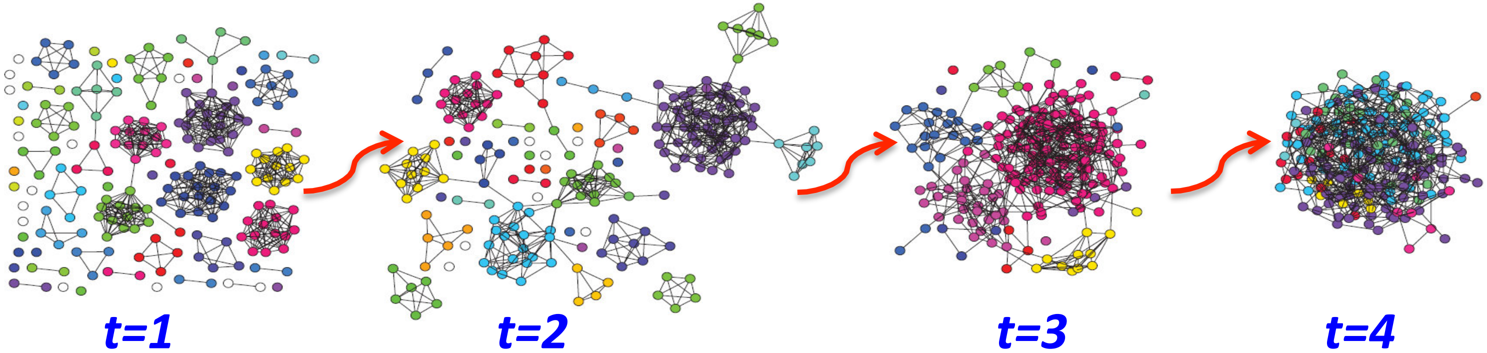
4322 North Quad, 105 S. State St.
Ann Arbor, MI 48109-1285

Social Network Under Stress

Daniel M. Romero
School of Information
University of Michigan

In collaboration with Brian Uzzi and Jon Kleinberg

Social Network Temporal Dynamics



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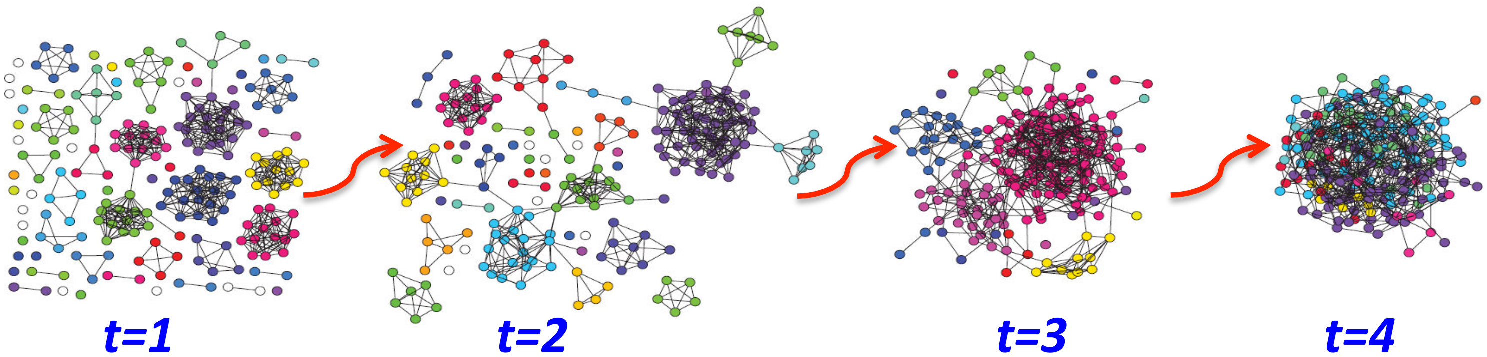

Temporal dynamics of networks:

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

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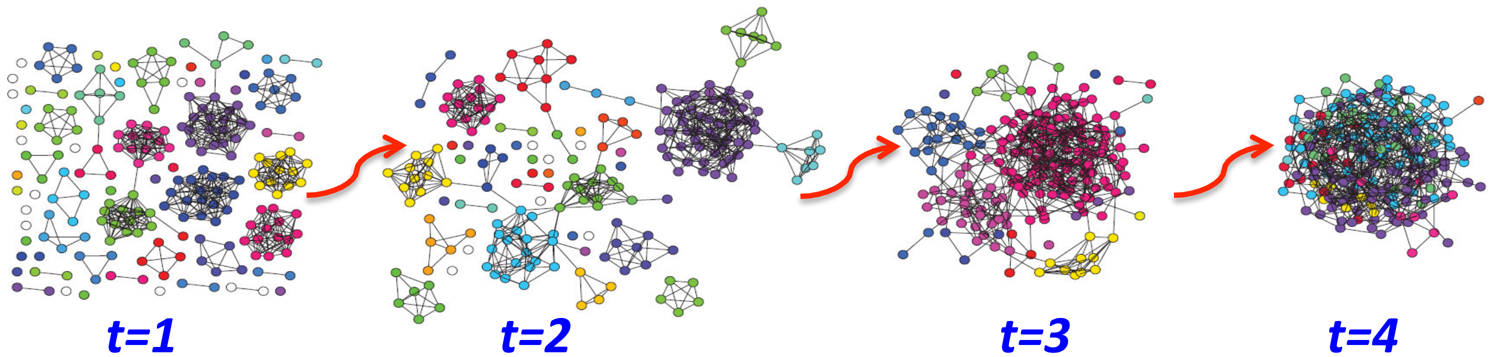

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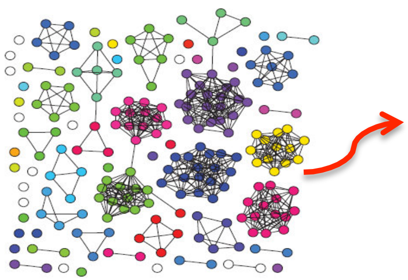
Short diameter, densification, clustering, heavy tail degree distribution, … [Leskovec et al. 2007, Barabasi et al. 1999, Kossinets et al. 2009, …]

Useful for:

- Link prediction
- Detecting influential nodes
- Finding communities

Social Network Temporal Dynamics



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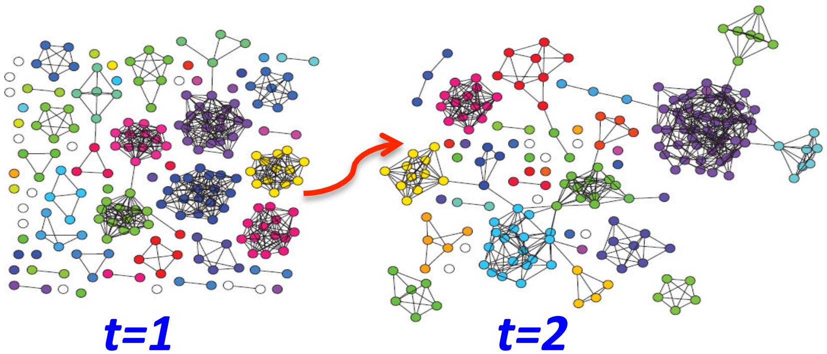

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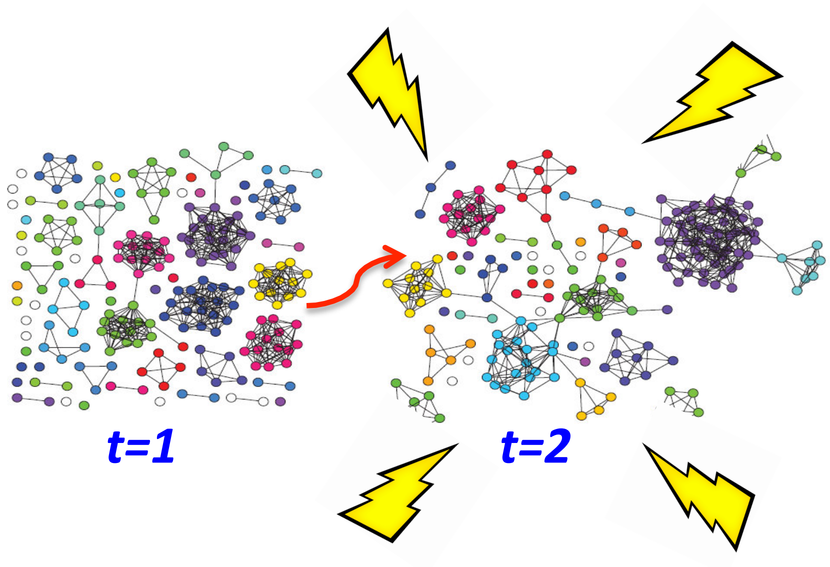

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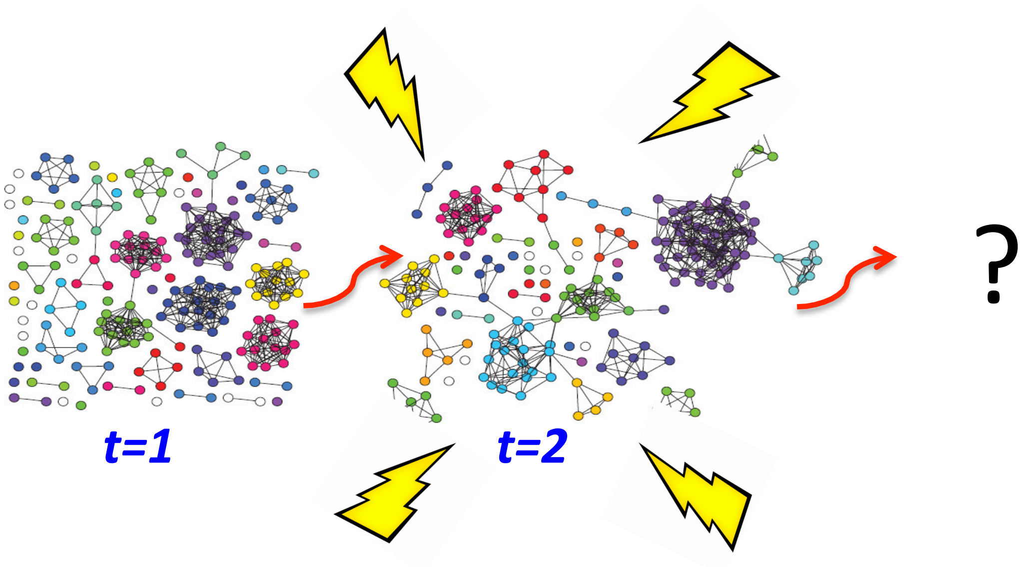

Hedge Fund Data

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

In This Talk

Market Movements
(Shocks)

Social Network

In This Talk

Trading

Market Movements
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Trading

Market Movements
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Performance

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Market Movements
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Emotional and
Cognitive Content

In This Talk

Market Movements (Shocks)

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Emotional and Cognitive Content

Measures

Shock: Change in price of stock **s** on day **d**

% change: (closing – opening) / opening

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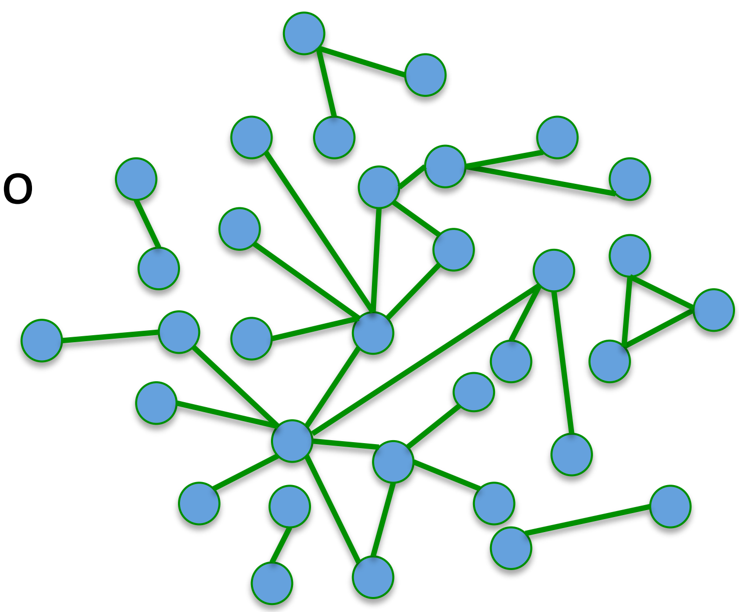

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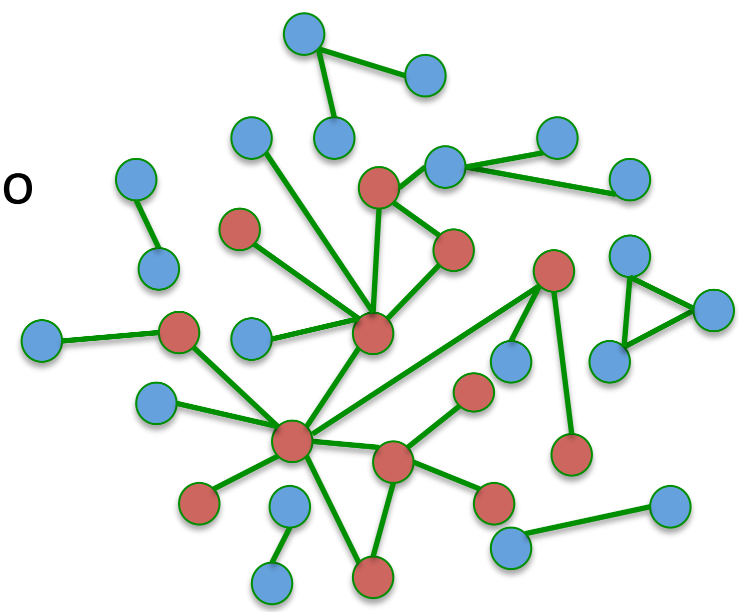

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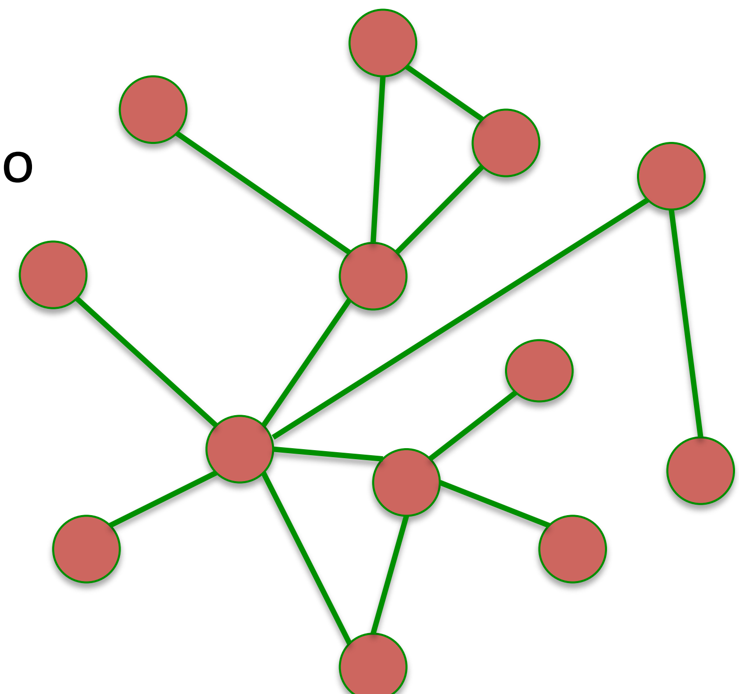

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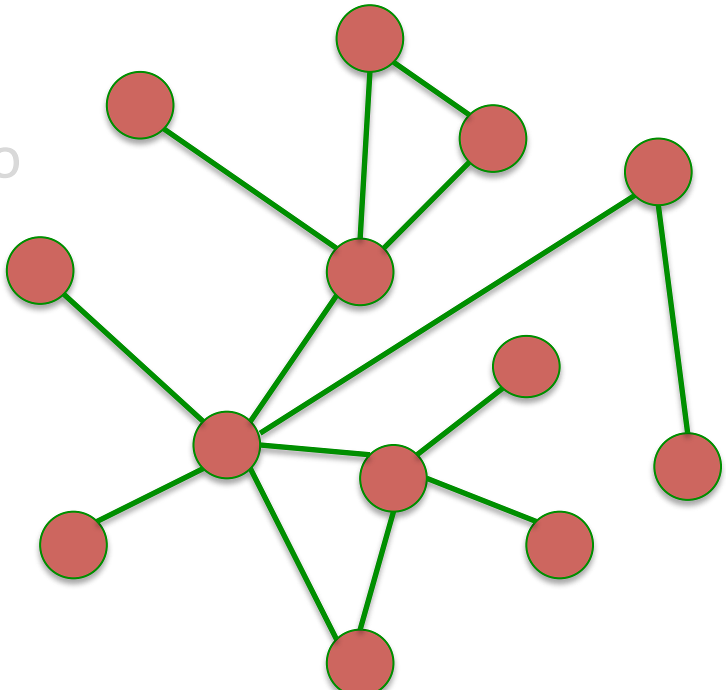

Network's features:

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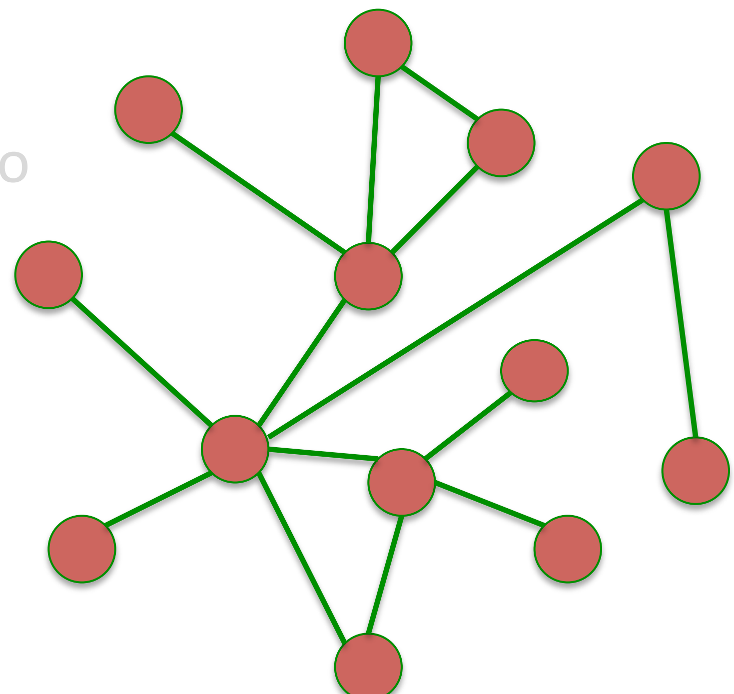

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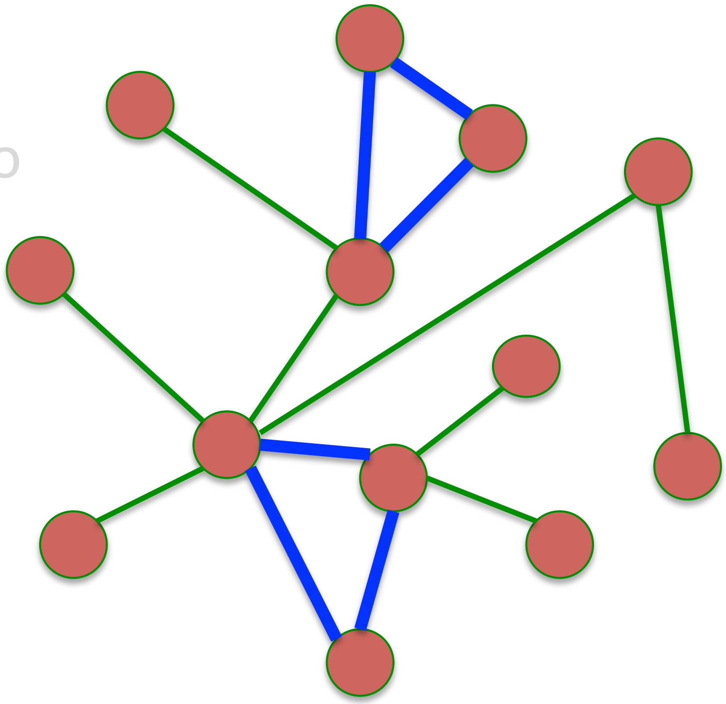

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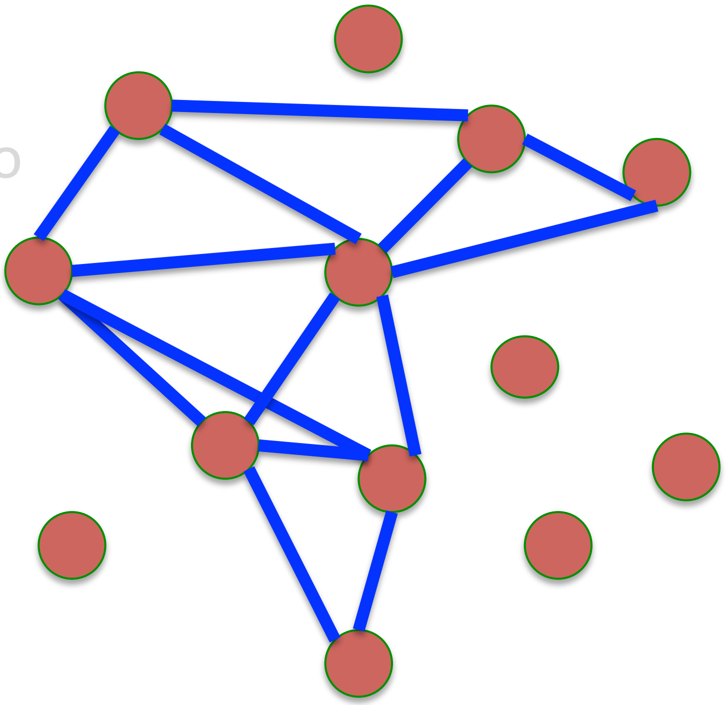

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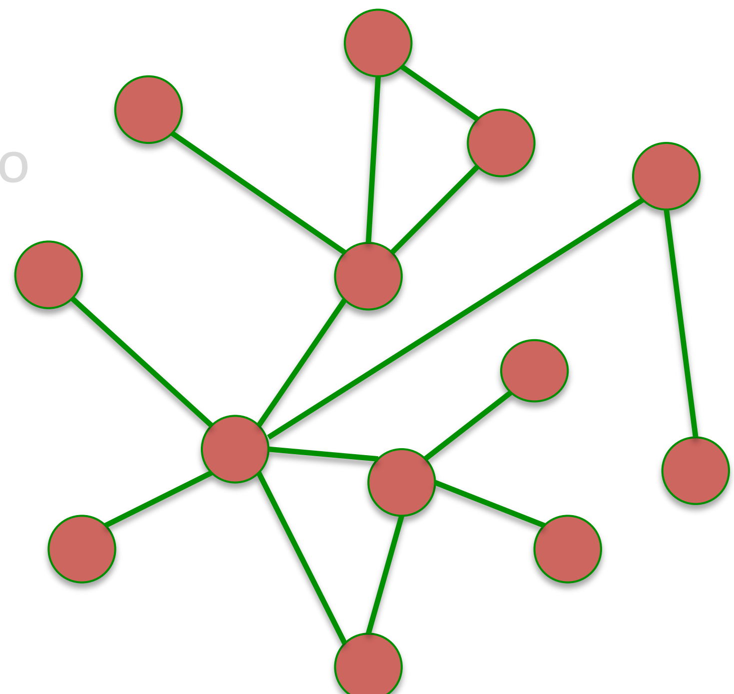

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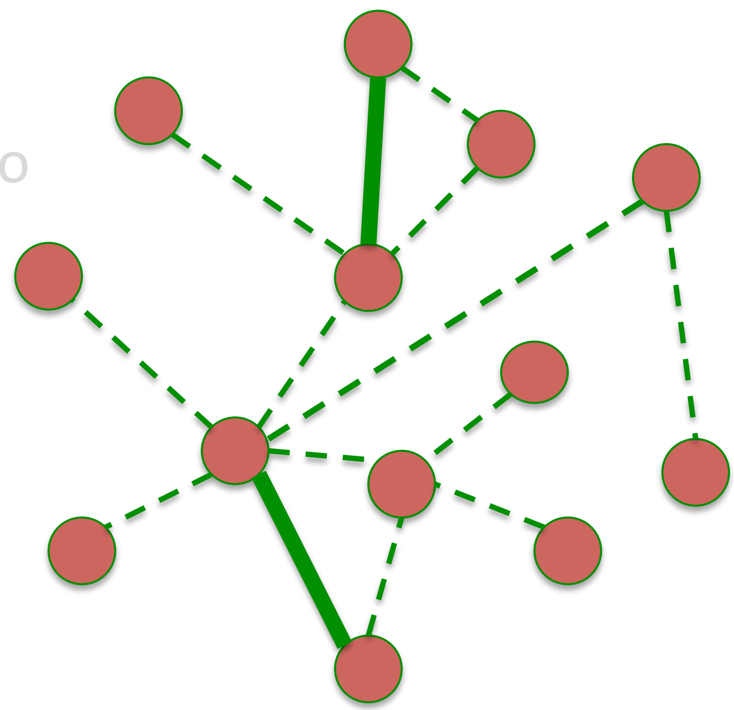

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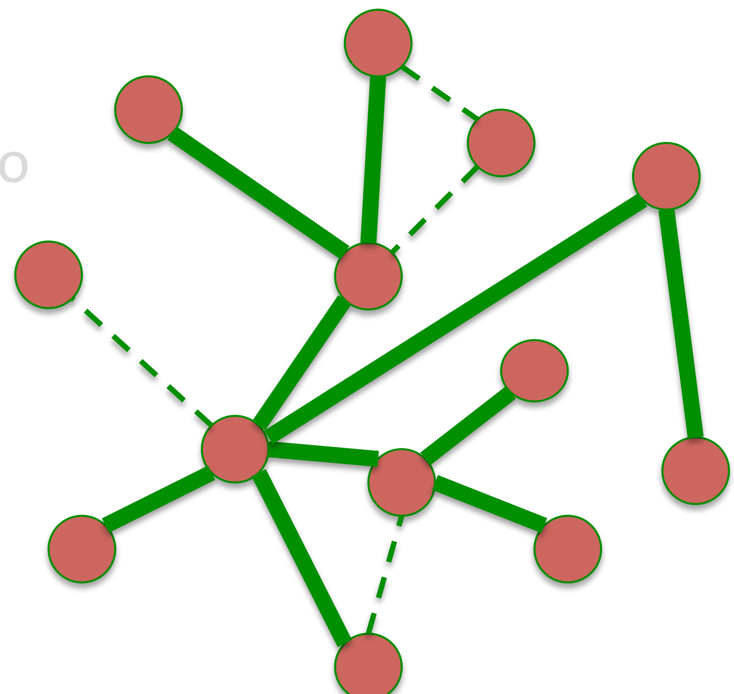

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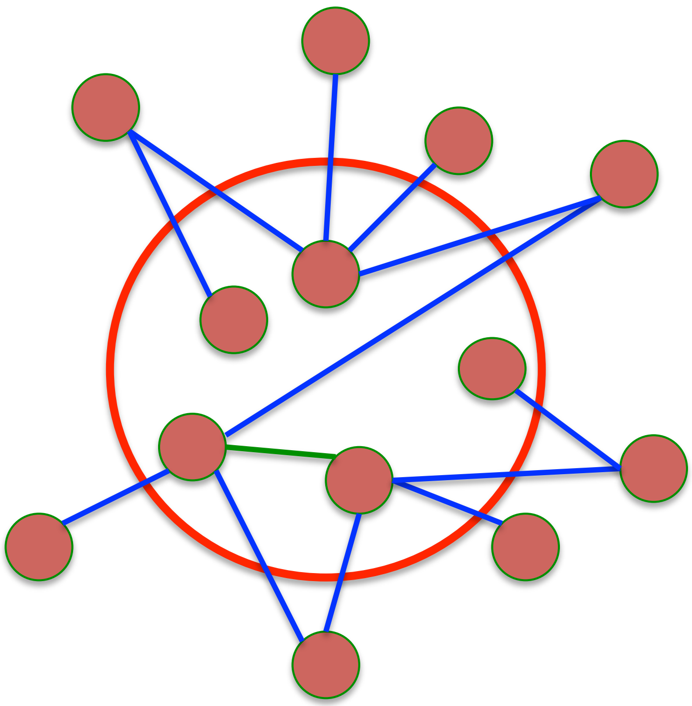

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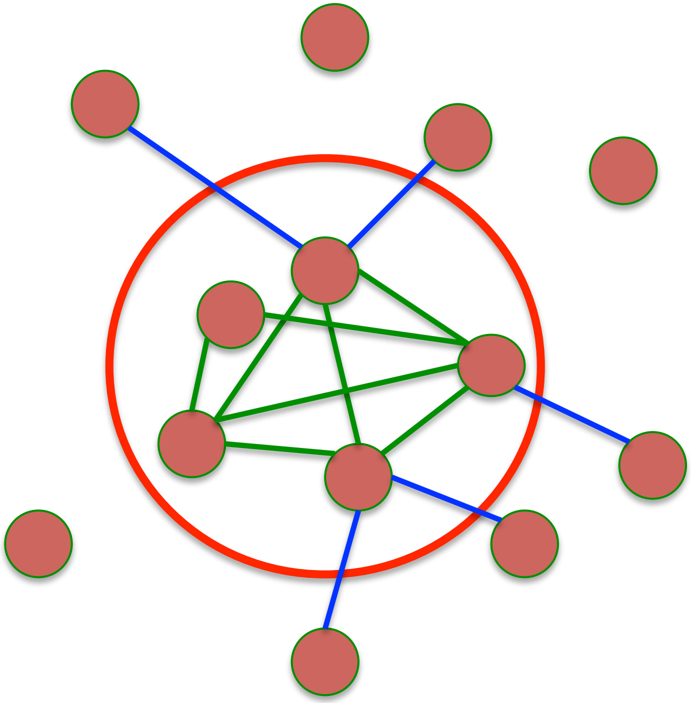

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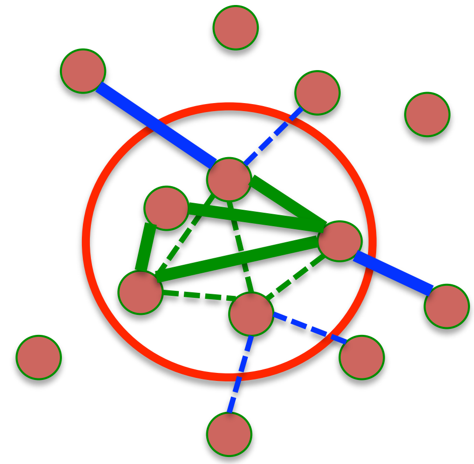
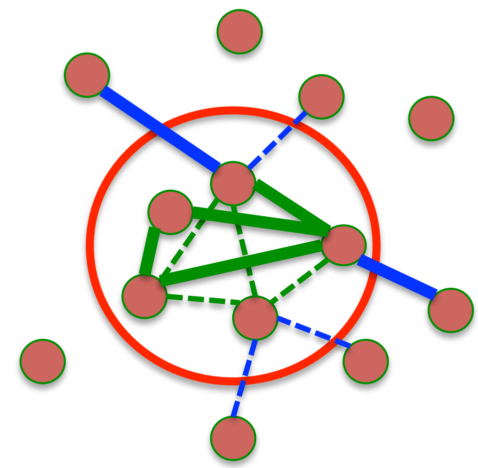


Turtled-up network



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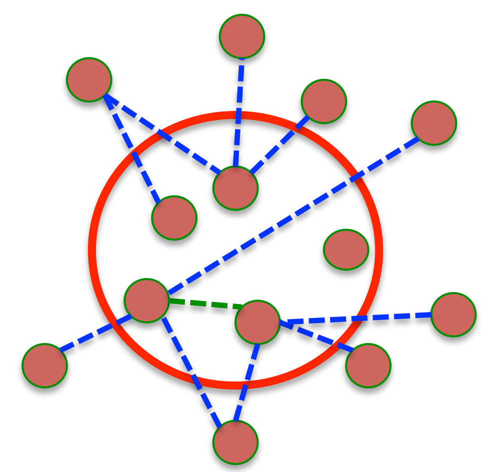
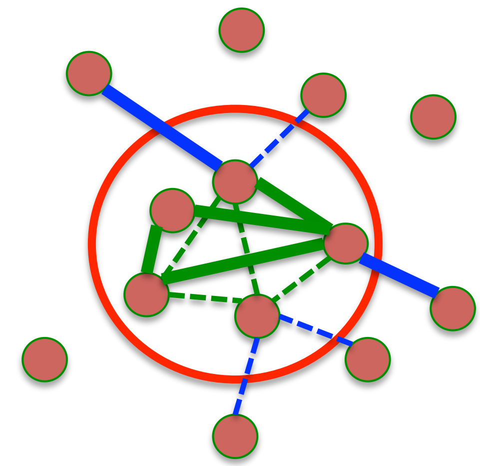


Open network

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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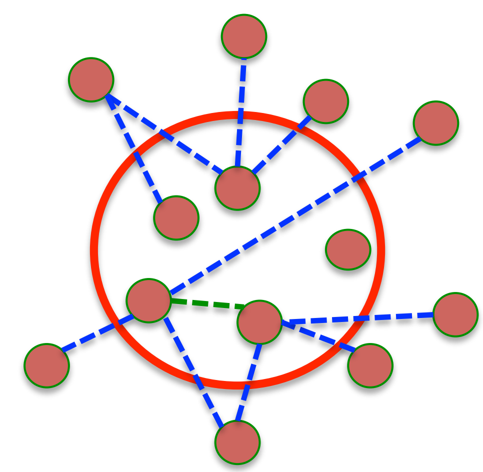

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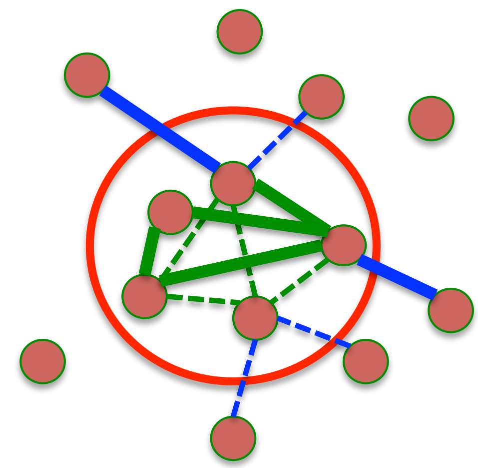
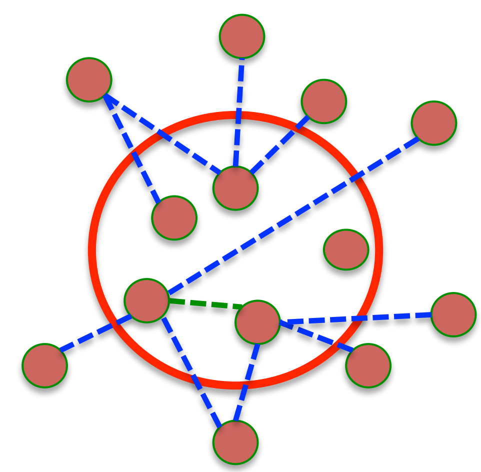


Turtled-up network

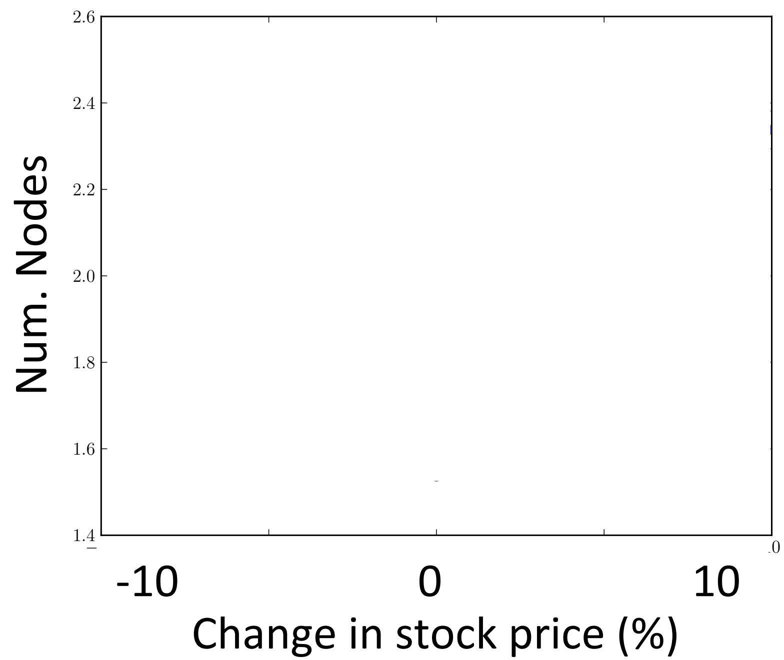
Networks may open-up during shocks:

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



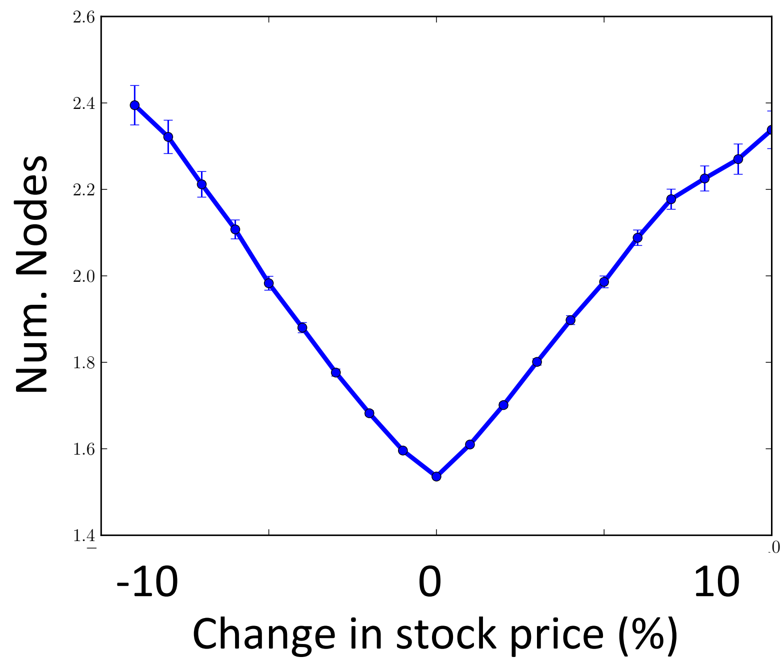
Open network

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*.

Findings: Size



Shocks → **More nodes and edges**

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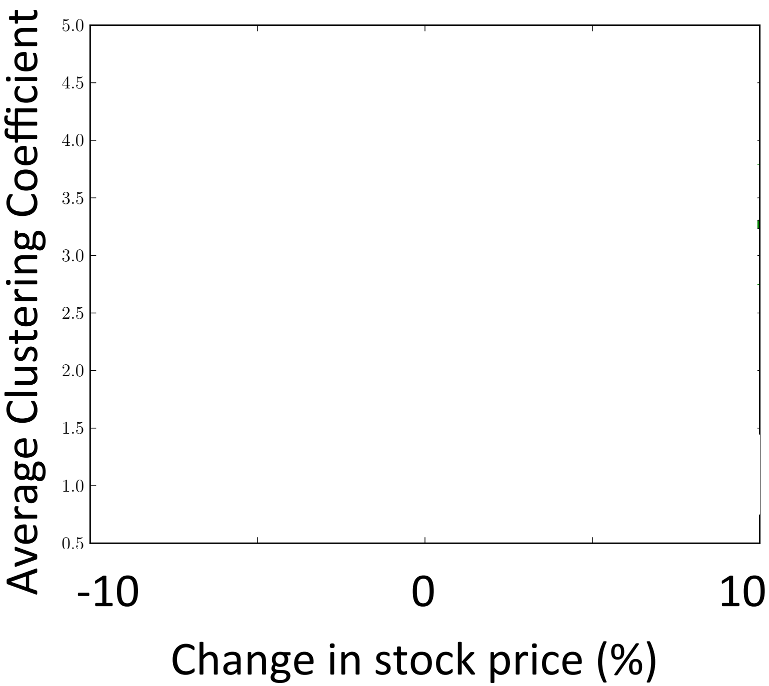
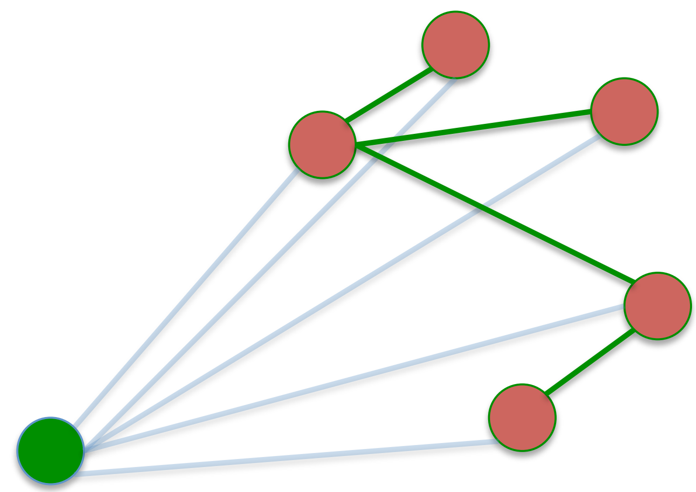
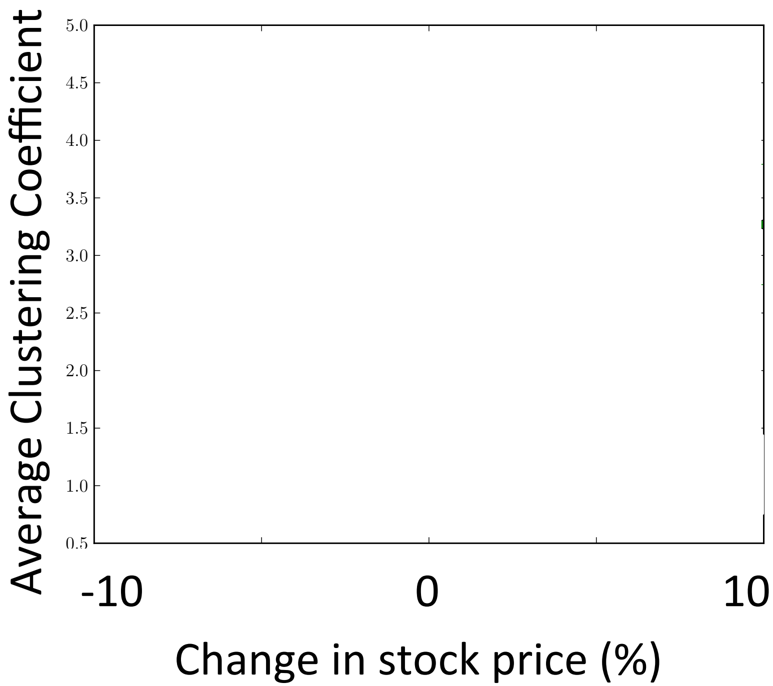
Findings: Clustering Coefficient

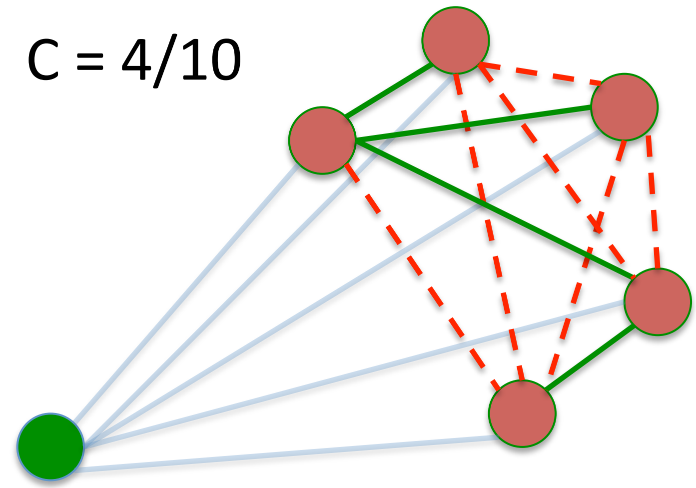




Clustering coefficient of a node *n*: the ratio of the existing and possible number of edges among the neighbors of *n*.

Findings: Clustering Coefficient





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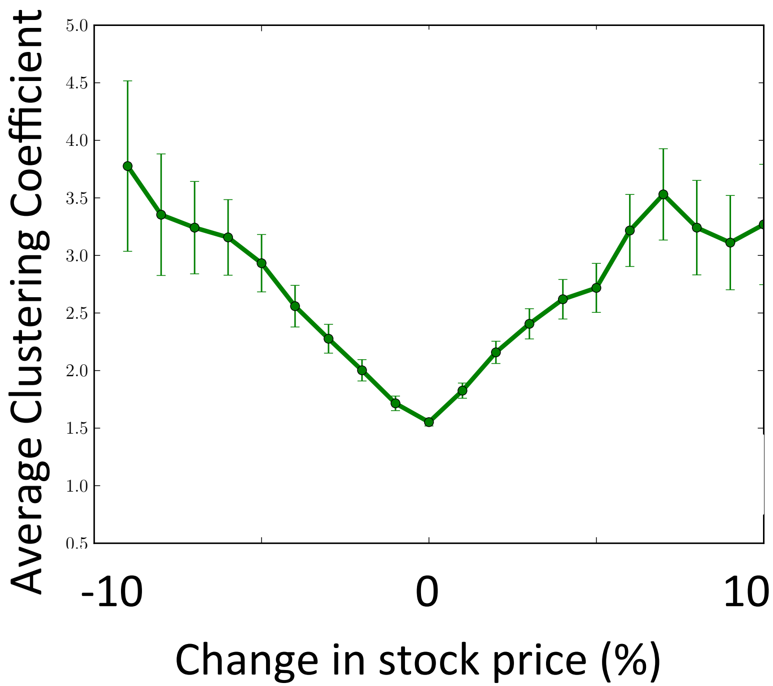
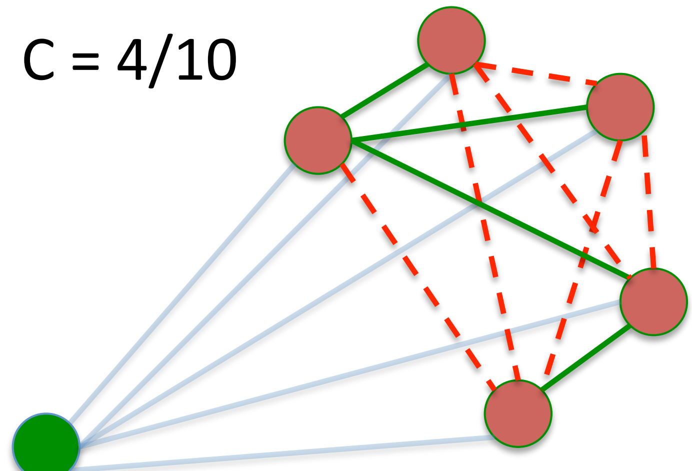
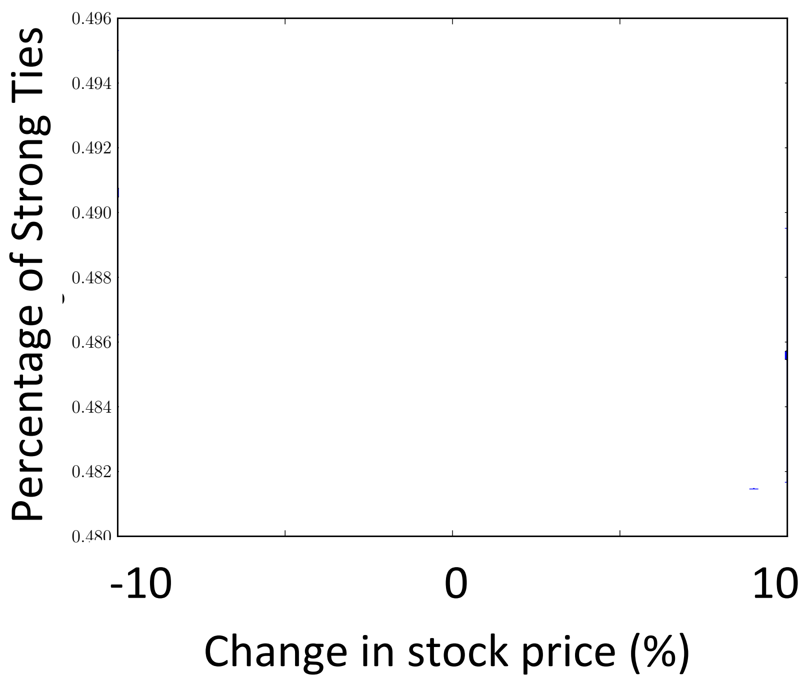


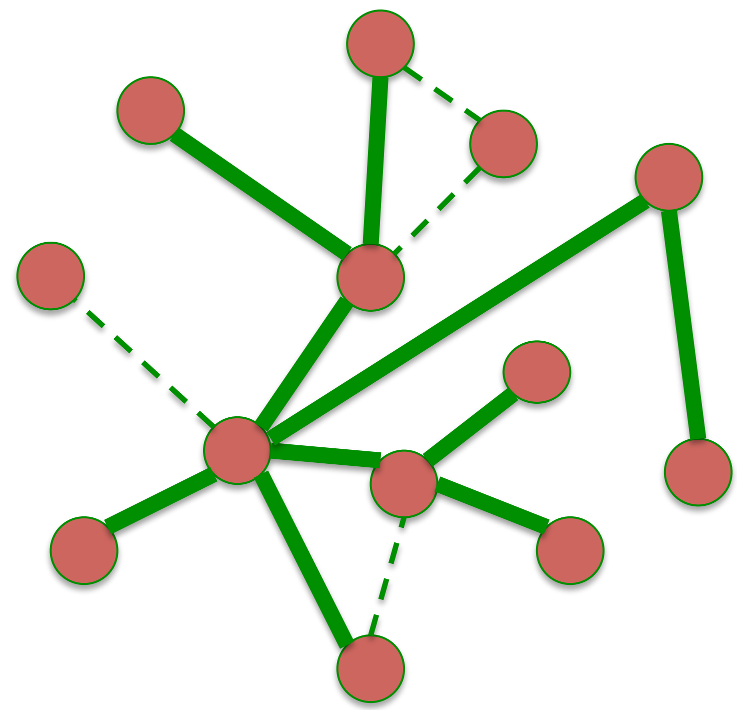


Shocks → **Higher Clustering coefficient**

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

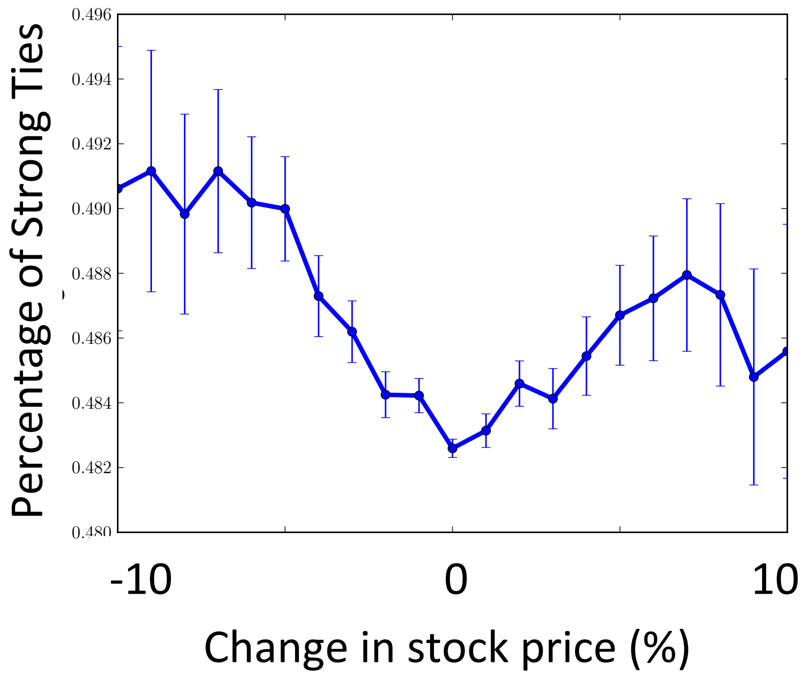
Findings: Tie Strength

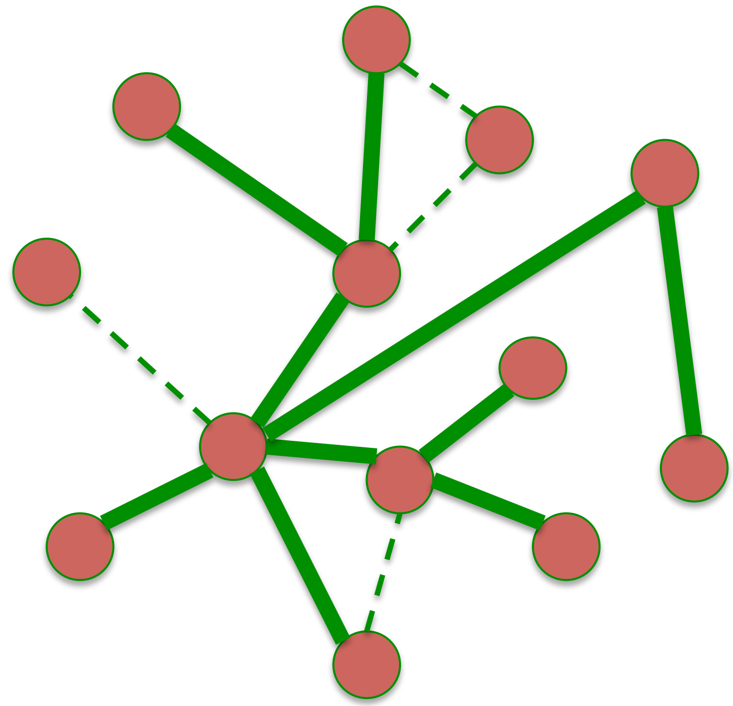




Tie strength: *(x,y)* is *k-strong*, if *y* is among the top *k%* most frequent connections of *x*

Findings: Tie Strength





Shocks → **Higher tie strength**

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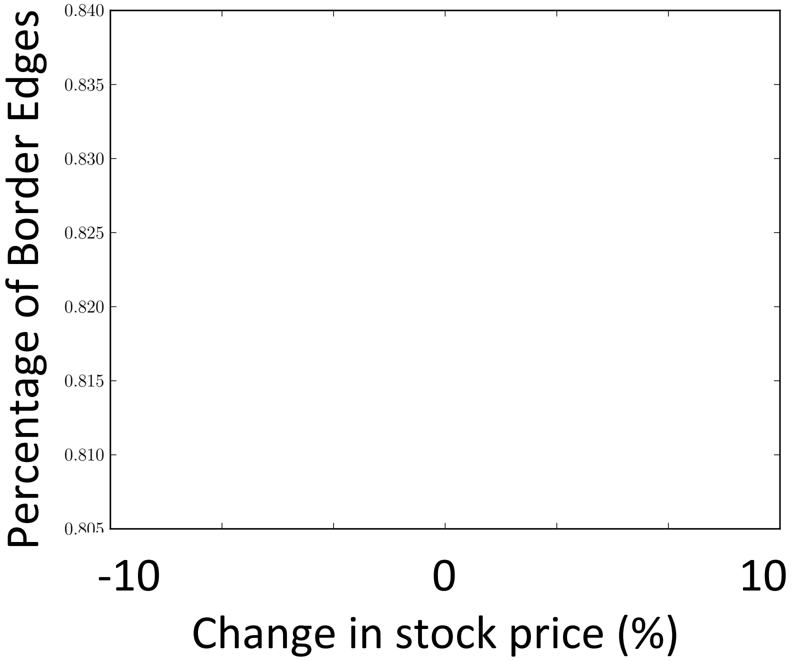
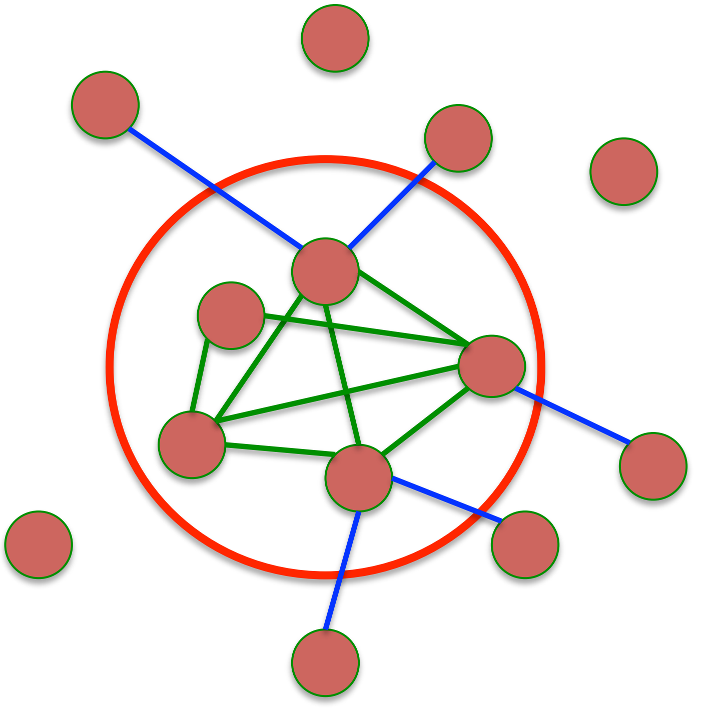
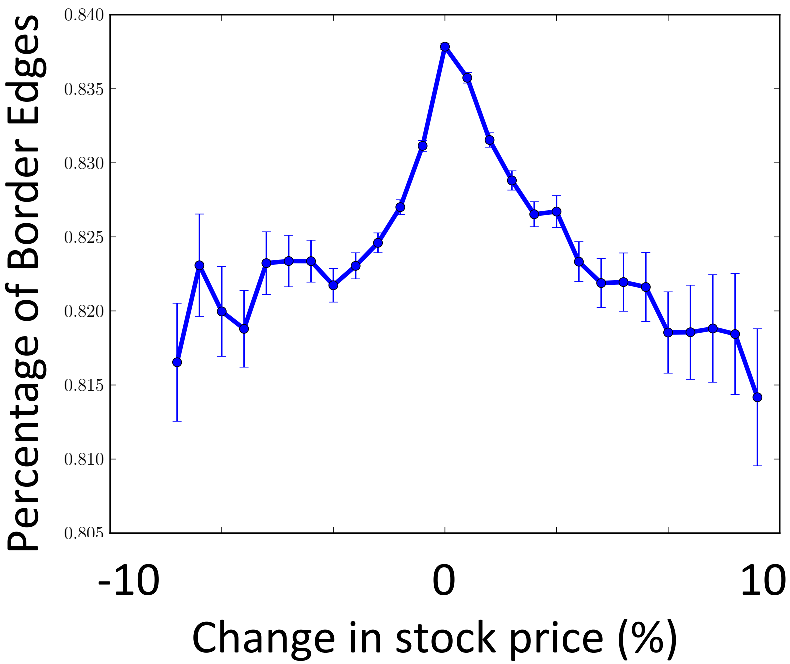
Findings: Openness

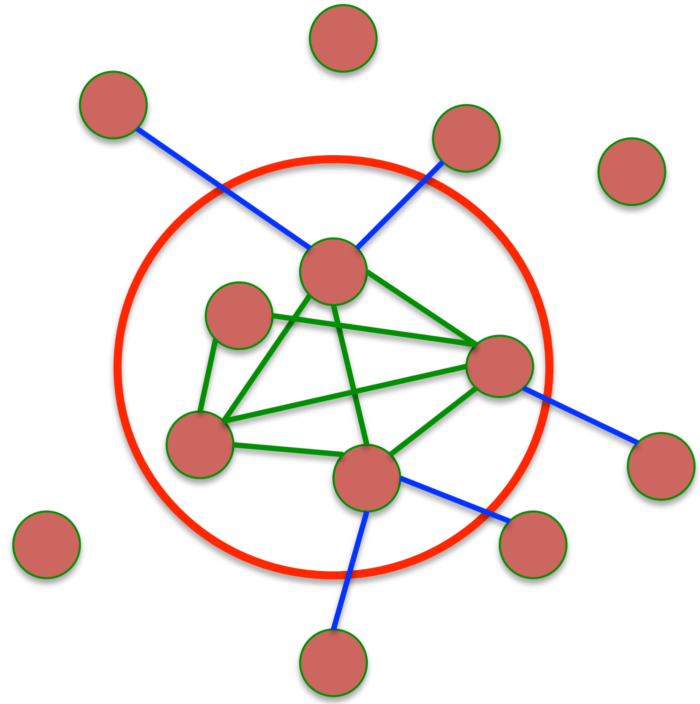




Border edges: involve an outside contact

Findings: Openness





Shocks → **More border edges**

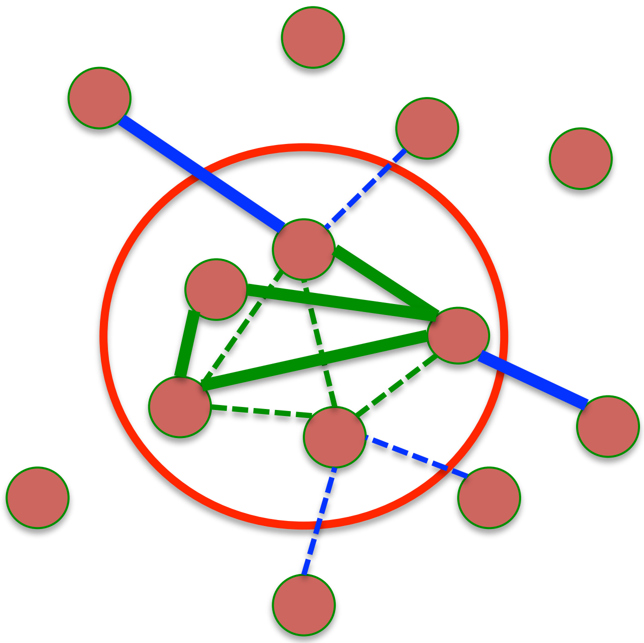
Border edges: involve an outside contact

Networks “Turtle-up” During Shocks

- Higher clustering
- Stronger edges
- More internal communication

Consistent with theories of:

- Trust
- Expertise knowledge, repeated information channels
- Threat rididity



Turtled-up network

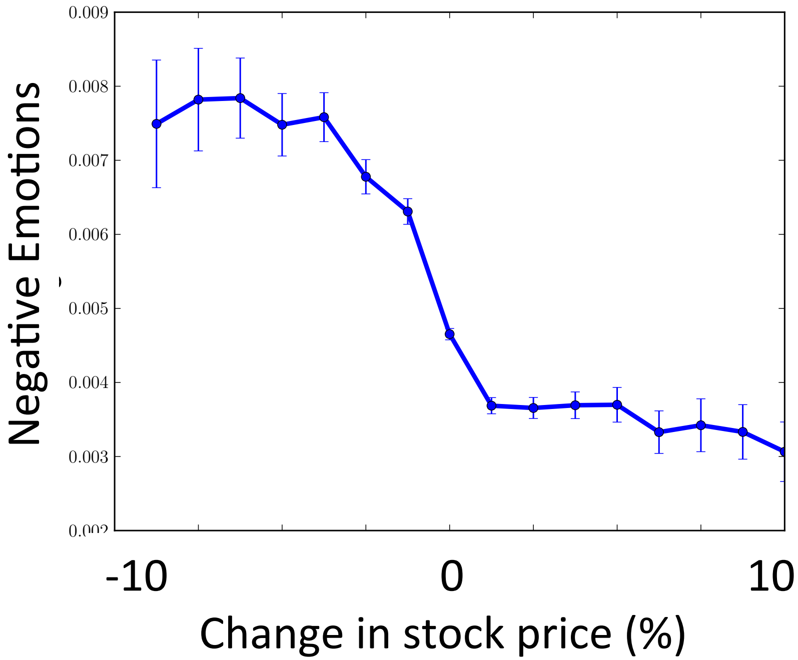
LIWC Categories

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

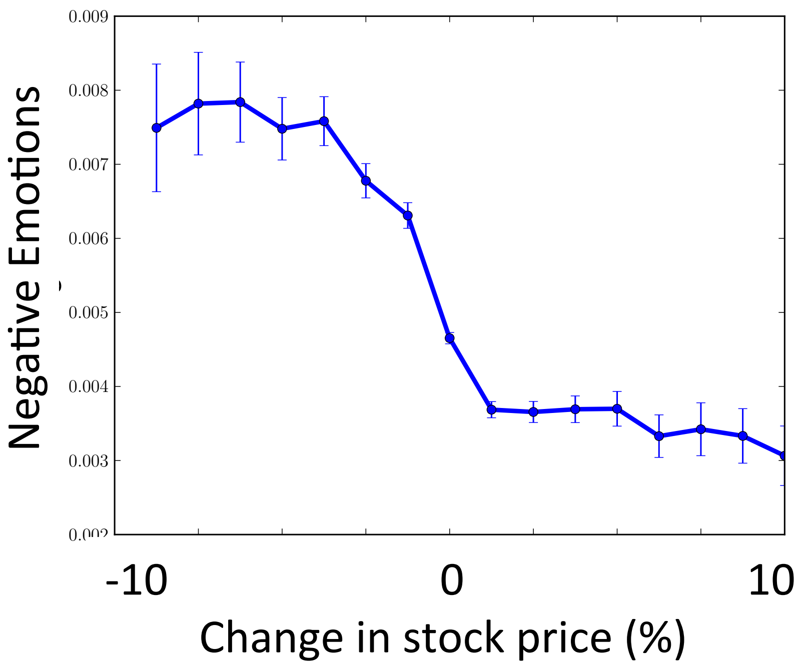
Cognitive Processes	
Insight	Think, Consider
Causation	Because, Hence
Discrepancy	Should, Could
Tentative	Maybe, Guess
Certainty	Always, Never
Inhibition	Block, Constrain
Inclusive	With, Include
Exclusive	But, Exclude

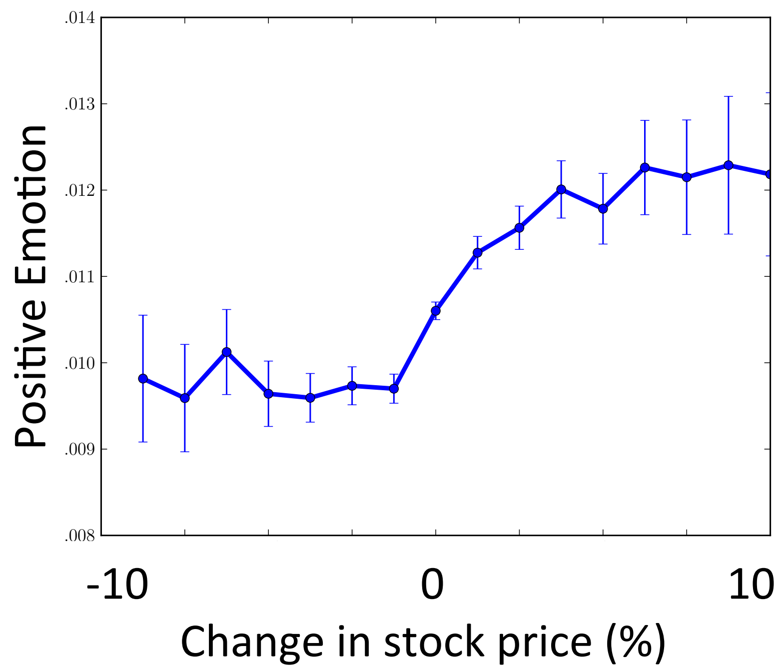
Price Changes vs. Emotions



Positive price changes → Higher positive emotions

Price Changes vs. Emotions



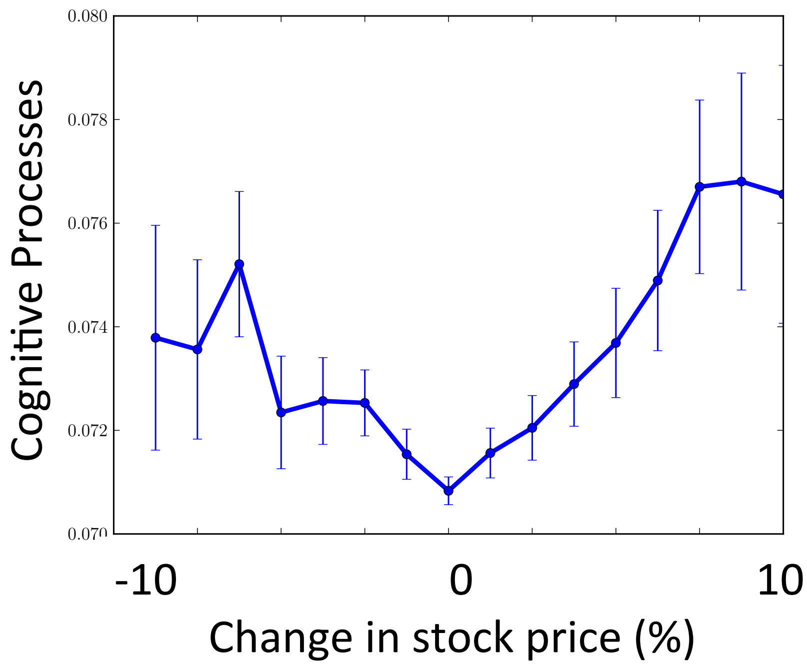


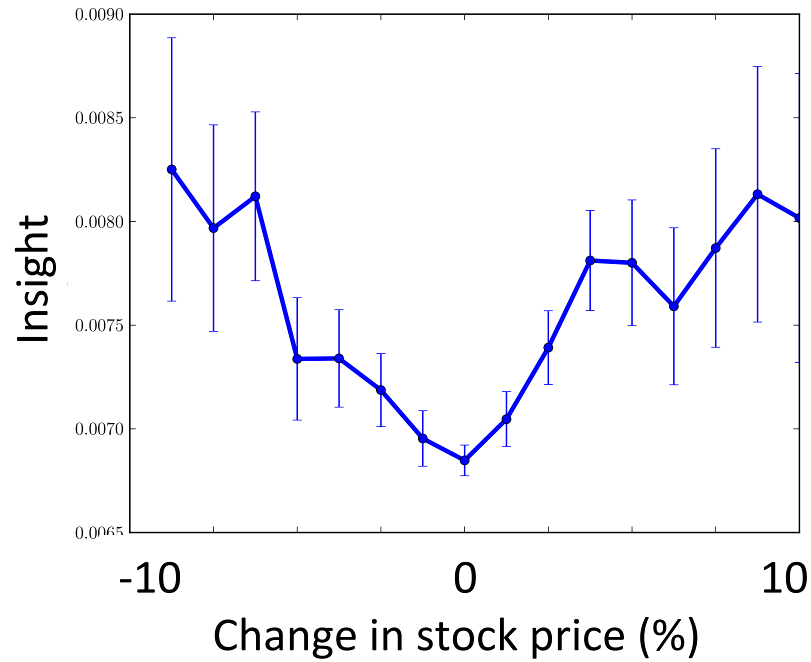
Positive price changes → Higher positive emotions

Negative price changes → Higher negative emotions

Emotions are asymmetric with respect to price change.

Price Changes vs. Cognitive Processes





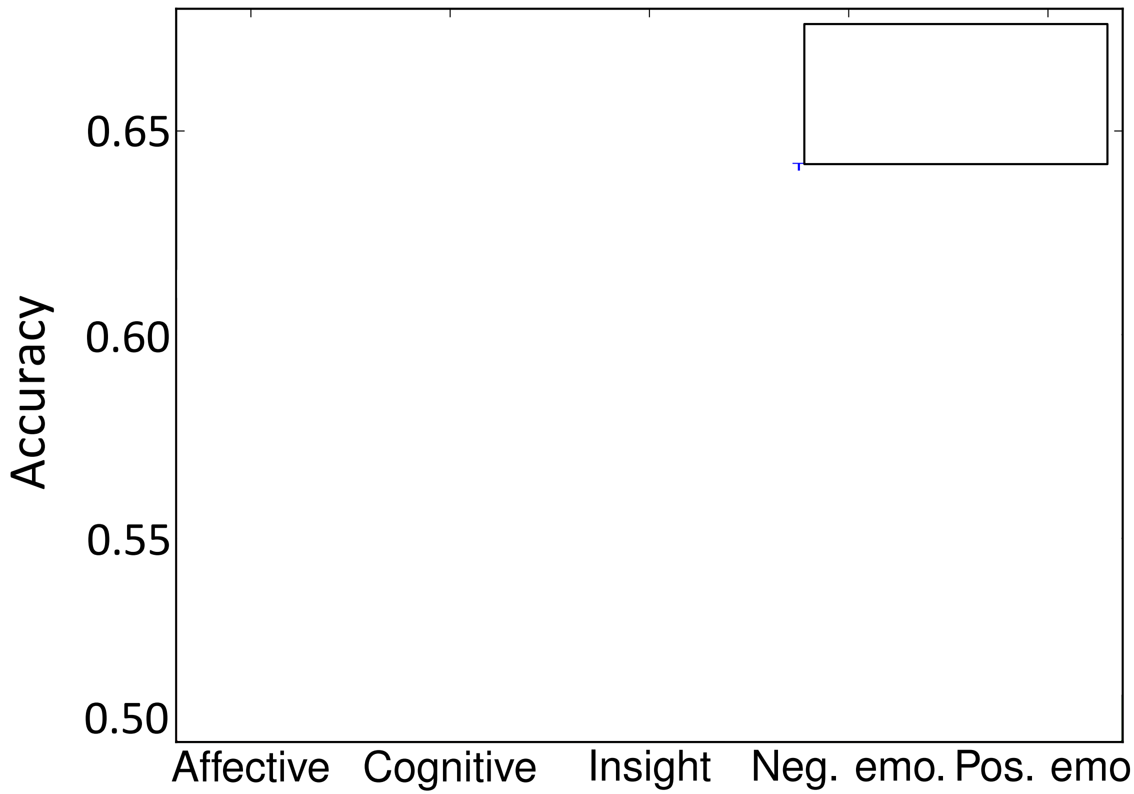
Price changes ⟶ Higher cognitive language

Cognitive processes are asymmetric with respect to price change.

Predicting 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.

Predicting Sentiment and Cognition



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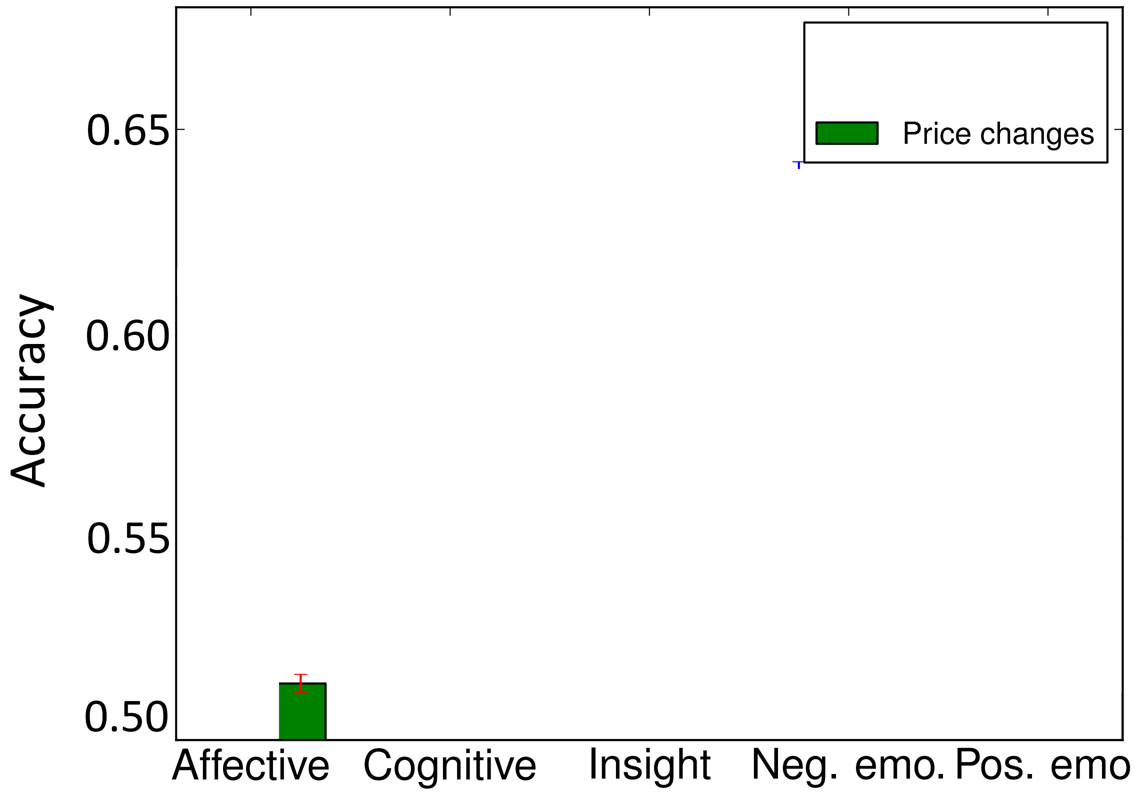

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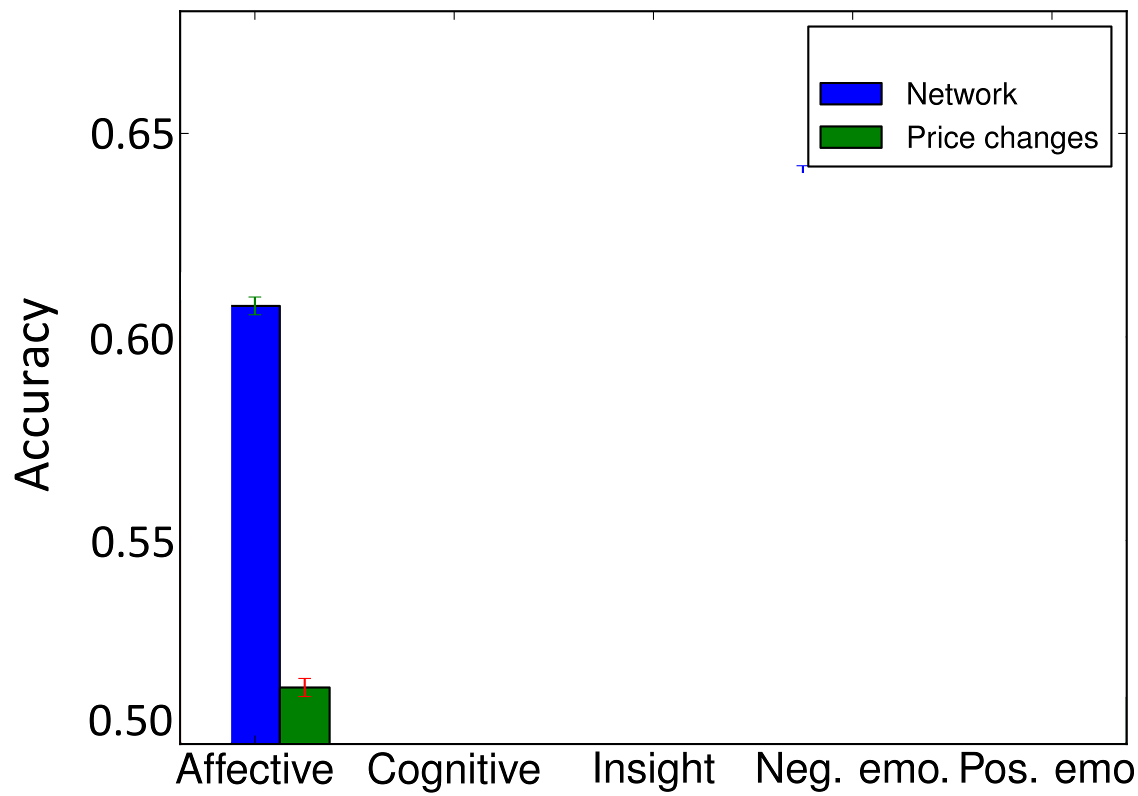

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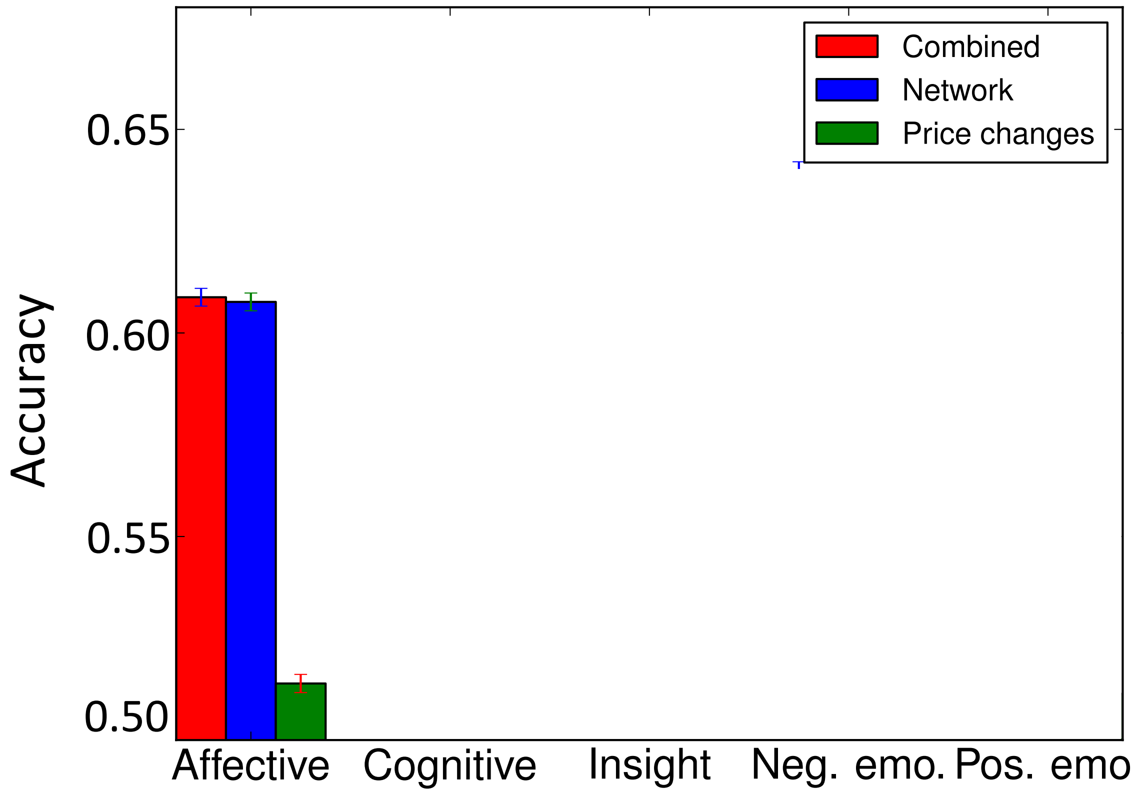

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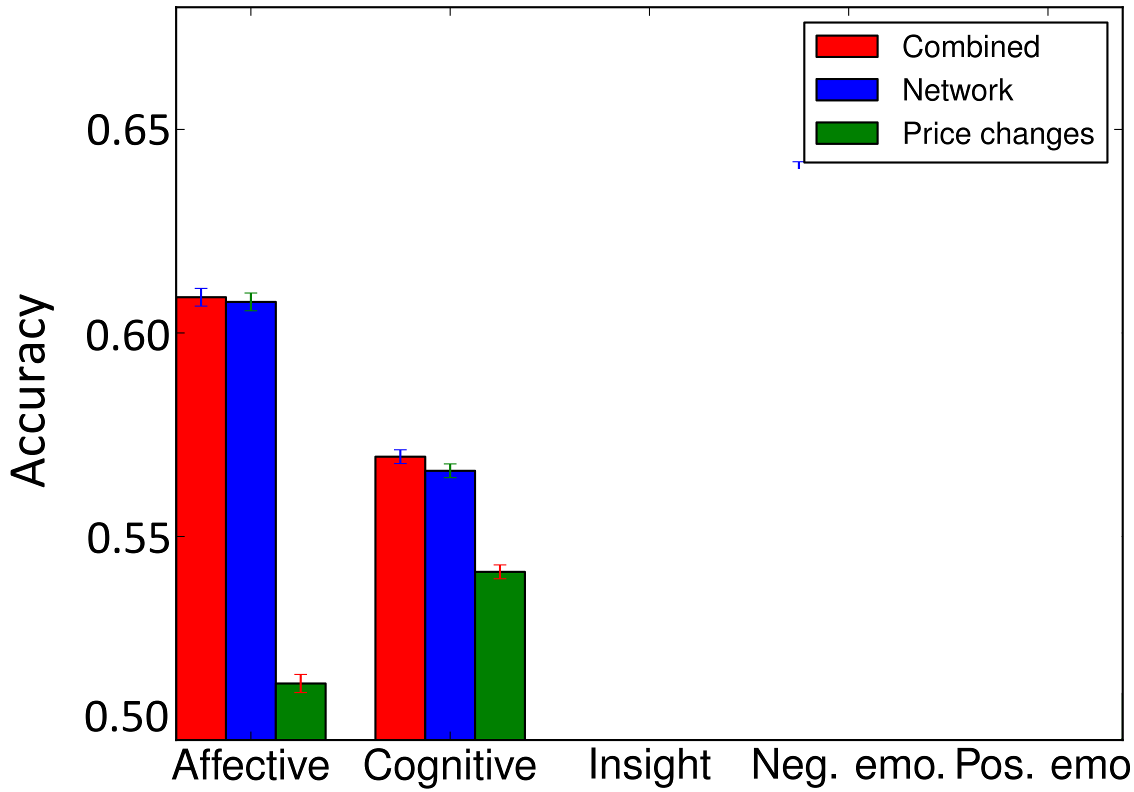
Predicting Sentiment and Cognition



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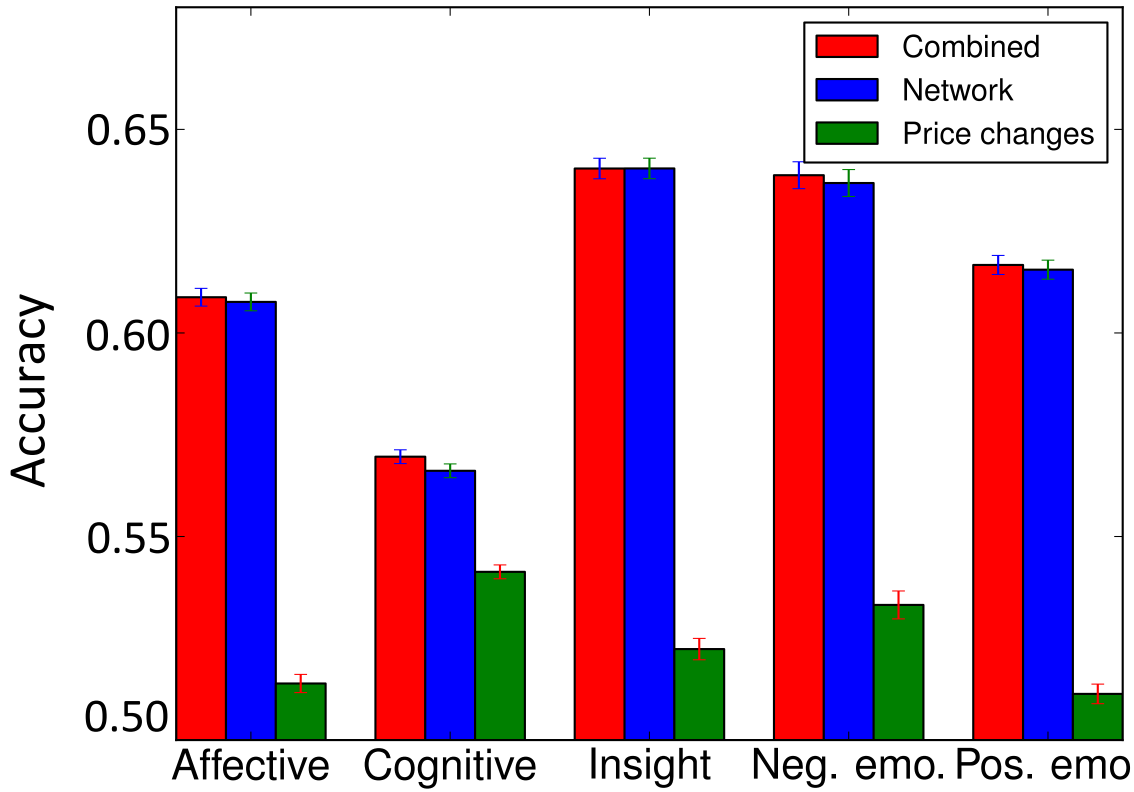
Predicting Sentiment and Cognition



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

Predicting Stock Trading

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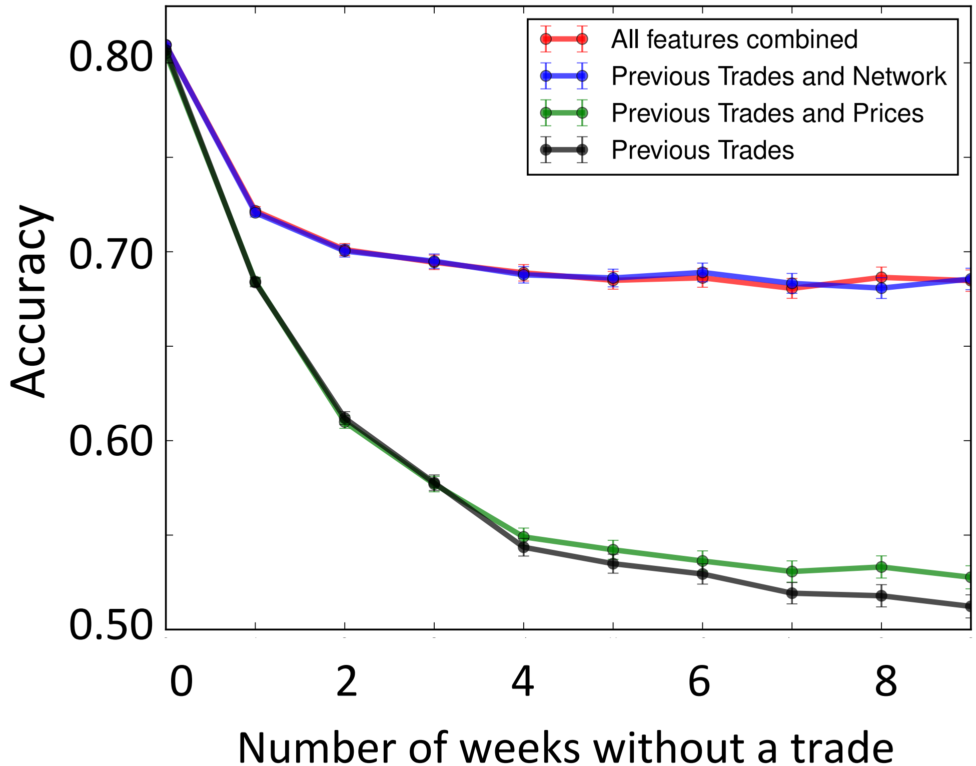
Task: Predict whether a stock that has not been traded for *k* weeks will be traded.

Predicting Stock Trading



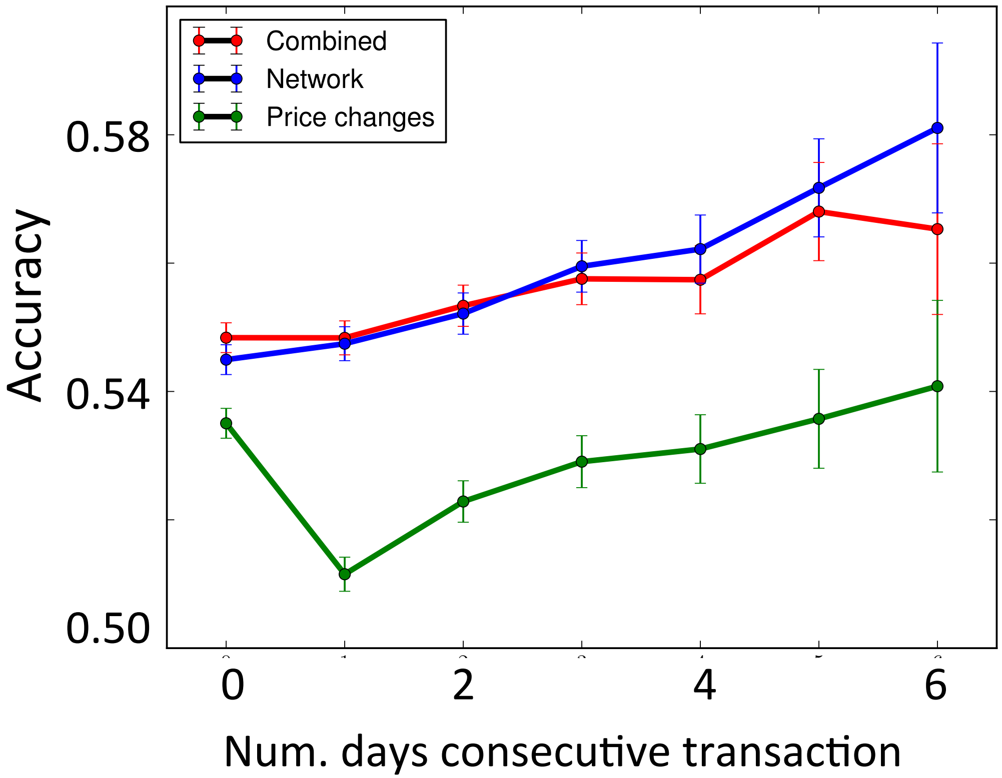
Task: Predict whether a stock that has not been traded for *k* weeks will be traded.

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

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.

Predicting Performance



Suboptimal trade: Worse price than the worst price the next day.

Task: For a fixed stock *s* traded on day *d*, predict if it's suboptimal

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

Network variables are more predictive of performance than price changes.