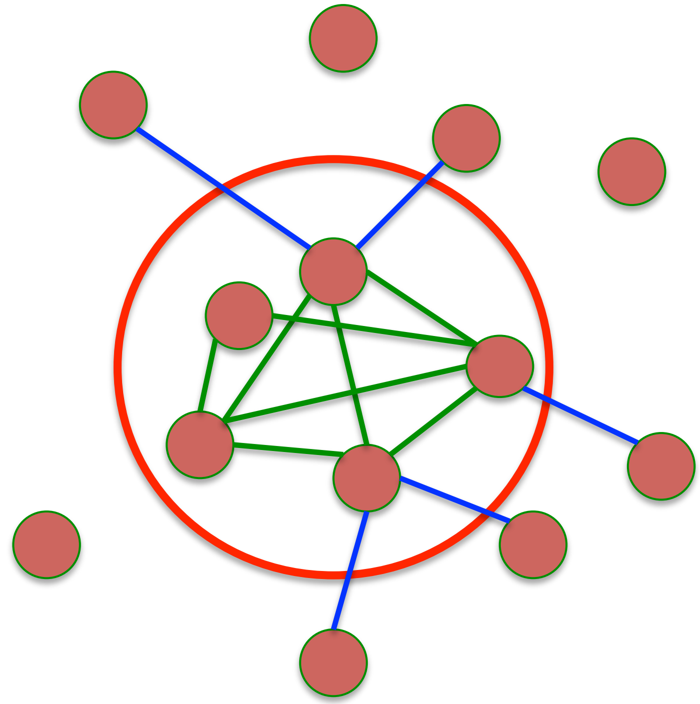
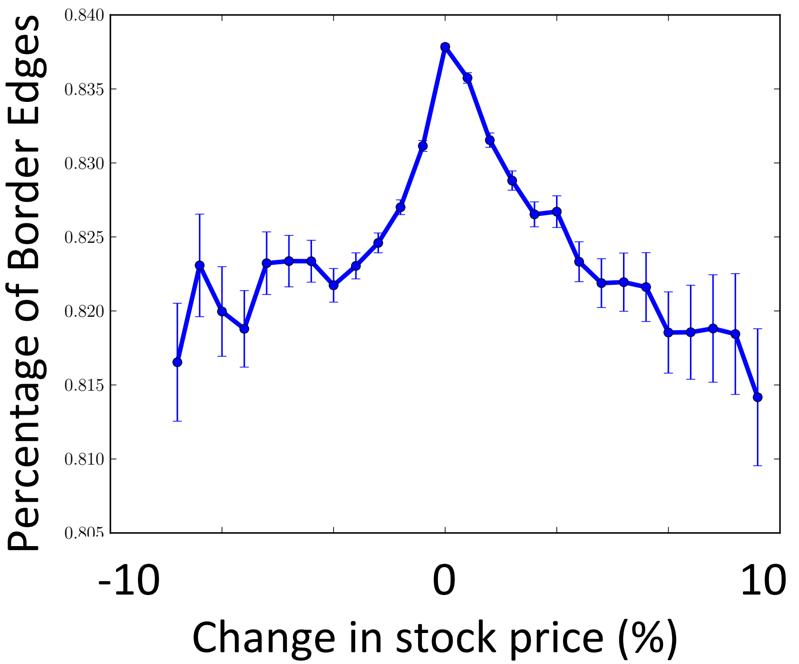
Findings: Openness

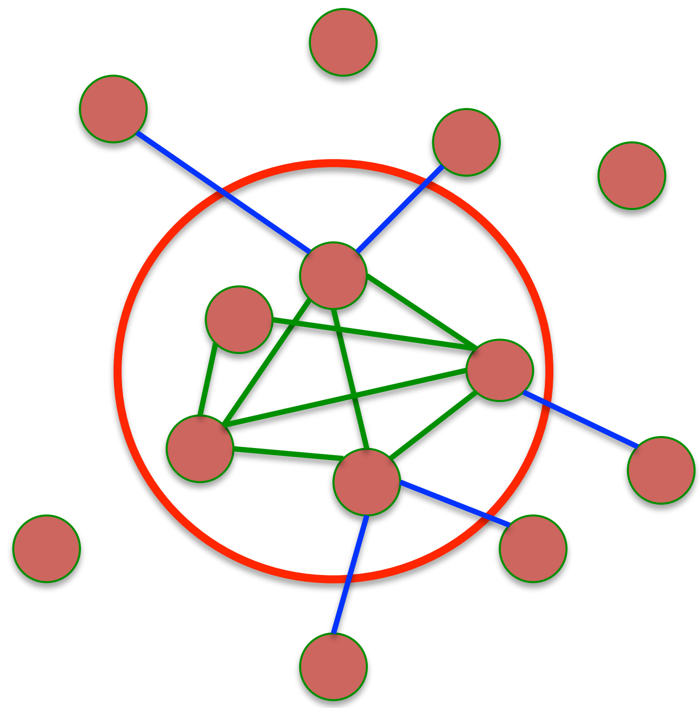




Border edges: involve an outside contact

Findings: Openness





Shocks → **More border edges**

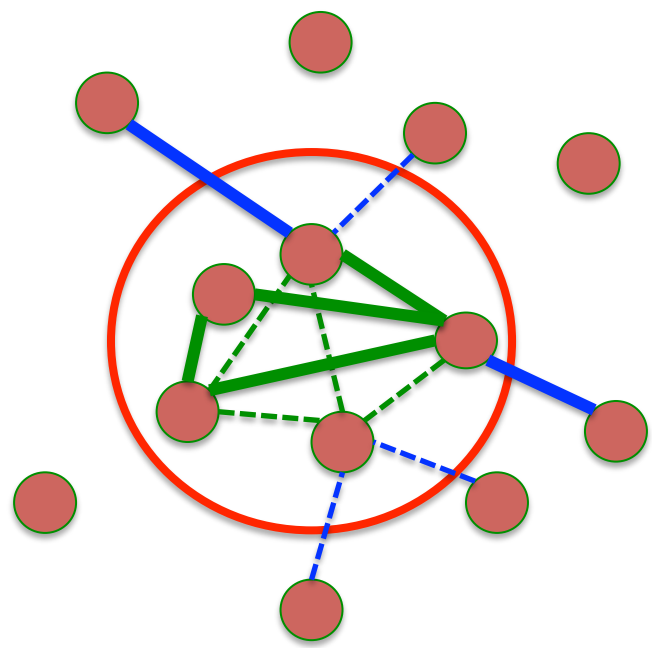
Border edges: involve an outside contact

Networks "Turtle-up" During Shocks

Networks as organisms that breath in and out – they can open and close with shocks.

Price changes are related to the network "turtle-up":

- Higher clustering
- Stronger edges
- More internal communication



Consistent with theories of:

- Trust
- Expertise knowledge, repeated information channels

Discrete Shocks and Network Recovery

Not all price changes are equally *surprising.*

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shock: price change > 5% on day d and < 5% on d-1, d-2, d-3

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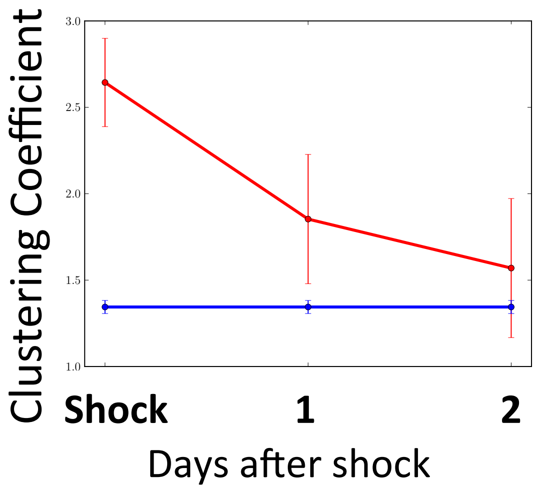

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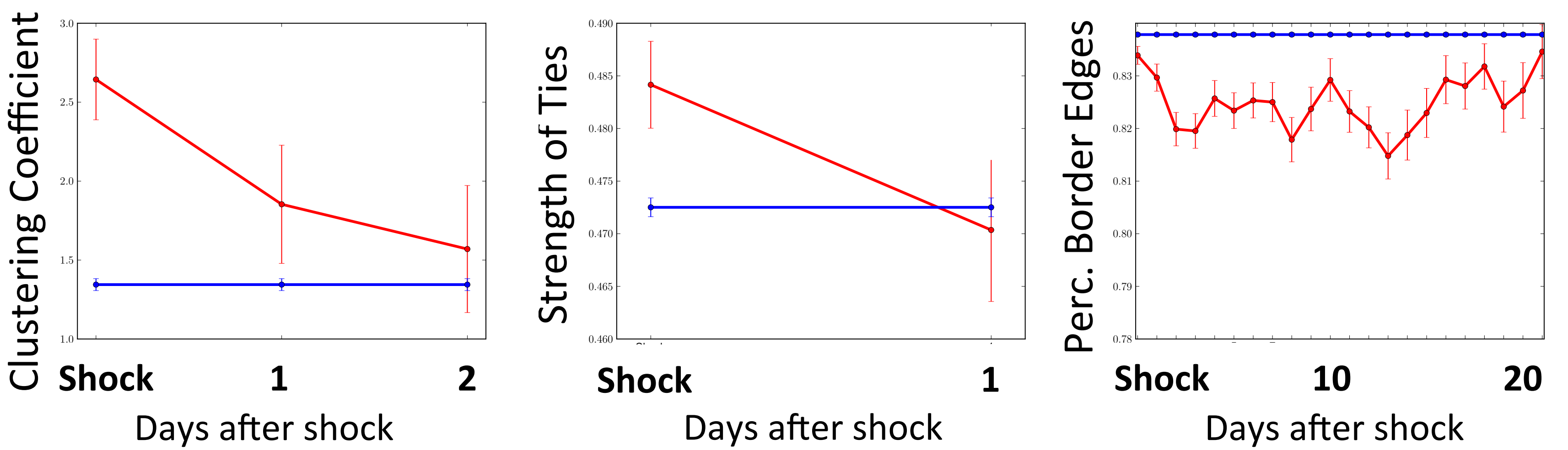


Changes in network structure after a shock are consistent.

Networks stabilize within several days after a shock.

Emotional and Cognitive Content

LIWC Categories

Linguistic Inquiry Word Count (LIWC): text analysis tool, which identifies words that belong to various categories.

Affective Processes	
Positive	Love, nice
Negative	Hurt, ugly
Anxiety	Worried, fearful
Anger	Hate, kill
Sadness	Crying, sad

Cognitive Processes	
Insight	Think, Consider
Causation	Because, Hence
Discrepancy	Should, Could
Tentative	Maybe, Guess
Certainty	Always, Never
Inhibition	Block, Constrain
Inclusive	With, Include
Exclusive	But, Exclude

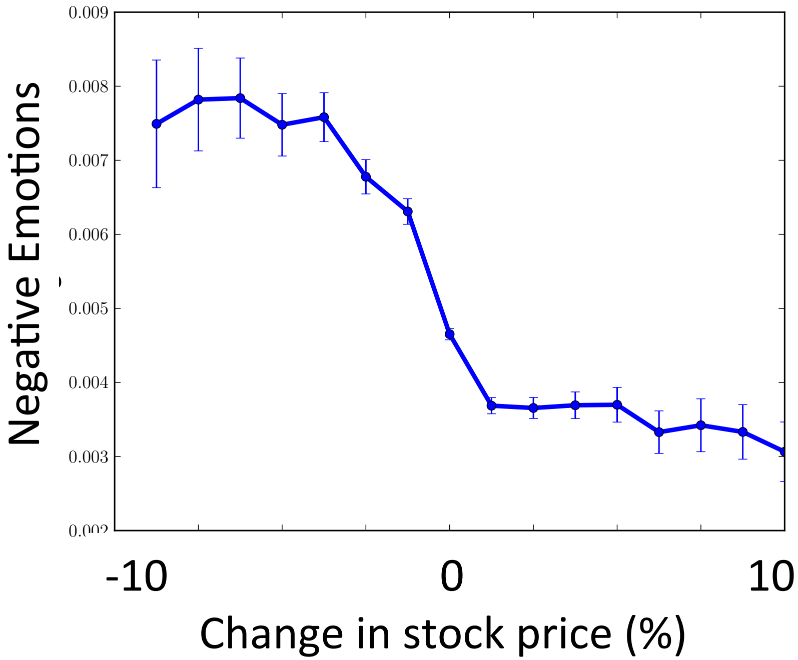
LIWC Categories

Linguistic Inquiry Word Count (LIWC): text analysis tool, which identifies words that belong to various categories.

Affective Processes	
Positive	Love, nice
Negative	Hurt, ugly
Anxiety	Worried, fearful
Anger	Hate, kill
Sadness	Crying, sad

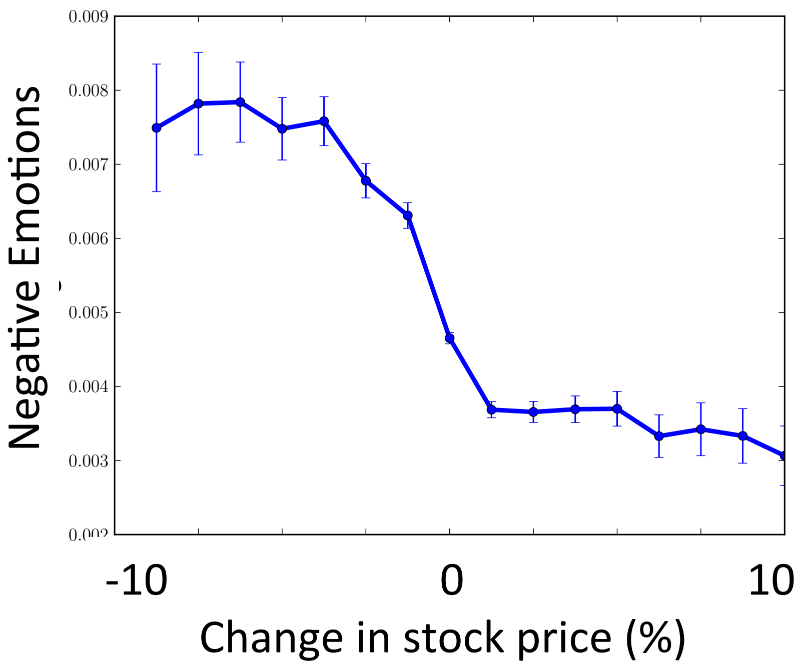
Cognitive Processes	
Insight	Think, Consider
Causation	Because, Hence
Discrepancy	Should, Could
Tentative	Maybe, Guess
Certainty	Always, Never
Inhibition	Block, Constrain
Inclusive	With, Include
Exclusive	But, Exclude

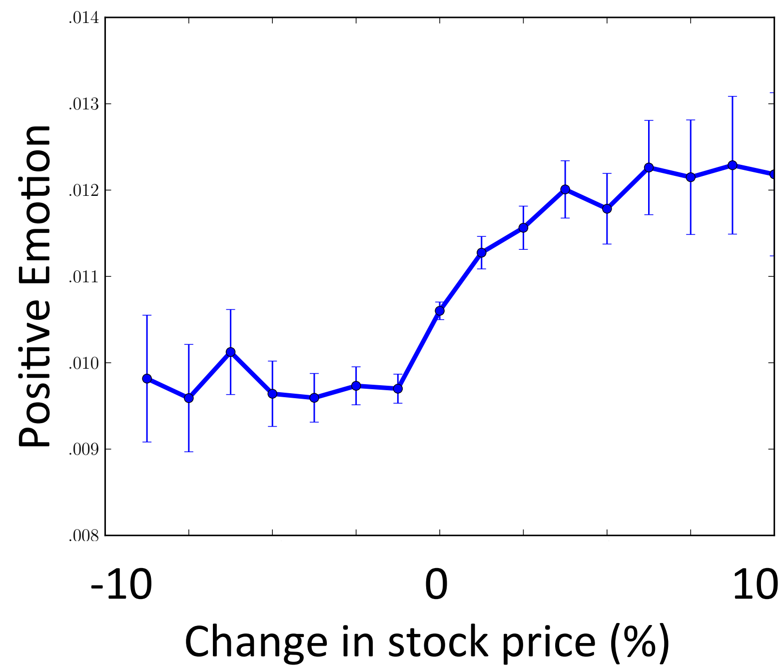
Price Changes vs. Emotions



Positive price changes → Higher positive emotions

Price Changes vs. Emotions



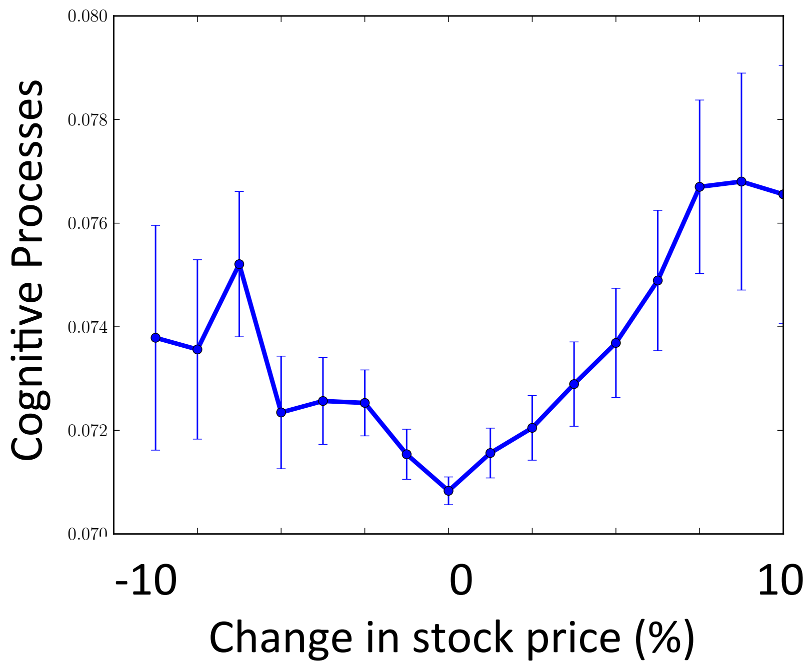


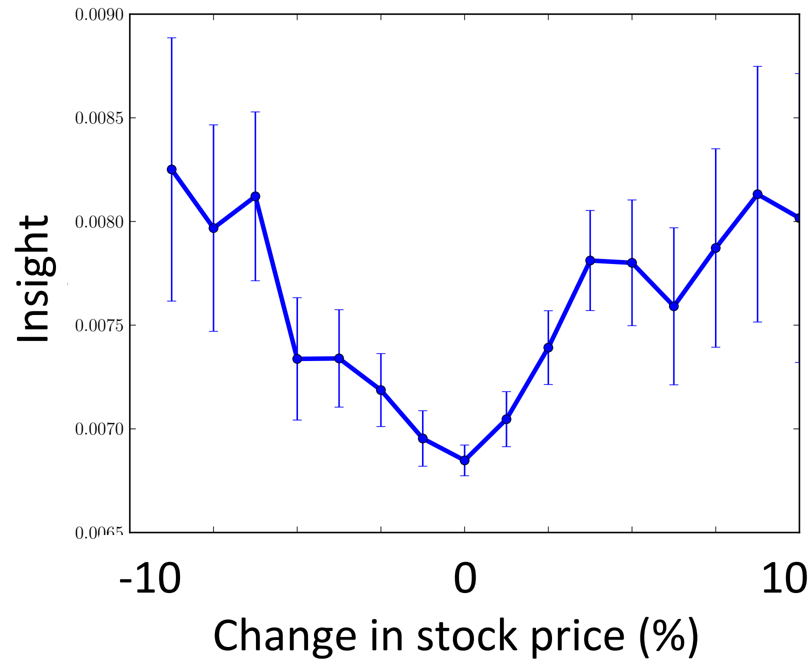
Positive price changes $\longrightarrow$ Higher positive emotions

Negative price changes $\longrightarrow$ Higher negative emotions

Emotions are asymmetric with respect to price change.

Price Changes vs. Cognitive Processes





Price changes → Higher cognitive language

Cognitive processes are asymmetric with respect to price change.

Prediction of Sentiment and Cognition

Task: For a fixed stock ***s*** and day ***d***, predict if IMs that mention ***s*** on day ***d*** contain more words in the category than average.

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Machine learning classifiers: SVM, Random Forest, Linear Discriminant Analysis, Naive Bayes, **Logistic regression.**

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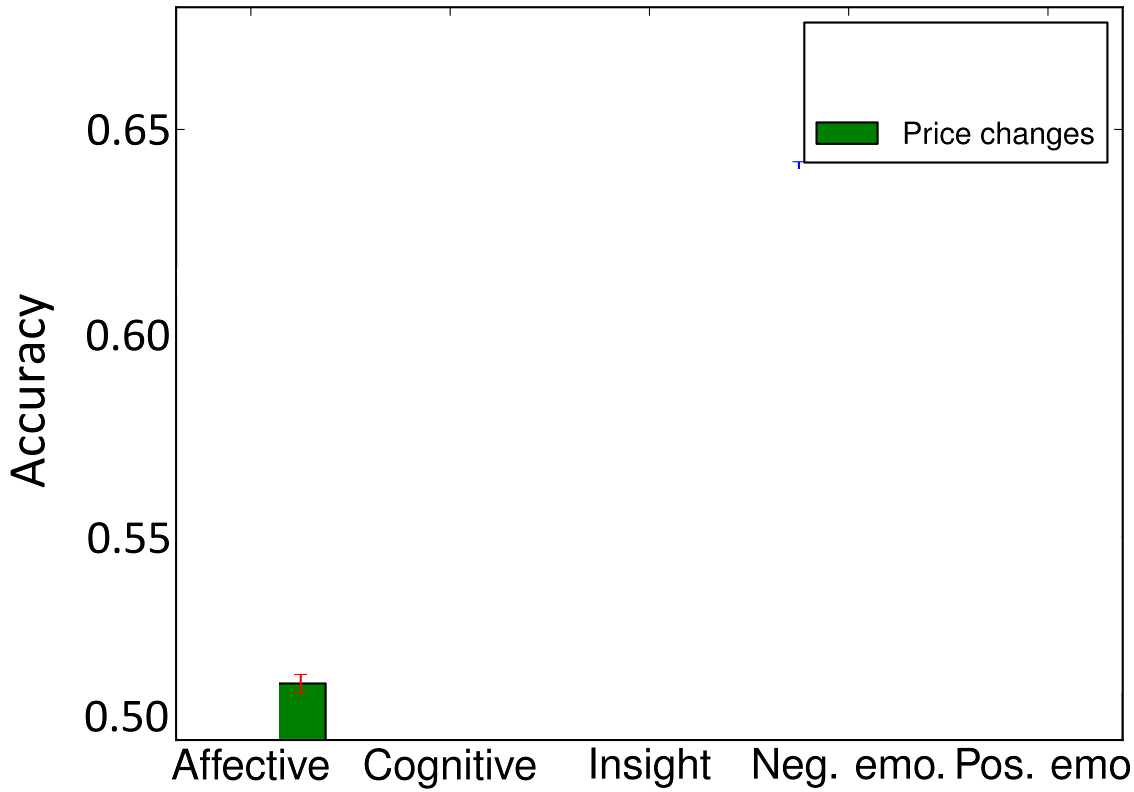
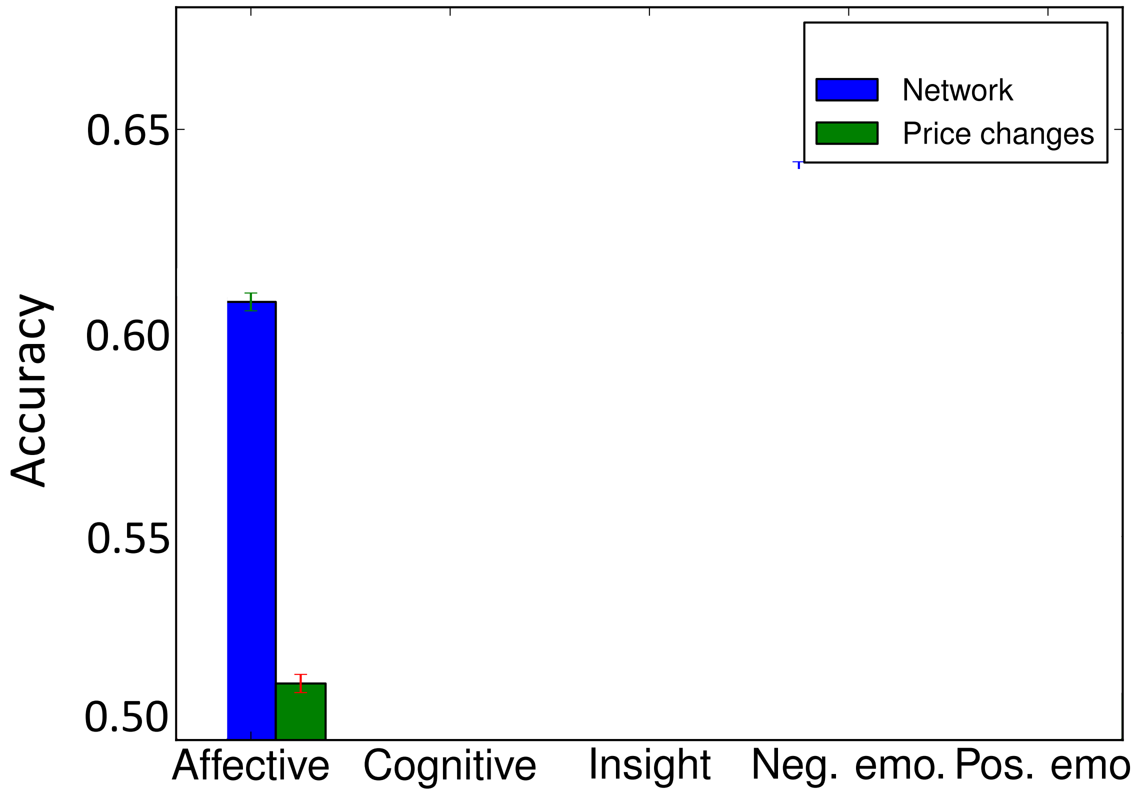


Prediction of Sentiment and Cognition



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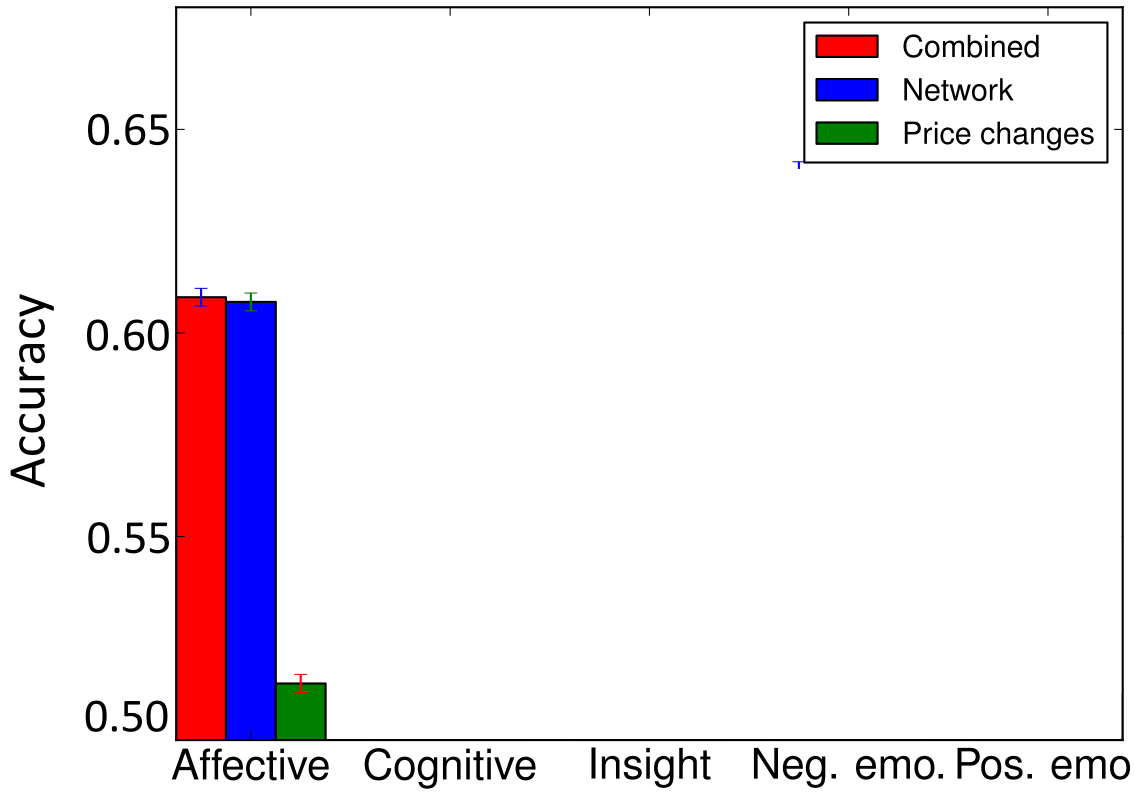

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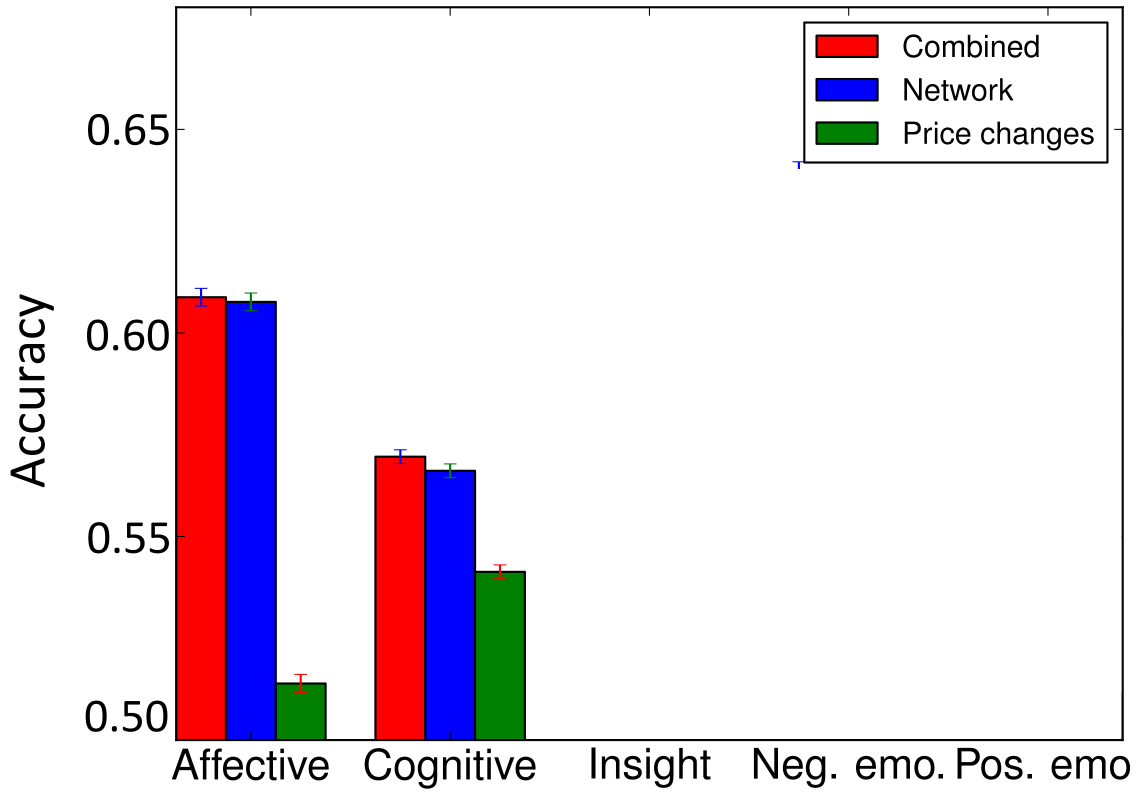

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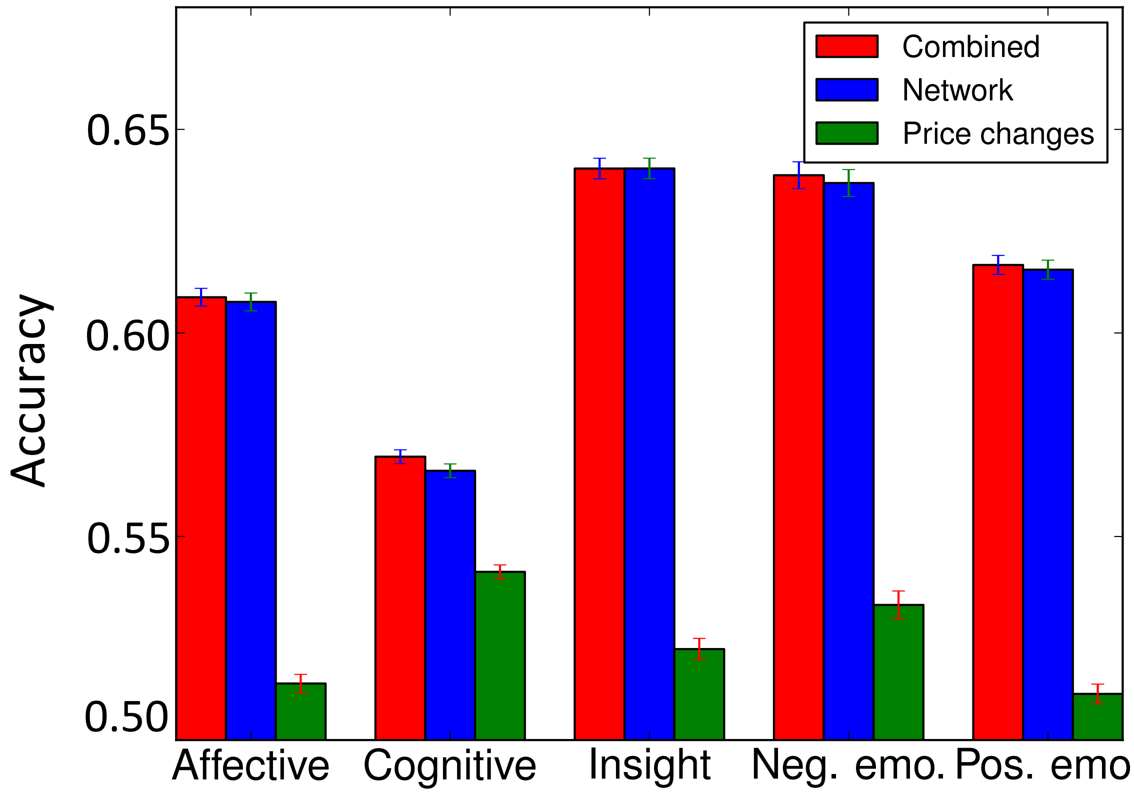

Network variables are more predictive of type of content than price changes.

Sample Trading Data

Date	Quantity	Time	Symbol	Type	Price
05/21/2008	100	03:22:00 PM	GOOG	BUY	290.61
05/21/2008	200	03:46:21 PM	GOOG	SELL	288.45
05/21/2008	100	03:55:08 PM	GOOG	BUY	291.98
05/21/2008	200	03:55:52 PM	GOOG	BUY	301.98
05/21/2008	100	03:37:04 PM	GOOG	BUY	288.61
05/21/2008	50	03:50:51 PM	GOOG	SELL	289.80
05/21/2008	100	03:59:09 PM	GOOG	SELL	299.99
05/22/2008	300	10:11:28 AM	AAPL	BUY	27.98
05/22/2008	100	10:31:07 AM	AAPL	BUY	26.76
05/22/2008	300	10:18:35 AM	AAPL	BUY	27.00
05/22/2008	100	10:27:02 AM	AAPL	BUY	27.43
05/22/2008	100	10:07:14 AM	AAPL	SHORT	28.21
05/22/2008	50	10:24:01 AM	AAPL	SELL	27.77
05/22/2008	100	10:14:10 AM	GOOG	SELL	298.61
05/22/2008	50	10:10:39 AM	GOOG	SHORT	301.87
05/22/2008	100	10:25:08 AM	AAPL	SHORT	36.16
05/22/2008	300	10:01:29 AM	APL	BUY	28.50

Prediction of Optimal Trading Time

Suboptimal trade: Traded at less optimal price than the worst price the next day

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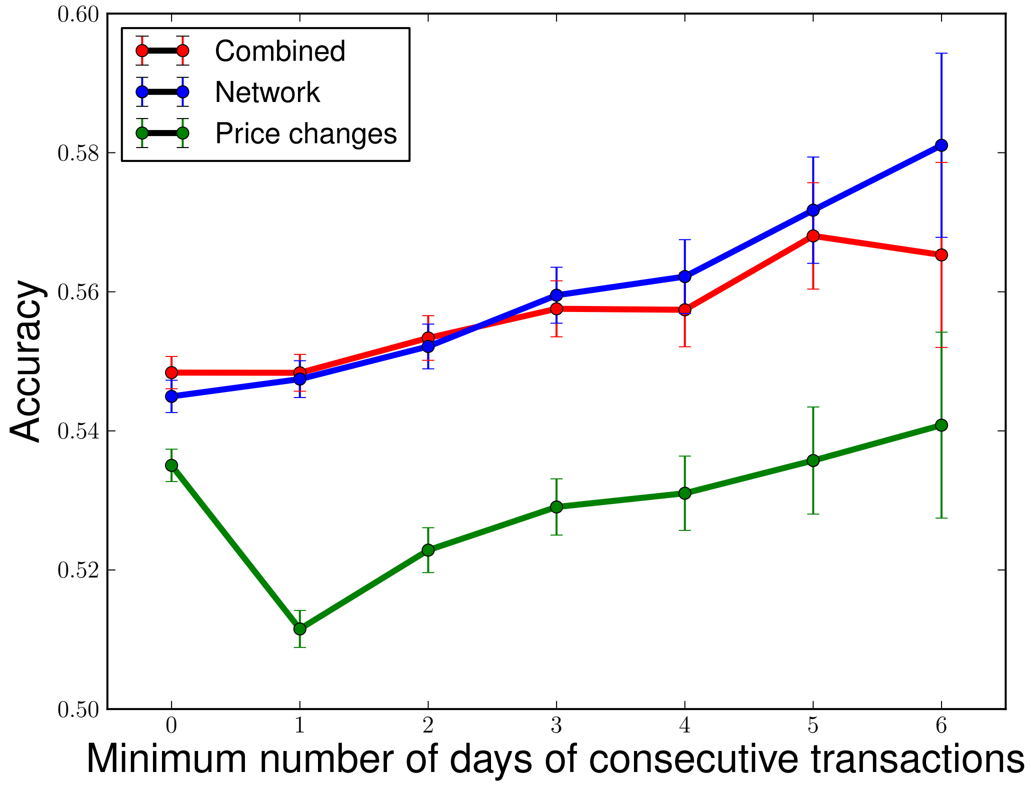
N-serial trades: A trade of stock *s* that has occurred for at least N consecutive days

Prediction of Optimal Trading Time



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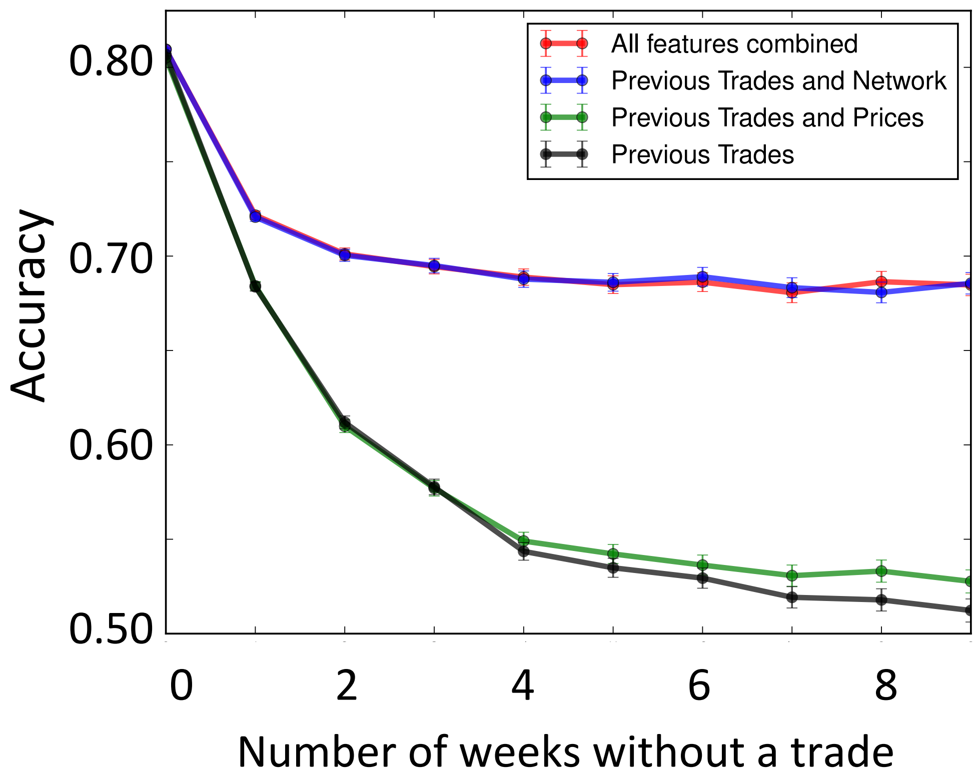
Features:

- Network (density, size, openness, lagged)
- Price change (signed, absolute, lagged)
- Indicator of trading during 7 days prior to *k* weeks of no trading.

Predicting Stock Trading



Task: Predict whether a stock that has not been traded for *k* weeks will be traded.

Network variables are more predictive of type of sudden stock trading than price changes.

Market Movements
(Shocks)

Social Network

Trading

Performance

Emotional and
Cognitive Content

Differentiation in Dating Sites

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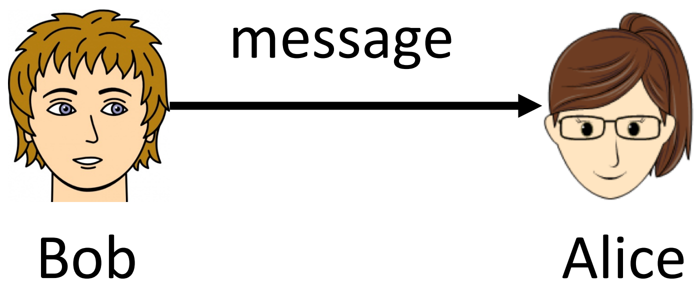
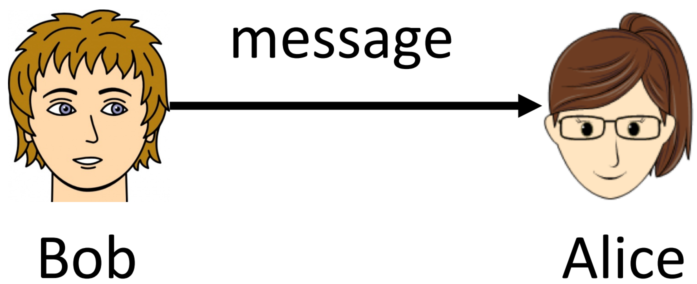
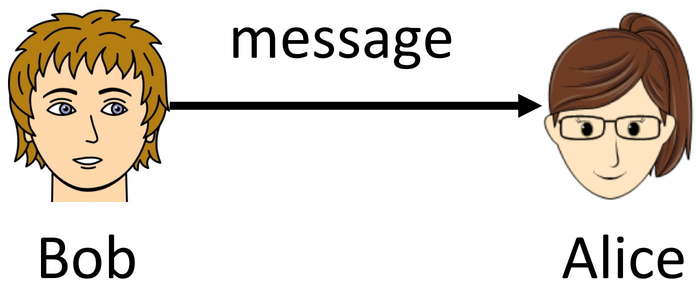


Differentiation in Dating Sites



Will Bob get a response?

Differentiation in Dating Sites



Will Bob get a response?

Does the probability that Bob gets a response depend on:

1. The text similarity between Bob and Alice?

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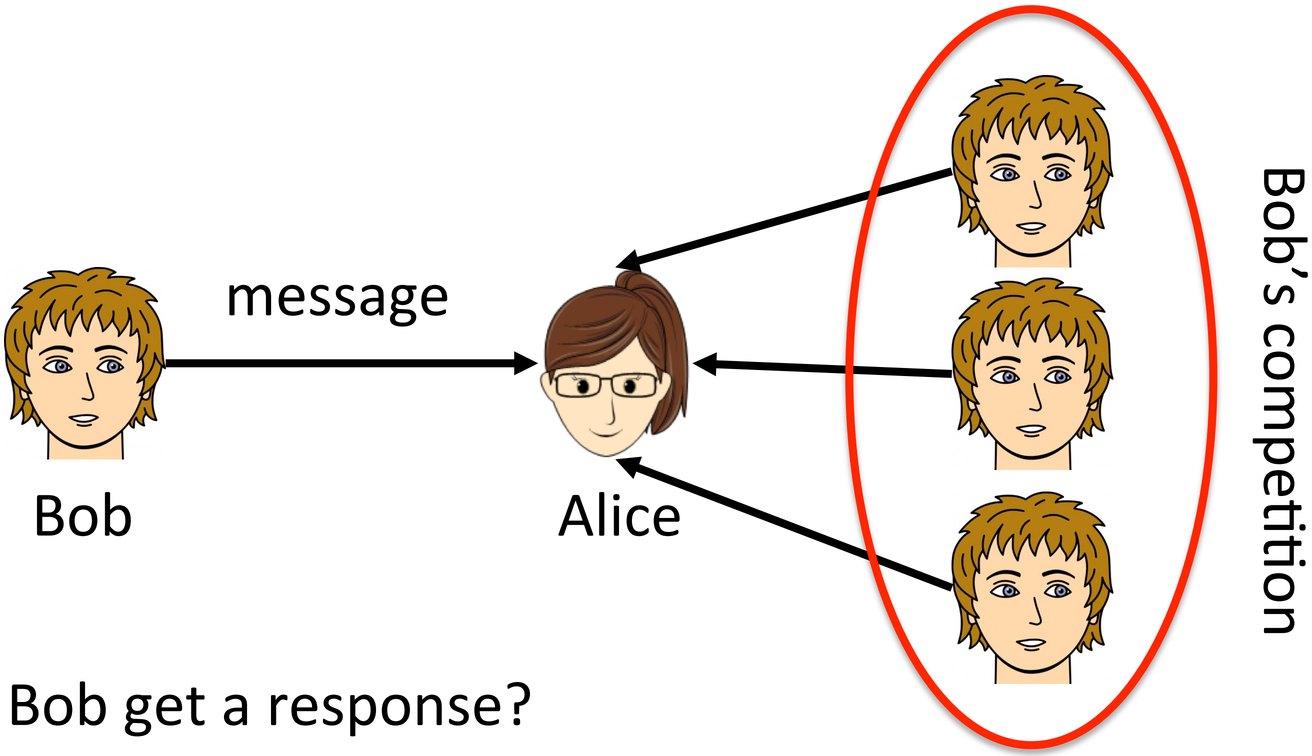


Will Bob get a response?

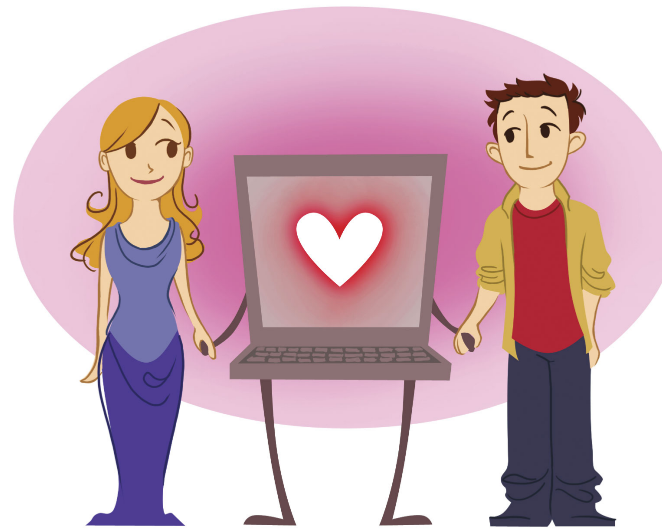
Does the probability that Bob gets a response depend on:

1. The text similarity between Bob and Alice?
2. The text similarity between Bob and his competition?

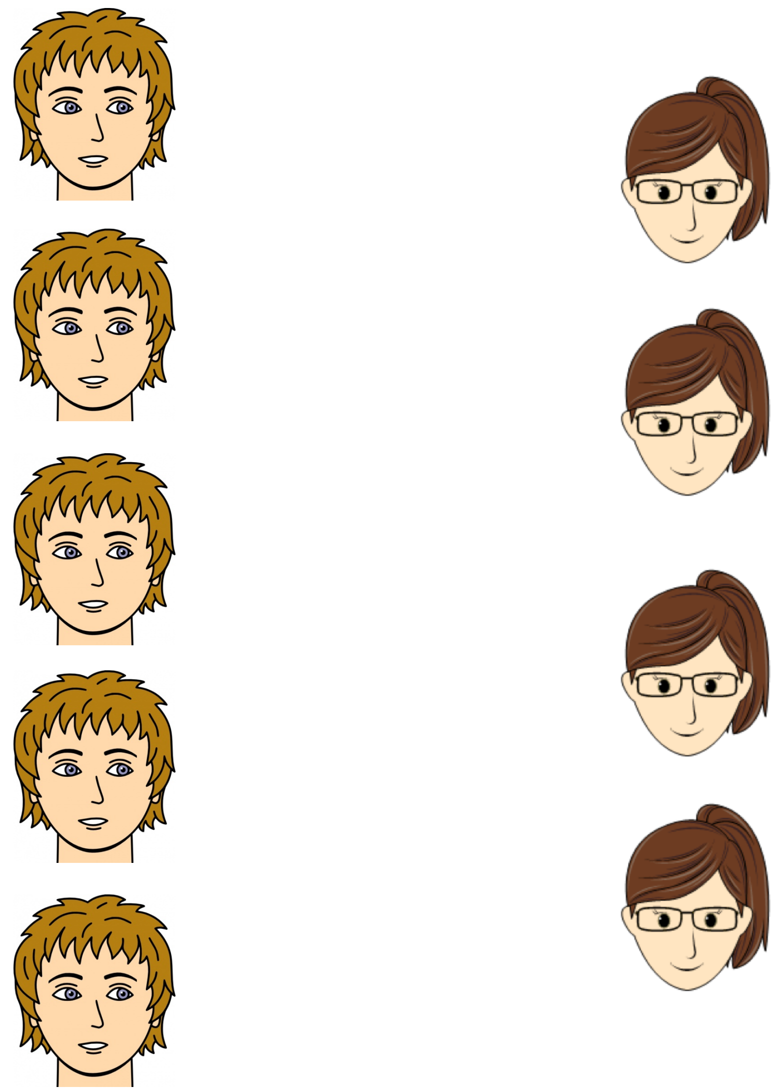
Dating Site Data

Data from a major online dating site:

- From 9/1/13 to 12/1/13
- 230K males and 180K females (active)
- 25 million exchanges messages
- Full profile data:
  - Demographic information
  - Free text responses



Market-level Competition Network



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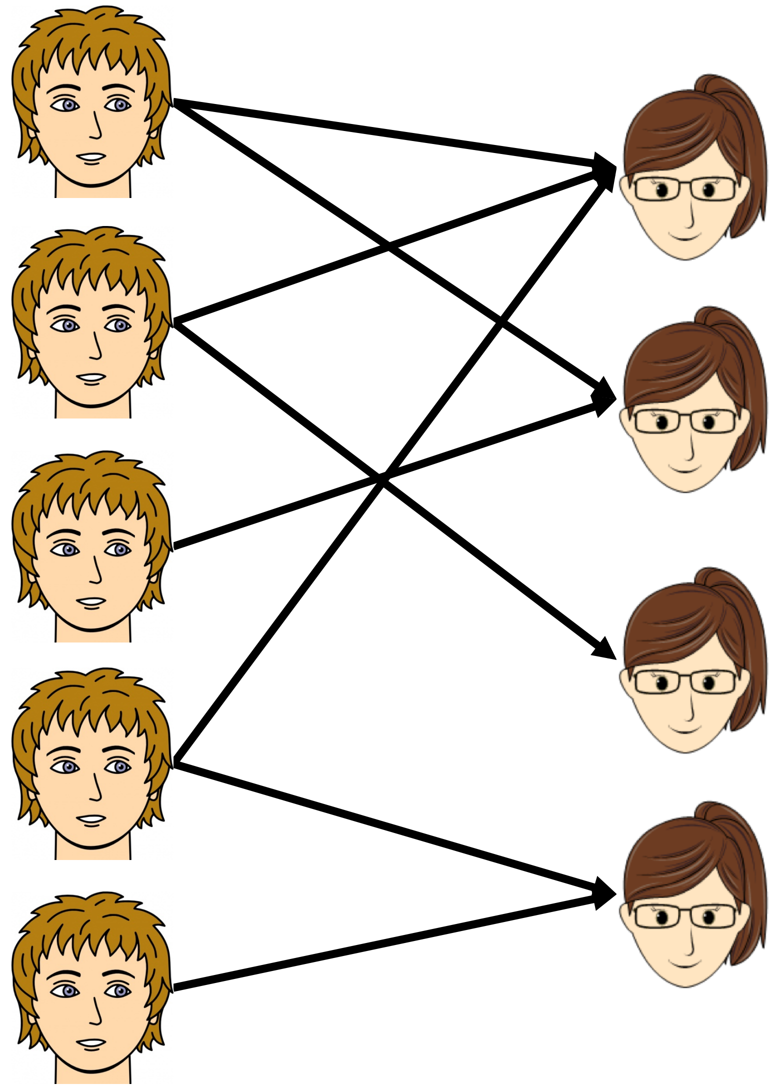
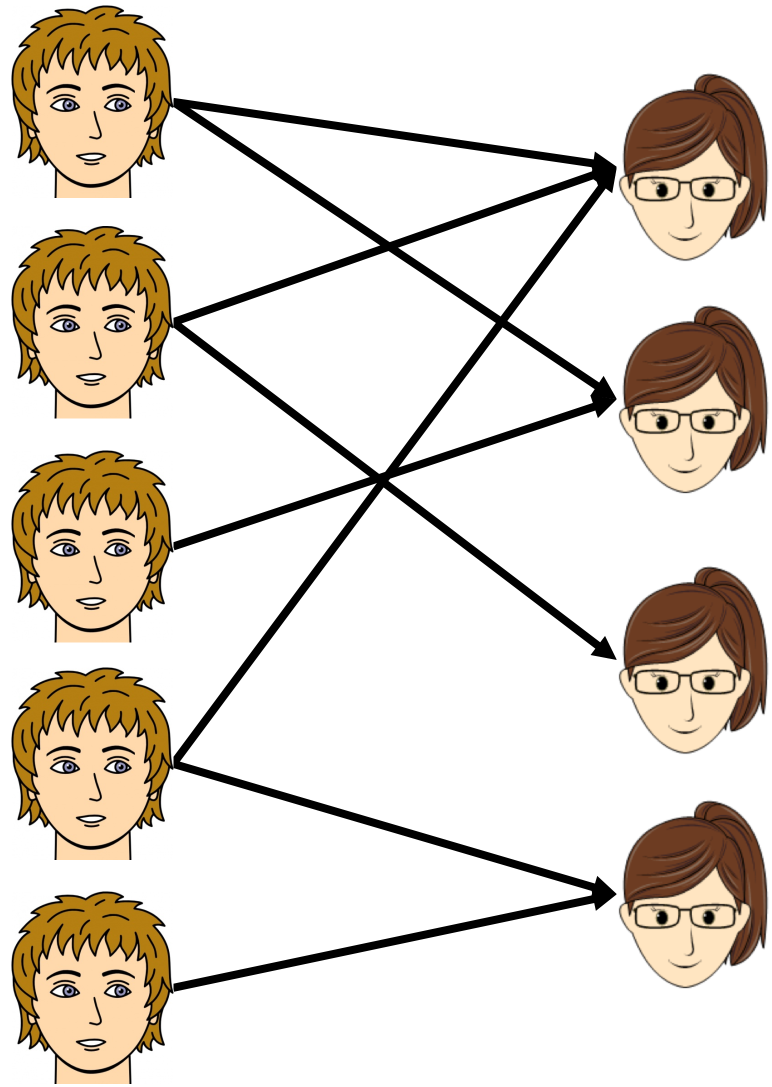


Market-level Competition Network

Connect any two males who messaged at least one female in common.



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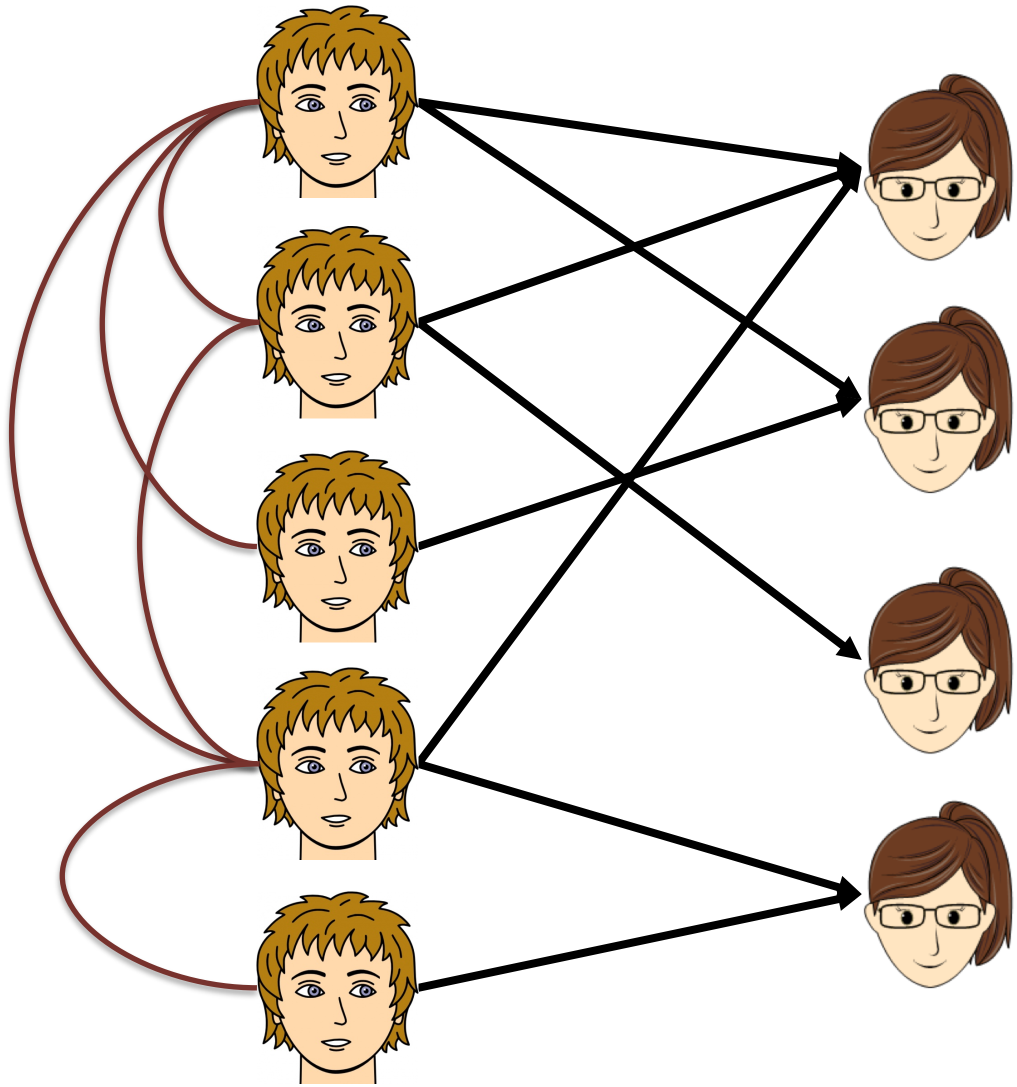
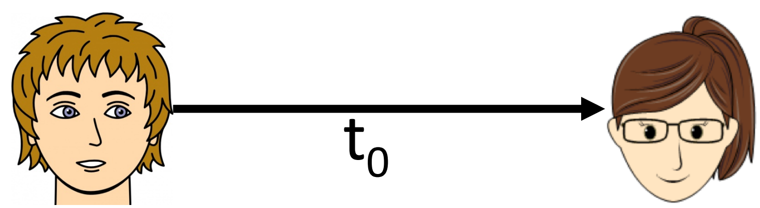


Female-choice Competition Network



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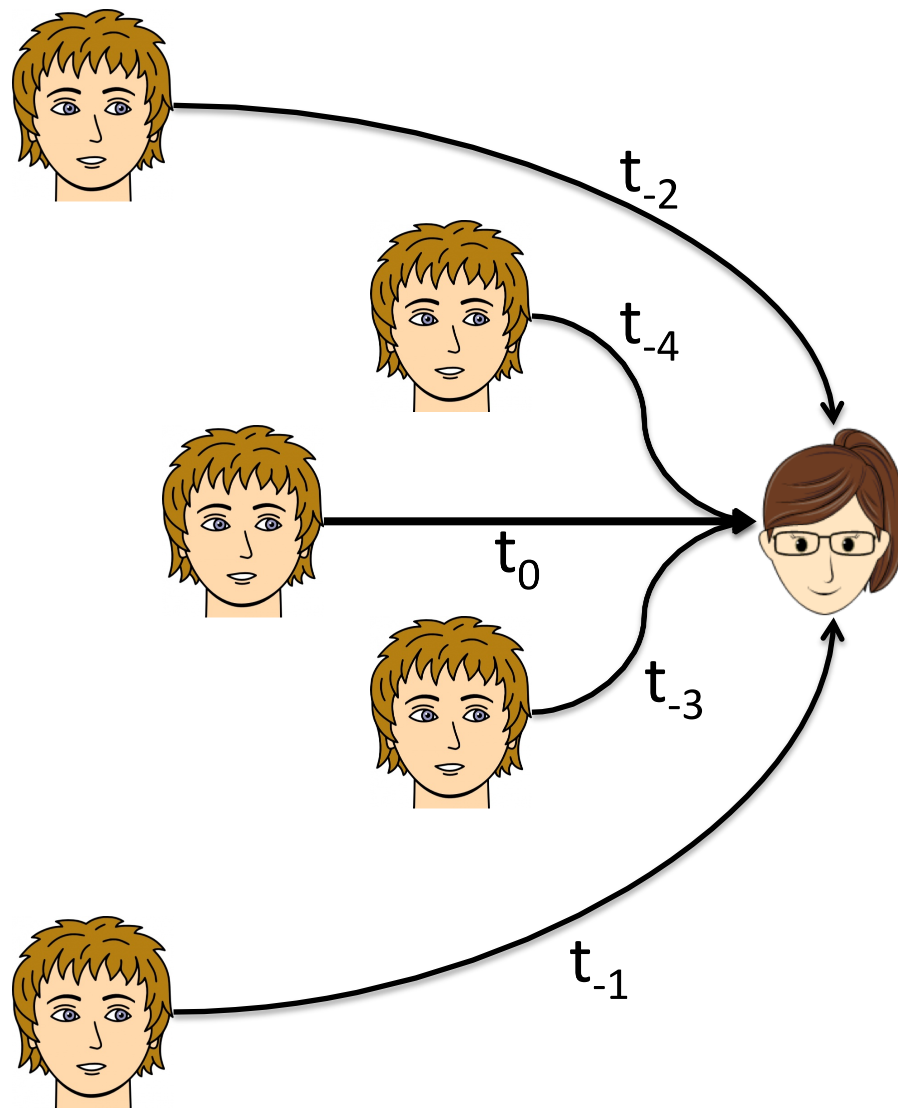
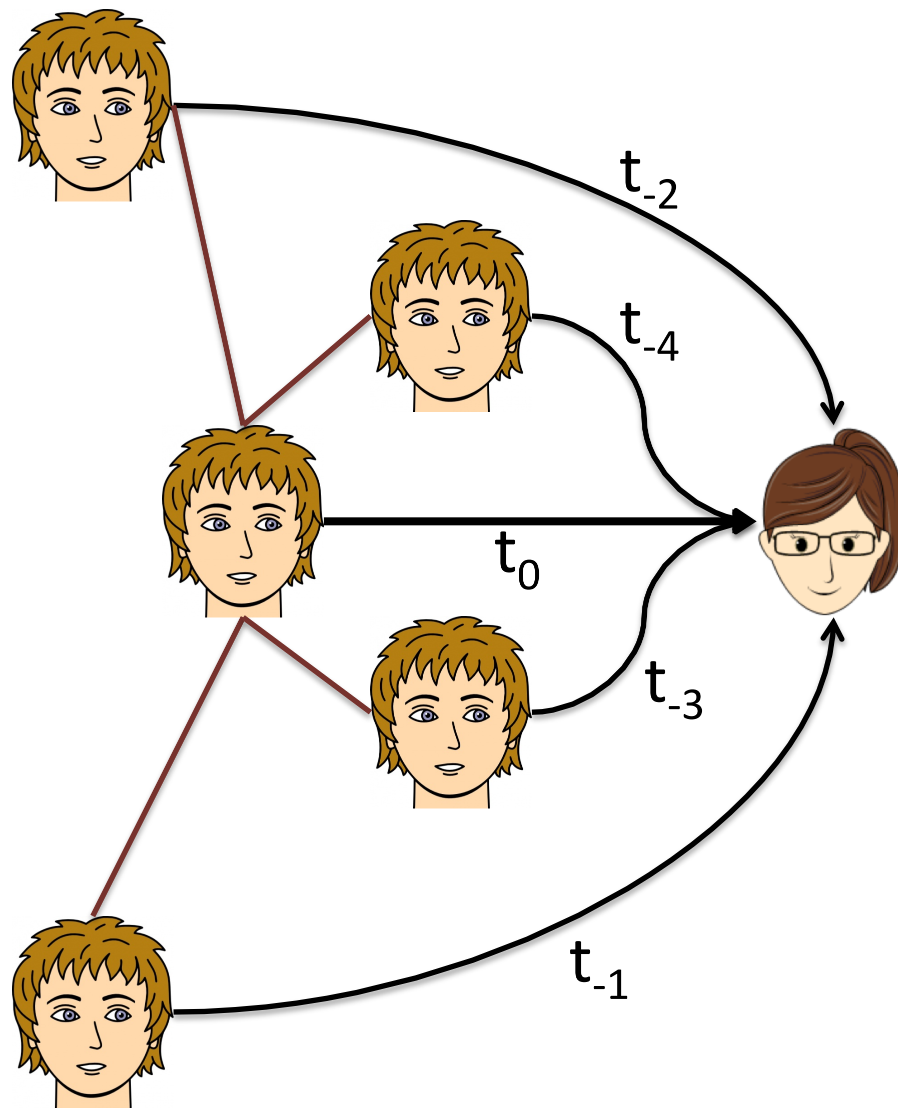
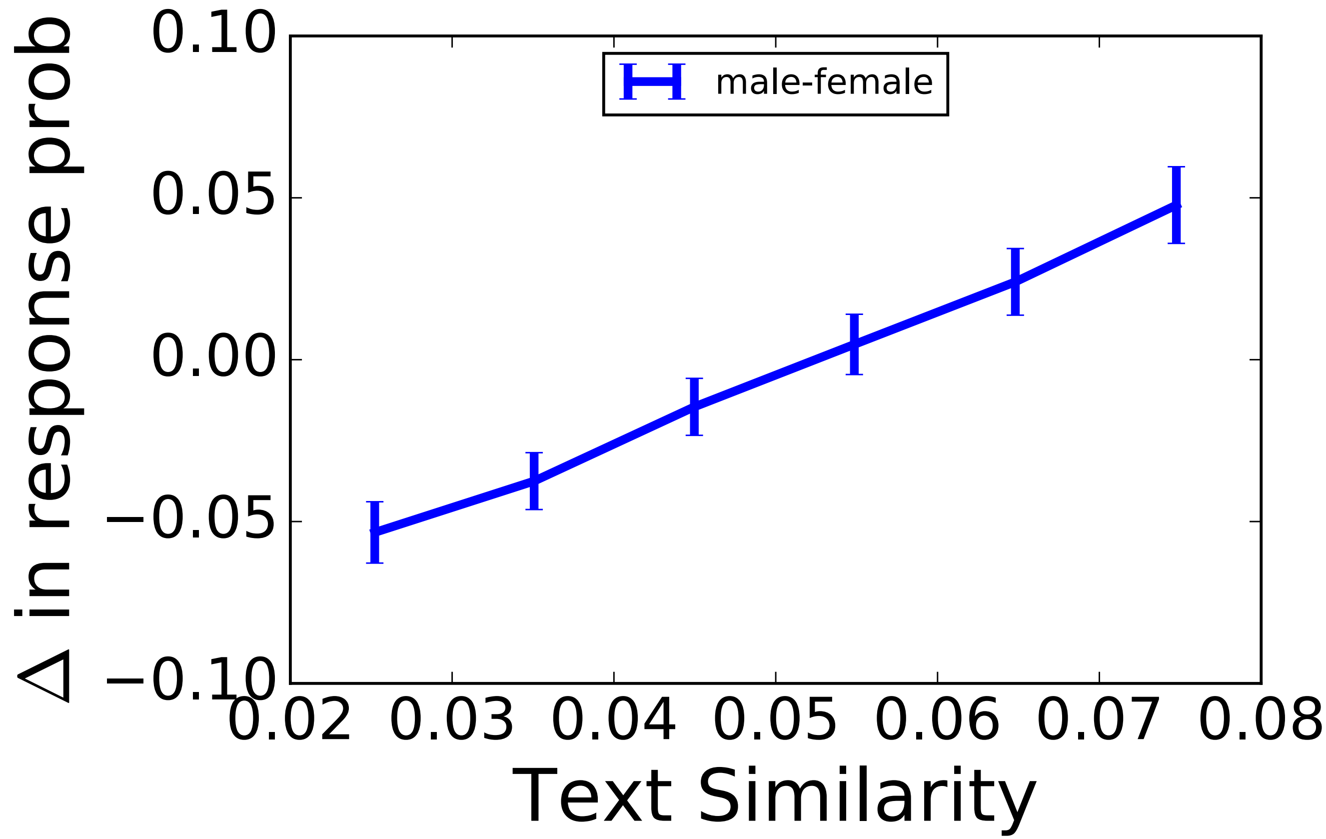


Female-choice Competition Network

Connect male to other males to messages same female in the past



Text Similarity vs. Message Response



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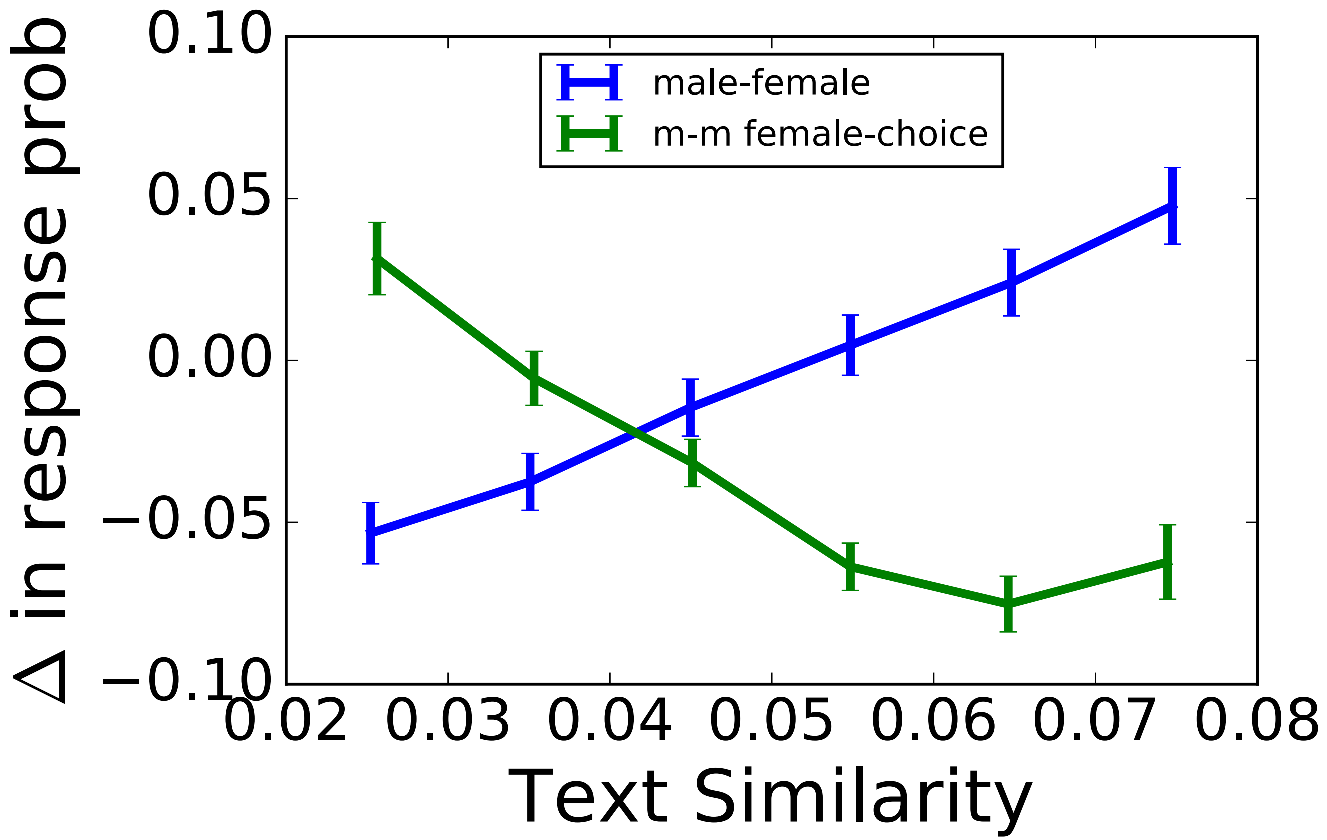

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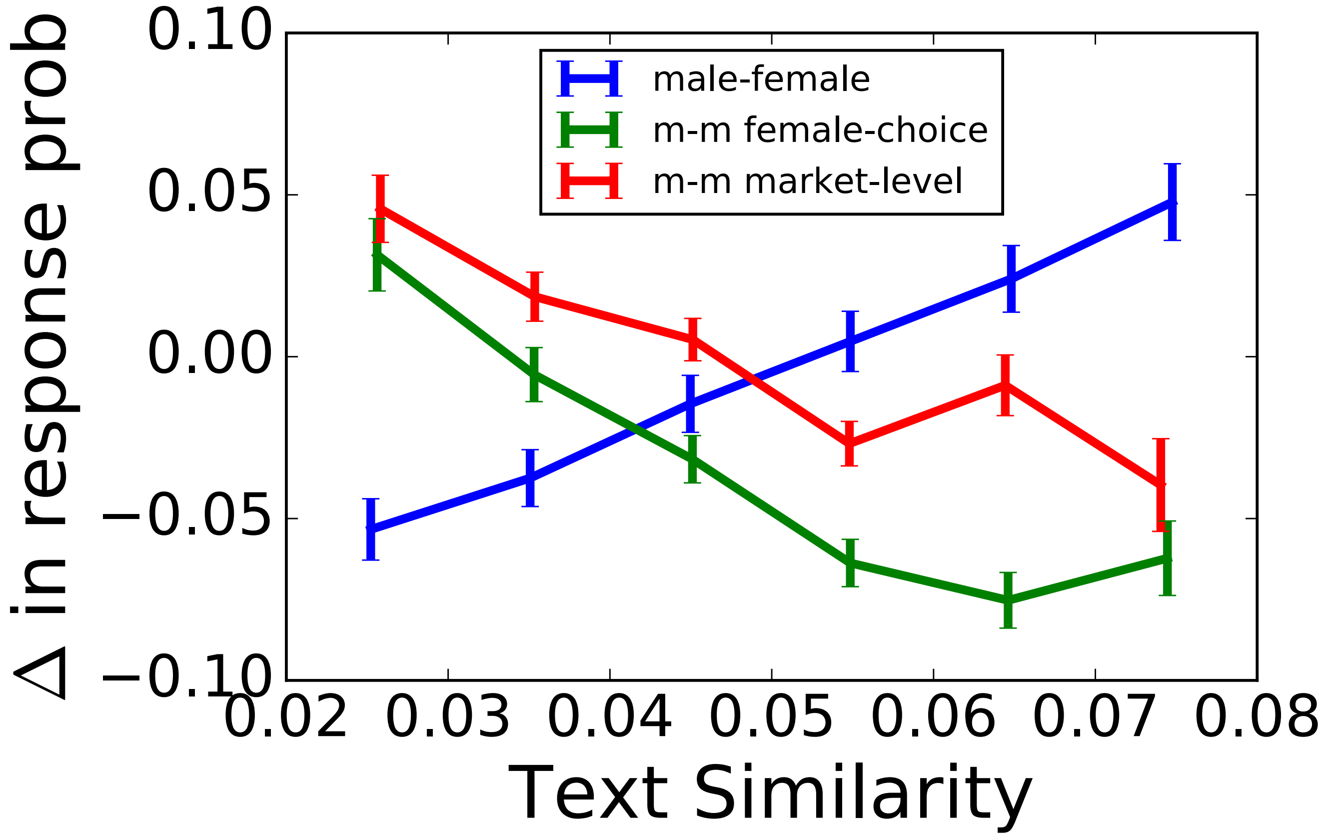

Logistic Regression

	Variable	Coefficient sign/ significance
	Female % response	+/***
Male-female control variables	Age diff	-/***
	Height diff	+/***
	Physical distance	-/*
	Same body type	-/***
	Same ethnicity	+/***
	Ave. vote diff	-/***
Text Similarity variables	Text similarity	+/***
	Competition text sim. (female choice)	-/***

Conclusions

- Relationship between stock market shocks and social network structure
- Competing hypotheses: turtle up vs. open network structure
- Communication “turtles-up” during shocks.
- Network structure is predictive of trading, performance, and emotional and cognitive content.
- Stock market changes do not improve prediction accuracy.

- Differentiating from competition appears to have a positive effect in dating sites.