Dynamic Interpretation of Emerging Systemic Risks

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We still know little about crises build, or how to predict and preempt them. Huge ramifications if progress can be made.

Theoretical Motivation

Detecting information about banks is challenging.

- Efficient debt contracting "requires that no agent finds it profitable to produce costly information about the bank's loans." [Dang, Gorton, Holstrom, and Ordonez (2016)]
- Reasons: Costly information, loan size incentives ...

Suppose 3 states of the world:

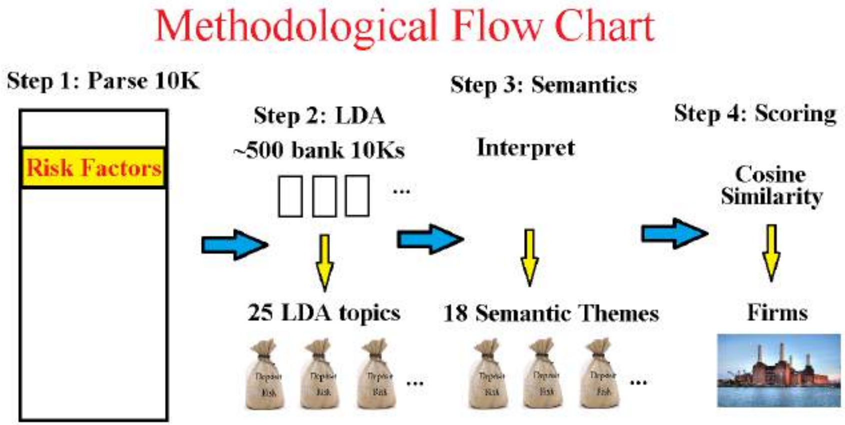
1. Non-crisis periods. No information production predicted.
2. Transition periods (we propose): Some info production.
3. Crisis periods. Extensive information production.

Central Premise: Information producers in transition period will trade and their actions might be detectable.

Properties of ideal predictive systemic risk model

- Automated and free of researcher bias.
- Interpretable without ambiguity.
- Can detect risks dynamically that did not appear in earlier periods.
- Permits flexibility to delve deeper into topics of interest.
- Detects risk factors well in advance of panics.

Our approach makes significant headway on all 5 dimensions.



RESULT: A firm-year panel database with 18 thematic scores for each observation.

Most Novel Innovation: Semantic Vector Analysis

LDA alone is popular but difficult to interpret. Yet it can pick up "systemic" content.

A second stage SVA model solves the interpretability problem.

- See Mikolov, Chen, Corrado, and Dean (2013) and Mikolov, Sutskever, Chen, Corrado, and Dean (2013).

We are not aware of other finance papers using this technology.

Examples of Semantic Vectors

	Mortgage Risk		Capital Requirements	
Row	Word	Cosine Dist	Word	Cosine Dist
1	mortgages	1	capital	0.789
2	mortgage	0.7974	requirements	0.789
3	impac alt	0.7148	meet	0.5369
4	residential mortgage	0.7085	regulatory	0.4508
5	originated	0.6939	additional	0.4422
6	residential mortgages	0.6922	capital expenditure	0.4404
7	adjustable rate	0.6726	minimum	0.4278
8	collateralizing	0.6372	expenditures	0.4273
9	originations	0.6363	requirement	0.4228
10	fhlmc	0.6303	iubfsb	0.4166
11	fnma	0.6271	fund	0.4096
12	fannie mae	0.6231	liquidity	0.407
13	single family	0.6174	comply	0.4004
14	freddie mac	0.6156	ratios	0.3963
15	mbs	0.6142	regulations	0.3939
16	originate	0.6095	satisfy	0.39
17	newly originated	0.6069	required	0.3864
18	association fnma	0.606	guidelines	0.3836
19	mortgage backed	0.6052	regulators	0.3798
20	loan originations	0.6049	needs	0.3781

Data Sources

- We consider banks as identified by firms having SIC codes from 6000 to 6199. We exclude all other firms.
- CRSP (stock returns), Compustat (accounting variables).
- FDIC Failures and Assistance Transactions List. We also consider VIX data.
- Call Reports for bank-specific accounting data.
- metaHeuristica is used to extract risk factor discussions from bank 10-Ks from 1997 to 2014.
- We require the firm to have a machine readable 10-K, with some non-empty discussion of risk factors, to be included.

Our emerging risk model based on pairwise covariance

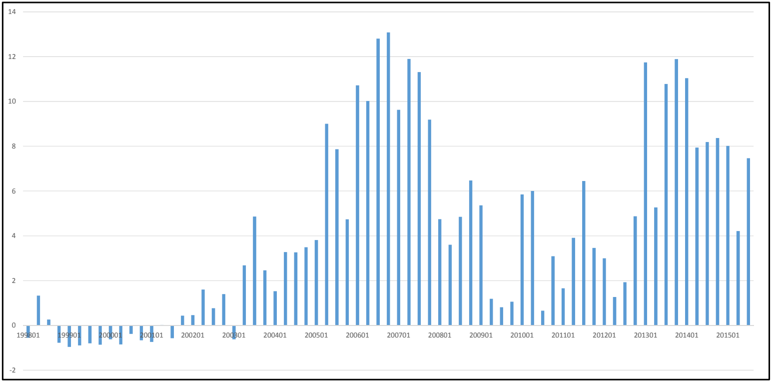
- Run regression once per quarter. One observation is a bank-pair (*i* and *j*).
- Dependent variable is return covariance of *i* and *j* measured using daily returns.
- Independent variable of interest is semantic theme of pair defined as the product $S_{i,j} = S_i \; S_j$
- X are control variables including pairwise of size, age, profitability, leverage, and TNIC+SIC industry.

$$Covariance_{i,j,t} = \alpha_0 + \gamma \mathbf{X_{i,j,t}} + \varepsilon_{i,j,t}, \tag{1}$$

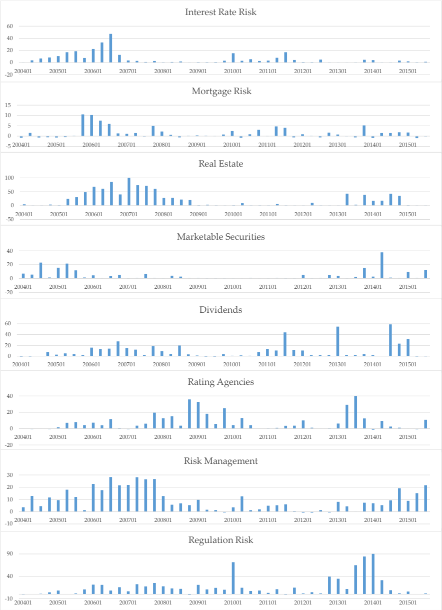
$$Covariance_{i,j,t} = \alpha_0 + \beta_1 S_{i,j,t,1} + \beta_2 S_{i,j,t,2} + \beta_3 S_{i,j,t,3} + ... + \beta_T S_{i,j,t,18} + \gamma \mathbf{X_{i,j,t}} + \varepsilon_{i,j,t}, \tag{2}$$

Aggregate Systemic Risk Signal

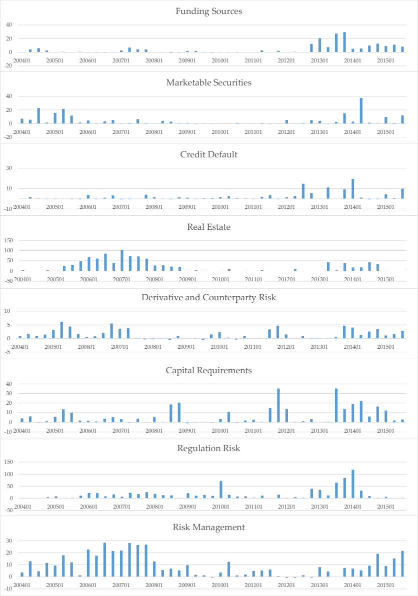
Our Main Result



Summary of 2008 Major Risks (t-stats)



Summary of 2015 Major Risks (t-stats)



Cross Sec. Regressions: Post 2008 Crisis Returns

Dependent variable: bank's stock return from 9/2008 to 12/2012

Row	Quarter	# Emerging Factors	# Obs	Predictive Timing
(1)	2004 1Q	-1.493 (-1.16)	412	Predictive
(2)	2004 2Q	-3.609 (-3.19)	393	Predictive
(3)	2004 3Q	-2.848 (-1.26)	393	Predictive
(4)	2004 4Q	-0.420 (-0.26)	393	Predictive
(5)	2005 1Q	1.014 (0.50)	454	Predictive
(6)	2005 2Q	0.653 (0.40)	444	Predictive
(7)	2005 3Q	0.659 (0.44)	444	Predictive
(8)	2005 4Q	1.291 (0.85)	444	Predictive
(9)	2006 1Q	0.337 (0.47)	488	Predictive
(10)	2006 2Q	-4.107 (-3.04)	462	Predictive
(11)	2006 3Q	-4.809 (-3.54)	462	Predictive
(12)	2006 4Q	-4.863 (-3.03)	462	Predictive
(13)	2007 1Q	-7.441 (-3.56)	517	Predictive
(14)	2007 2Q	-7.169 (-4.03)	508	Predictive
(15)	2007 3Q	-8.040 (-4.51)	507	Predictive
(16)	2007 4Q	-8.332 (-3.85)	507	Predictive
(17)	2008 1Q	-6.780 (-1.83)	545	Predictive
(18)	2008 2Q	-6.788 (-1.93)	512	Predictive
(19)	2008 3Q	-8.761 (-3.38)	512	Non-Predictive
(20)	2008 4Q	-7.503 (-3.60)	512	Non-Predictive
(21)	2009 1Q	-8.710 (-7.13)	563	Non-Predictive
(22)	2009 2Q	-9.591 (-7.92)	521	Non-Predictive
(23)	2009 3Q	-7.084 (-4.81)	520	Non-Predictive
(24)	2009 4Q	-5.767 (-2.96)	519	Non-Predictive

Predict Late 2015 Returns (Mkt Instability Period)

Dependent variable: bank's stock return from 12/2015 to 2/2016

Row	Quarter	# Emerging Factors	# Obs	Predictive Timing
(1)	2010 1Q	-0.861 (-7.67)	357	Predictive
(2)	2010 2Q	-0.658 (-2.93)	338	Predictive
(3)	2010 3Q	-0.760 (-3.96)	338	Predictive
(4)	2010 4Q	-0.867 (-2.68)	338	Predictive
(5)	2011 1Q	-1.592 (-2.24)	360	Predictive
(6)	2011 2Q	-1.843 (-2.98)	353	Predictive
(7)	2011 3Q	-1.729 (-2.50)	353	Predictive
(8)	2011 4Q	-1.169 (-1.94)	352	Predictive
(9)	2012 1Q	-0.566 (-1.51)	369	Predictive
(10)	2012 2Q	-0.424 (-2.94)	360	Predictive
(11)	2012 3Q	-0.559 (-3.81)	360	Predictive
(12)	2012 4Q	-0.341 (-1.23)	360	Predictive
(13)	2013 1Q	-0.603 (-2.88)	372	Predictive
(14)	2013 2Q	-0.888 (-3.58)	337	Predictive
(15)	2013 3Q	-0.704 (-2.78)	337	Predictive
(16)	2013 4Q	-0.649 (-2.53)	337	Predictive
(17)	2014 1Q	-0.950 (-3.11)	346	Predictive
(18)	2014 2Q	-0.758 (-1.55)	294	Predictive
(19)	2014 3Q	-1.522 (-3.88)	294	Predictive
(20)	2014 4Q	-1.706 (-6.22)	294	Predictive
(21)	2015 1Q	-1.327 (-3.25)	297	Predictive
(22)	2015 2Q	-1.738 (-5.31)	295	Predictive
(23)	2015 3Q	-1.806 (-7.17)	295	Predictive
(24)	2015 4Q	-1.373 (-3.25)	295	Non-Predictive

Bank Failure Regressions

Dependent variable: failure dummy (in 9/2008 to 12/2012)

Row	Quarter	Emerging Risk Exposure	Log Assets	Loans Assets	Loss/ Assets	Cap-ital
(1)	2004 1Q	-0.005 (-2.14)	-0.006 (-0.94)	0.039 (112.21)	0.012 (10.12)	-0.016 (-2.14)
(2)	2004 2Q	0.002 (0.85)	-0.004 (-0.58)	0.043 (21.54)	0.007 (3.11)	-0.014 (-1.13)
(3)	2004 3Q	0.003 (1.56)	-0.003 (-0.55)	0.043 (21.37)	0.007 (3.13)	-0.014 (-1.13)
(4)	2004 4Q	0.000 (0.26)	-0.004 (-0.66)	0.043 (22.84)	0.007 (3.09)	-0.014 (-1.15)
(5)	2005 1Q	-0.001 (-0.45)	-0.003 (-0.48)	0.044 (12.09)	0.027 (5.25)	-0.022 (-2.97)
(6)	2005 2Q	0.008 (3.59)	0.004 (0.54)	0.048 (11.69)	0.041 (12.16)	-0.026 (-3.86)
(7)	2005 3Q	0.009 (6.47)	0.004 (0.62)	0.048 (11.53)	0.041 (12.30)	-0.026 (-3.74)
(8)	2005 4Q	0.011 (14.09)	0.004 (0.77)	0.049 (11.68)	0.041 (12.52)	-0.026 (-3.66)
(9)	2006 1Q	0.004 (1.66)	-0.002 (-0.29)	0.053 (17.68)	0.042 (9.91)	-0.029 (-6.79)
(10)	2006 2Q	0.005 (1.12)	-0.005 (-0.48)	0.061 (8.77)	0.034 (5.38)	-0.030 (-5.53)
(11)	2006 3Q	0.012 (3.18)	-0.003 (-0.24)	0.061 (8.55)	0.034 (5.30)	-0.030 (-6.07)
(12)	2006 4Q	0.018 (5.57)	0.000 (0.03)	0.061 (8.42)	0.033 (5.11)	-0.029 (-6.95)
(13)	2007 1Q	0.024 (7.57)	0.003 (0.32)	0.068 (14.24)	0.050 (5.80)	-0.044 (-7.44)
(14)	2007 2Q	0.025 (4.99)	0.003 (0.32)	0.072 (23.08)	0.055 (6.77)	-0.047 (-4.17)
(15)	2007 3Q	0.027 (4.74)	0.003 (0.42)	0.072 (19.06)	0.055 (6.61)	-0.047 (-4.52)
(16)	2007 4Q	0.029 (3.98)	0.003 (0.41)	0.072 (18.68)	0.055 (6.74)	-0.046 (-4.48)
(17)	2008 1Q	0.025 (4.02)	-0.004 (-0.62)	0.067 (7.70)	0.043 (8.43)	-0.049 (-3.47)
(18)	2008 2Q	0.014 (6.41)	-0.016 (-3.48)	0.044 (2.70)	0.013 (1.73)	-0.033 (-2.06)
(19)	2008 3Q	0.016 (5.19)	-0.015 (-3.64)	0.044 (2.78)	0.013 (1.75)	-0.033 (-2.07)
(20)	2008 4Q	0.017 (3.44)	-0.016 (-4.19)	0.044 (2.87)	0.013 (1.78)	-0.033 (-2.09)
(21)	2009 1Q	0.023 (3.07)	-0.015 (-3.39)	0.033 (4.45)	0.037 (5.65)	-0.042 (-2.08)
(22)	2009 2Q	0.011 (4.59)	-0.028 (-3.63)	-0.001 (-0.78)	0.018 (4.88)	-0.023 (-1.49)
(23)	2009 3Q	0.008 (5.26)	-0.029 (-3.61)	-0.001 (-0.38)	0.019 (5.21)	-0.024 (-1.53)
(24)	2009 4Q	0.005 (3.08)	-0.029 (-3.55)	-0.000 (-0.24)	0.019 (5.12)	-0.023 (-1.52)

Conclusions

- We propose a dynamic model of emerging systemic risks based on computational linguistic analysis of financial firm disclosures and return covariances.
- Benefits of model:
  - Provides little or no signal in “normal times”.
  - Provides aggregate measure of trading on systemic risks.
  - When systemic risk is building, produces **interpretable** information about specific channels.
  - Model is dynamic and reveals risks researcher might be unaware of. Yet SVA also allows researcher to drill down.

* Suggests an interpretable early warning system is possible.
* Results also suggest that SEC’s risk factor disclosure program is useful (not a priori clear from existing work).

News and narratives in financial systems: exploiting big data for systemic risk assessment

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*Bank of England, **University College London

Presentation to 3rd Annual MIT-GCFP Conference on "Causes of and Policy Responses to the U.S. Financial Crisis: What Do We Know Now that the Dust Has Settled?"

Cambridge (MA), 29 September 2016

The views expressed in this presentation are those of the speaker and should not be thought to represent those of the Bank of England, Monetary Policy Committee members, or Financial Policy Committee members

Motivation

- Policy: when to deploy time-varying macroprudential policies?
  - need to identify emerging exuberance
- Theory: narratives and emotions as key drivers of economic and financial activity (eg Keynes, 1936; Akerlof & Shiller, 2009):
  - within the context of Knightian uncertainty, agents act by gaining conviction through the use of narratives – such *conviction narratives* (Chong & Tuckett, 2014) must have emotional support: excitement about gain, suppressing doubt and anxiety about loss
  - narratives can spread ‘systemically’ via social networks or media (Shiller, 2000) and precipitate ‘consensus’
- Empirical: growing text-based analysis linked to sentiment:
  - economic policy uncertainty (Baker *et al*, 2016) and asset prices (eg Loughran and McDonald, 2011; Tetlock, 2007, 2011; Soo , 2013)

This Paper

- Exploits big text data to investigate the effect of narratives on the economy and financial system
- Aim to get a quantitative lens on market news and intelligence for systemic risk assessment:
  - can text-based measures of shifts in the relative balance between excitement and anxiety be useful as an early indicator?
  - can we gauge the extent of consensus to yield further insight?
- We provide evidence of increasing narrative consensus high in excitement and lacking anxiety prior to the crisis

- Key contributions:
  - theoretical filter to text-based analysis
  - focus on systemic risk: exploring the role of market intelligence
  - financial system data sources, including an internal BoE source

Outline

- Data
- Text-based analysis of sentiment
- Gauging consensus in narratives
- Summary and further work

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Data

Data	Range	Description	Abbreviation
Internal Market Commentary	January 2000 through July 2010	Daily comments on market events	MCDAILY
Broker Circulars (Macro view)	January 2008 through June 2013	Low volume prior to June 2010. Primarily weekly economic research reports	BROKER
Reuters News London	January 1996 through September 2014	Reuters (wire) news published in London	RTRS

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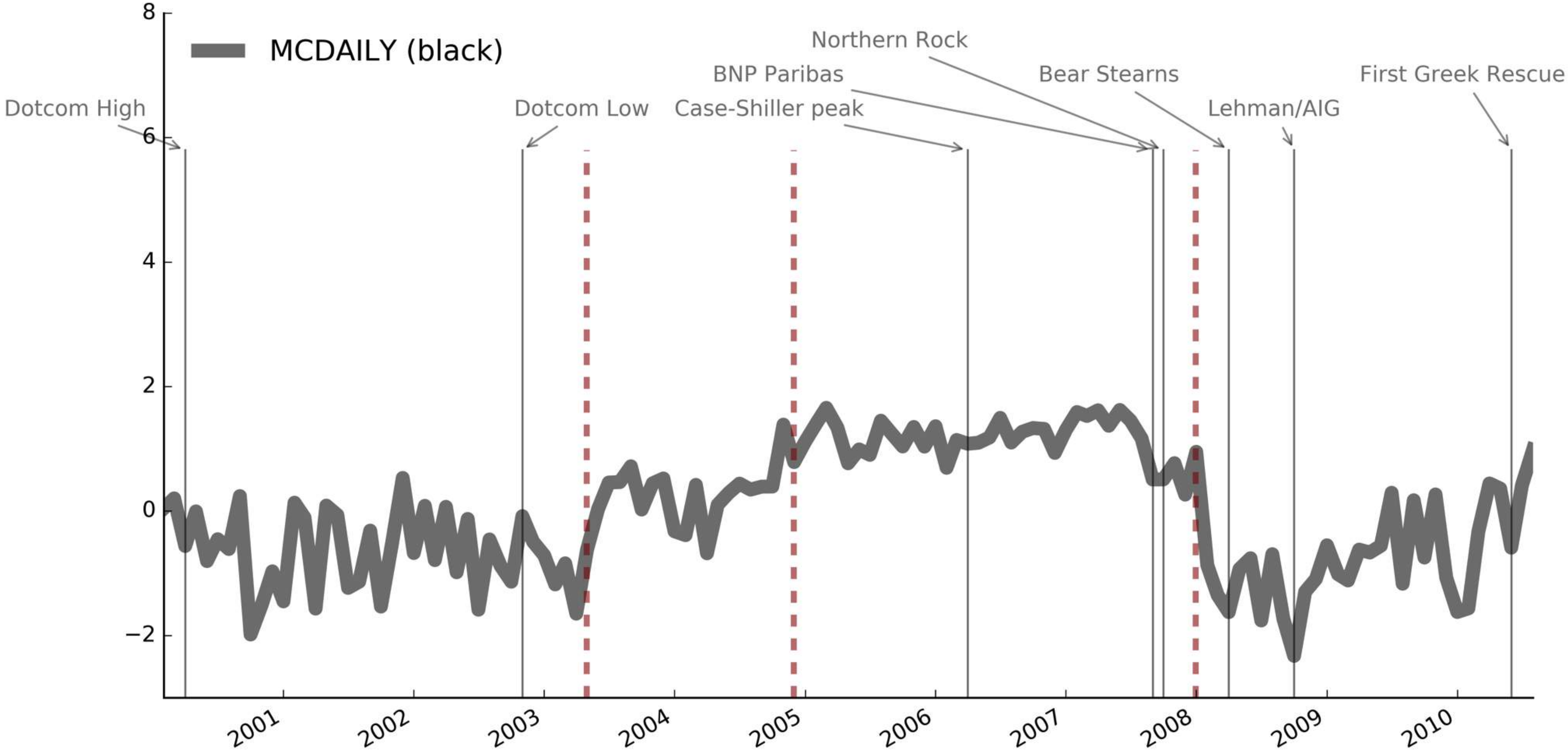
Relative Sentiment – Methodology

- Relative Sentiment Shifts
  - Theoretically motivated (and validated) word dictionaries are used
  - Ordinary English words

- Excitement/Anxiety word samples ~ 150 words each
  - Amaze, amazed, amazes, amazing, attract, attracted, attraction, etc.
  - Anxiety, anxious, avoid, avoids, bother, bothers, bothered, etc.

- *Relative sentiment metric* = (# excitement - # anxiety) / # characters

Sentiment – Results (Internal Market Commentary)



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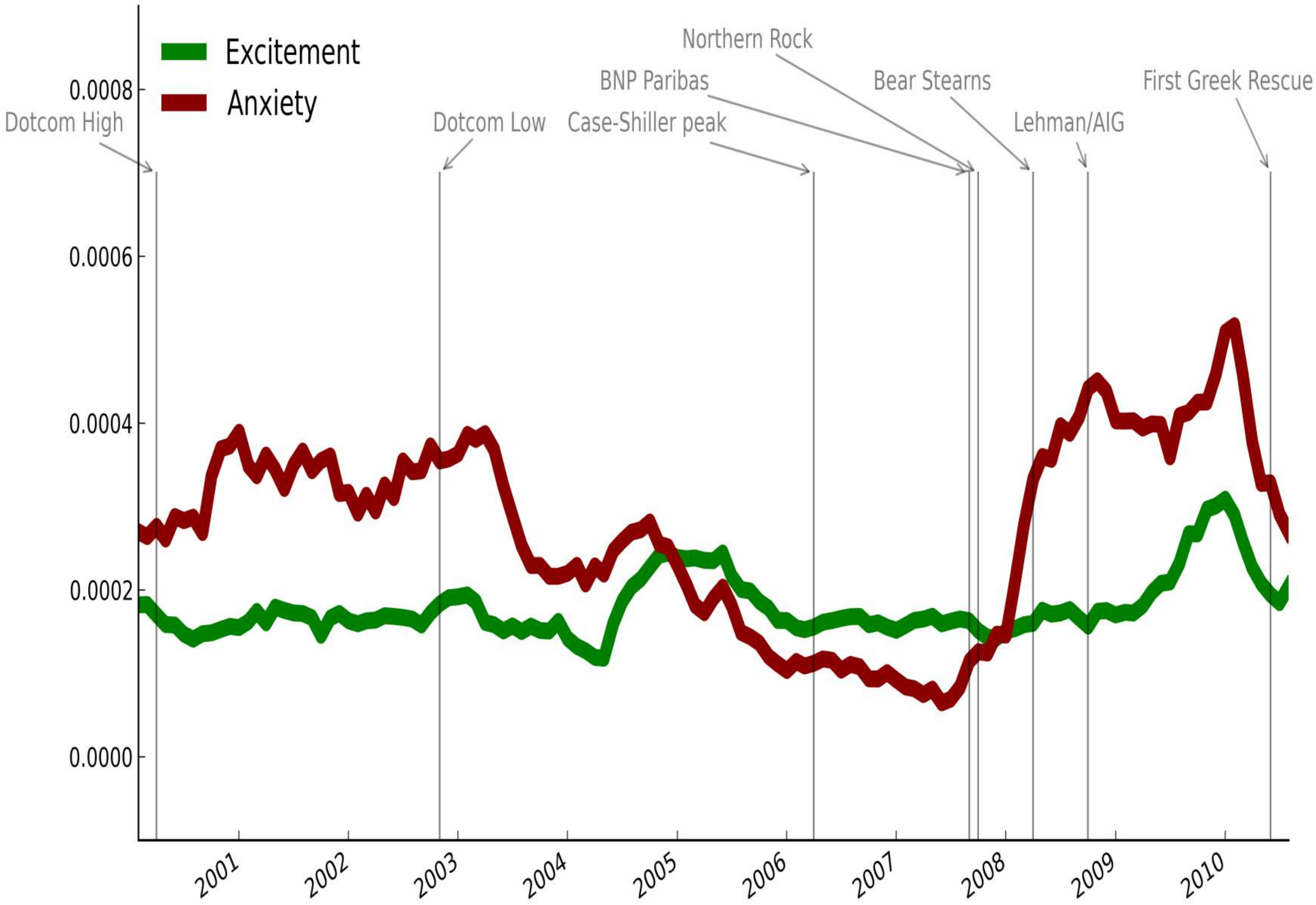
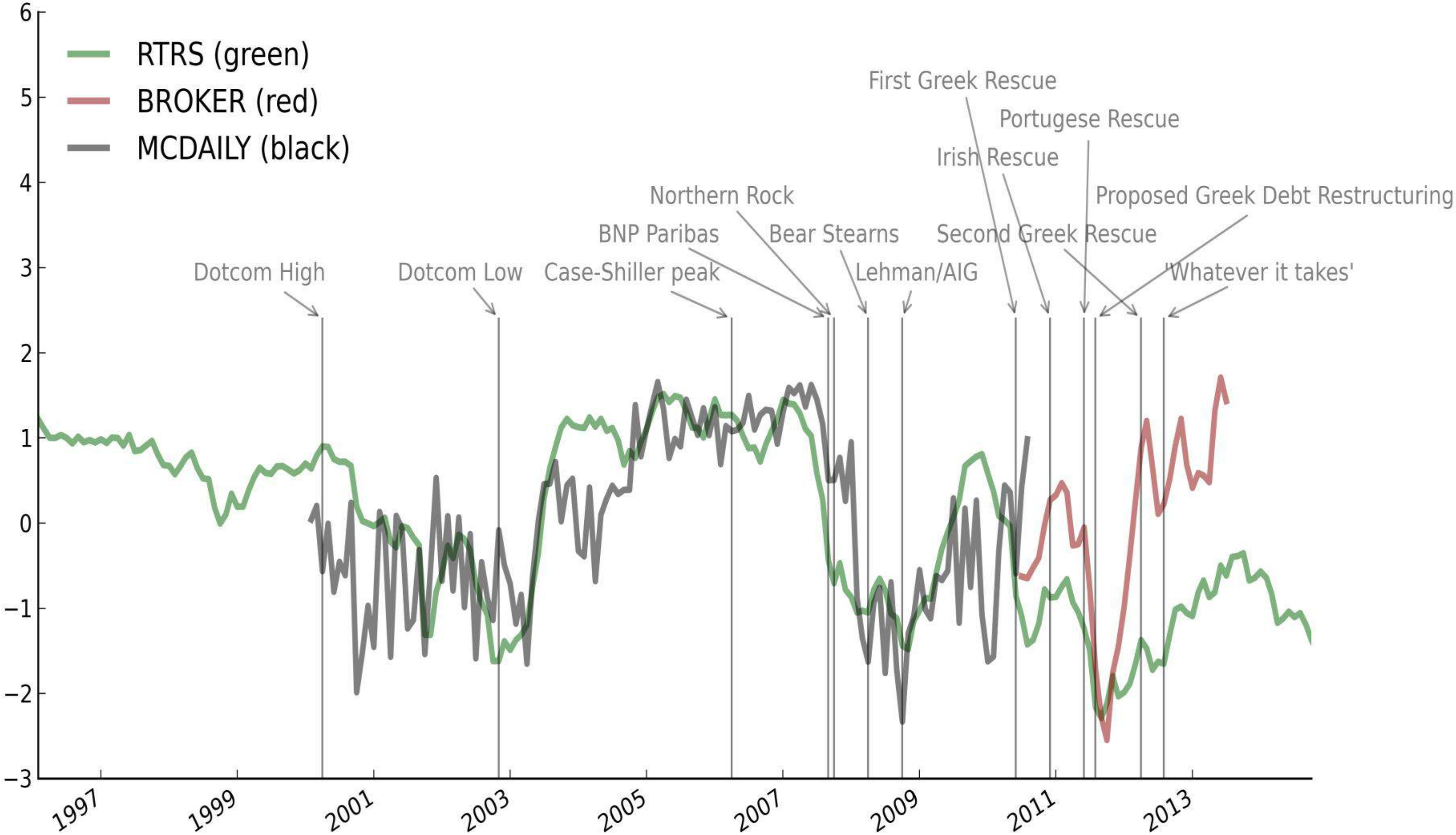
Biggest component of sentiment increase in mid-2000s is anxiety (red)



Largely correlated with RTRS (green) and BROKER (red)



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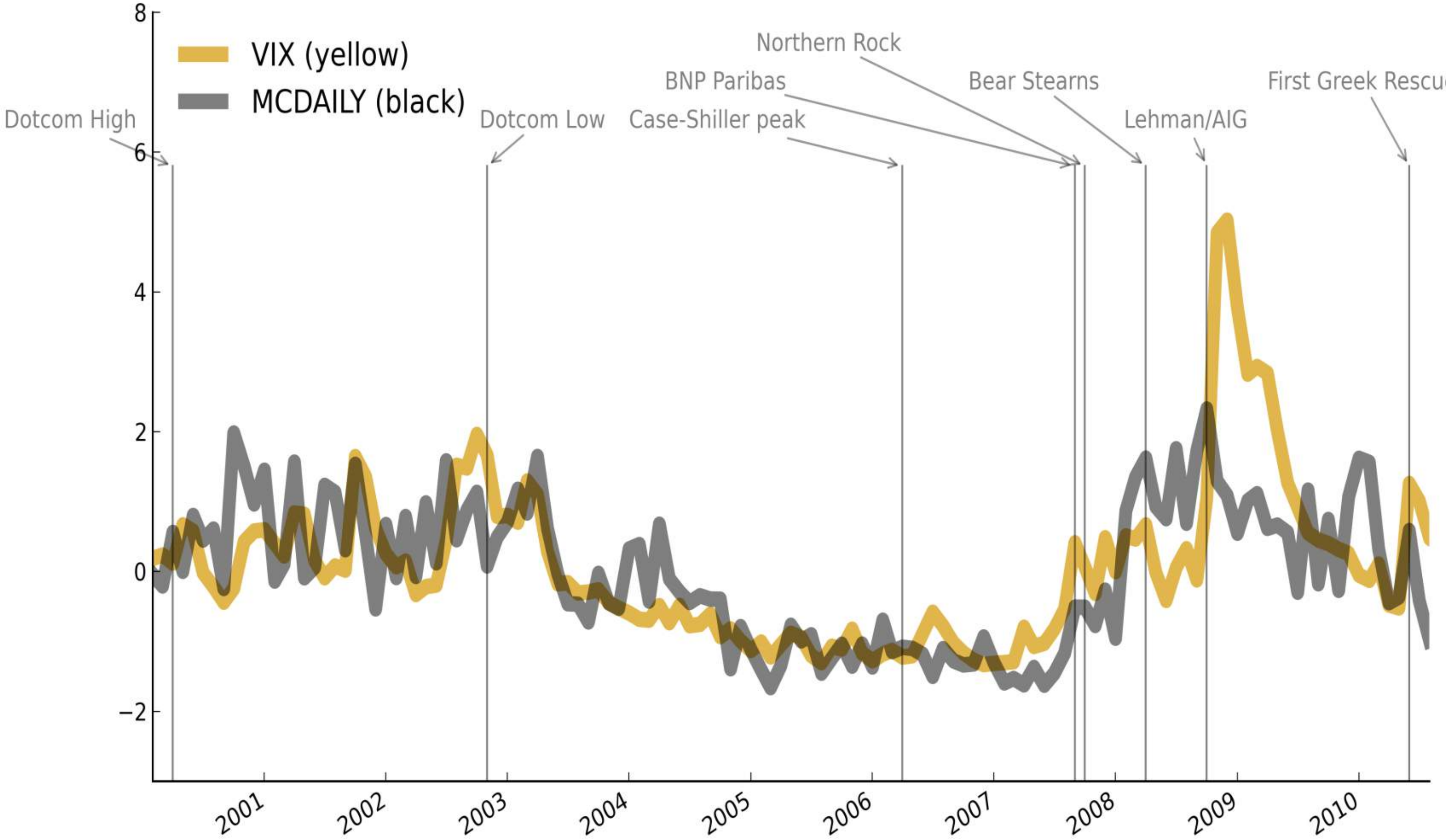
Comparing with other metrics (1)



Anxiety

Excitement

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Comparing with other metrics (2)

Correlations between relative sentiment series and common measures of sentiment, ignoring signs (-1 is -1)

	MCD	RTRS	BRO	VIX	MCI	EPU	BoEU	CDS	PMI
MCD	1	0.59	-	0.65	0.26	0.43	0.54	0.67	0.38
RTRS	-	1	0.71	0.37	0.54	0.61	0.52	0.71	0.51
BRO	-	-	1	0.57	0.66	0.06	0.60	0.23	0.42
MCD (-1)	-	-	-	0.65	0.27	0.41	0.61	0.63	0.43
RTRS (-1)	-	-	-	0.37	0.58	0.63	0.67	0.69	0.57
BRO (-1)	-	-	-	0.65	0.87	0.01	0.76	0.22	0.42

Granger causality

Wald test p-values of Granger-causality from the relative sentiment shift series

RSS Series	MCI	VIX	BoEU	EPU	CDS	PMI
RTRS EXC-ANX	0.005**	0.28	4e-06**	0.3		0.0002**
RTRS EXC	0.032*	0.044*	0.0013**	0.03*	0.05*	0.05*
RTRS ANX	0.003**	0.56	7e-05**	0.1		0.0004**
MCDAILY EXC-ANX	0.5	0.09	6e-05**	0.05*	0.09	0.06
MCDAILY EXC	0.8	0.44	0.13	0.85	0.57	0.57
MCDAILY ANX	0.8	0.38	0.001**	0.06	0.12	0.33
BROKER EXC-ANX	2e-11**	0.18		0.92	0.6	0.1
BROKER EXC	0.022*	0.84		0.77	0.43	0.82
BROKER ANX	3e-05**	0.12		0.72	0.68	0.03*

Note: $*p<0.05$; $**p<0.01$

Impact on the Wider Economy (1)

- Explore the impact on economic activity using a simple VAR of the UK economy from 1996-2015:

$$\begin{bmatrix} rss_t \\ GDP_t \\ L_t \\ CPI_t \\ r_t \\ credit_t \end{bmatrix} = A_1 \begin{bmatrix} rss_{t-1} \\ GDP_{t-1} \\ L_{t-1} \\ CPI_{t-1} \\ r_{t-1} \\ credit_{t-1} \end{bmatrix} + A_2 \begin{bmatrix} rss_{t-2} \\ GDP_{t-2} \\ L_{t-2} \\ CPI_{t-2} \\ r_{t-2} \\ credit_{t-2} \end{bmatrix} + \varepsilon_t$$

  - *rss:* quarterly relative sentiment shift series for the UK (RTRS),
  - *GDP*: quarterly level of GDP,
  - *L*: quarterly level of employment in hours worked,
  - *CPI*: seasonally adjusted level of the consumer price index,
  - *r*: level of Bank Rate
  - *credit*: an indicator of credit conditions

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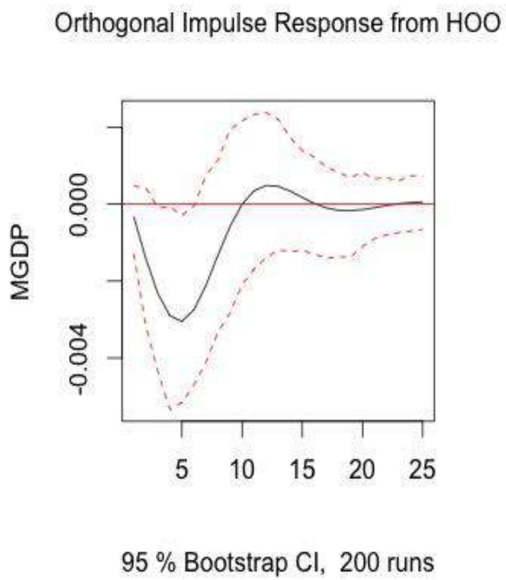
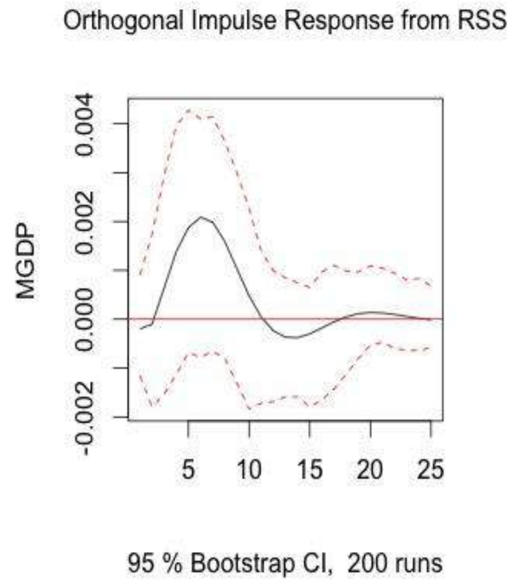
Impact on the Wider Economy (2)

- VAR structure follows Haddow *et al* (2013) estimating the impact of *uncertainty* on the UK economy, in which they showed uncertainty had a significant negative impact (left)
- Relative sentiment has a similar but opposite impact (right) – however, not significant





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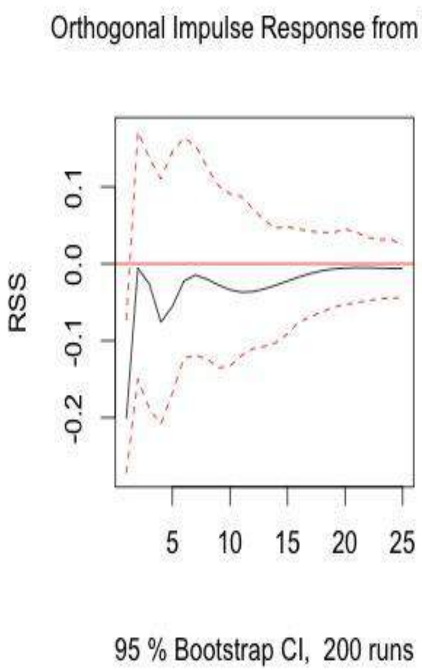
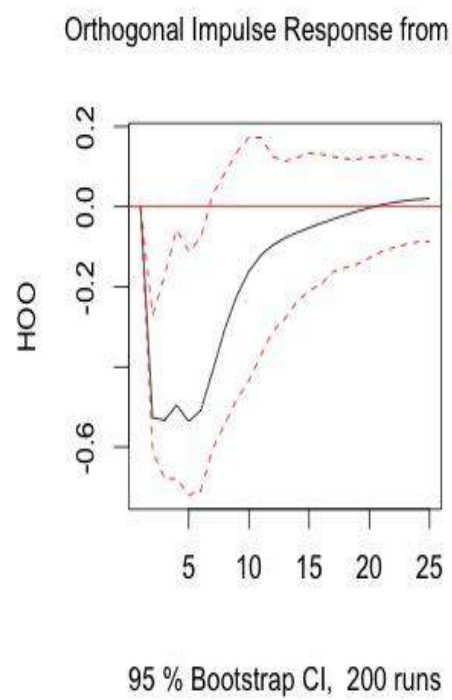
Impact on the Wider Economy (3)

- Including both uncertainty and RSS we notice RSS impacts uncertainty but not vice versa, confirming Granger-causality
- Anxiety → “perceived uncertainty” → growth ?





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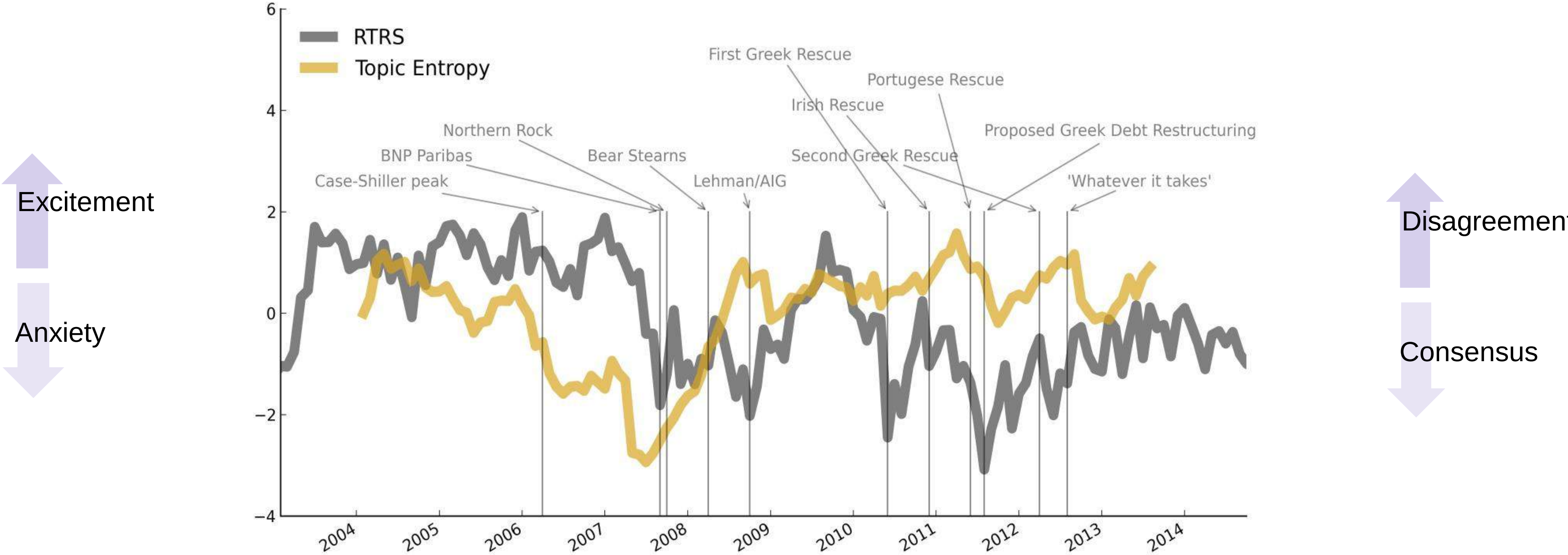
Measuring Consensus in Narratives

- We attempt to quantify ‘consensus’ in Reuters, by measuring
  - the number of narratives at a given moment
  - the ‘size’ of each such narrative
- Analyse the *entropy* (dispersion) of the distribution of topics
- Automatic topic detection: cluster stories into distinct groups; each cluster treated as a topic
- Method yields a distribution of documents over topic clusters
  - eg 100 articles about sovereign debt, 300 about oil etc.

Consensus – Results



Reflects news content – does not explicitly model opposing views or capture market consensus, but market consensus may reflect what people read:

– "*The history of speculative bubbles begins roughly with the advent of newspapers. […] Although the news media… present themselves as detached observers of market events, they are themselves an integral part of these events. Significant market events generally occur only if there is similar thinking among large groups of people, and the news media are essential vehicles for the spread of ideas.*" (Shiller, 2000)

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Summary

- We have explored a measure of relative sentiment shifts and narrative consensus in a variety of financial market data sources
- Metrics seem useful for both high & low frequency developments
  - evidence from text-sources of pre-crisis belief in a new paradigm?
- Potential use for systemic risk assessment
- Demonstrate value of theoretical filter for big data text-based analysis

Further Work

- Development of sentiment series and consensus, including enhanced identification and visualisation of topics and narratives

- Macroeconomic applications, including to forecasting & nowcasting

- More generally, big data and text-based analysis are key elements of the BoE's One Bank Research Agenda
  - Scottish referendum tweets Bank Underground blog
  - supervisory letters; online vacancy postings; Agency reports; gauging central bank credibility

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A Network View on Interbank Liquidity[1]

Co-Pierre Georg

University of Cape Town and Deutsche Bundesbank

[1] Joint work with Silvia Gabrieli (Banque de France).

Introduction

Interbank markets are...

- ... the major source of funding liquidity for euro area banks
  $\Rightarrow$ Functioning interbank market crucial for financial stability

- ... first intermediary market in the implementation of monetary policy
  $\Rightarrow$ Market disruptions can have real economic consequences

How did the Lehman event affect unsecured interbank lending in the euro area?

A Market Freeze in the Euroarea Interbank Market?

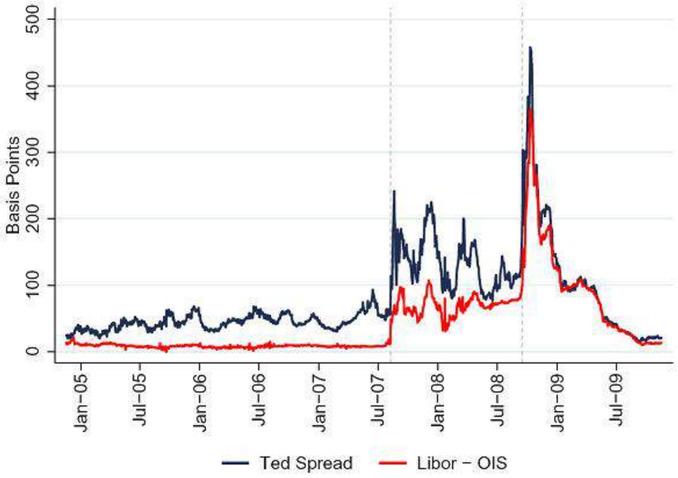


Figure: The Libor-OIS and Ted spread, measuring risk premia in the interbank market

Studying market freeze with payment system data

- Increase in risk premia is indication of market freeze
- Corresponding drop in volume in theory due to asymmetric information or precautionary liquidity hoarding

  $\Rightarrow$ Remedy: provide bank capital and liquidity

Payment system data allow more detailed view

- TARGET2 settles $\geq 90\%$ of all transactions between all European banks
- Unparalleled precision of data on unsecured interbank loans

Lending volumes increased after Lehman event and decreased after ESCB intervention

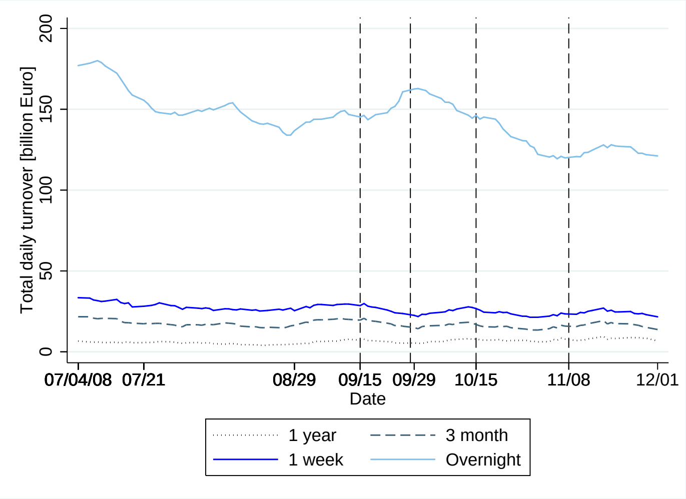


Figure: Normalized volume of the euro area overnight and term interbank market.

Prices remained stable, but price dispersion increased in the overnight segment after Lehman event

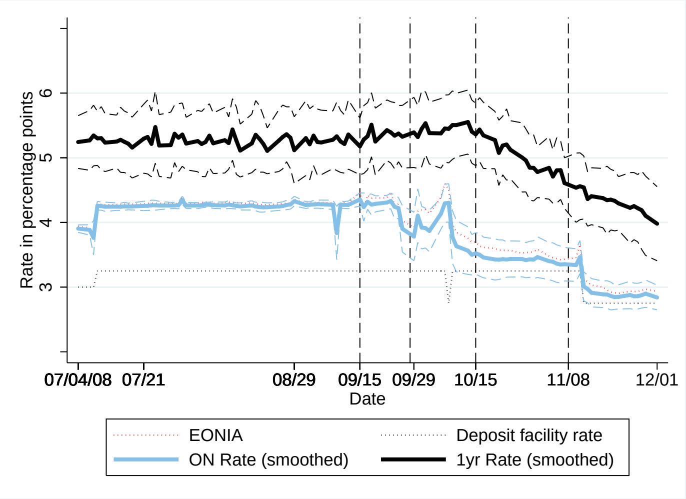


Figure: Daily price of liquidity in the euro area overnight and term interbank market.

Cross-sectional variance in access to liquidity

- Our analysis shows signs of counterparty risk concerns in the overnight segment two weeks before Lehman event
- After Lehman event, banks engage in maturity shortening (largely) irrespective of counterparty risk

- The fact that the aggregate price for liquidity remained constant after Lehman event masks a large heterogeneity in banks' access to liquidity
- Heterogeneity is revealed when studying the interbank **network** structure
- More than half of all bilateral lending relationships change from pre- to post-Lehman period

$\Rightarrow$ Consequences of this structural change?

Simple Intuition why Betweenness Centrality Matters

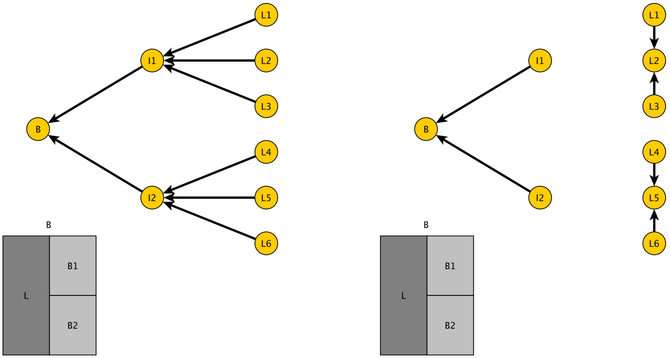


Figure: Sample interbank network. Each node is a bank, each link is an interbank loan. Balance sheet of borrower B is identical in both situations. Network position can be measured e.g. through betweenness centrality.

Higher centrality implies more bargaining power

Main Hypothesis:

- Banks with higher betweenness centrality make larger intermediation spreads
- Intermediation in networks through bilateral and multilateral bargaining

Betweenness centrality $\Longleftrightarrow$ **Bargaining power**

Supporting Hypotheses

- Banks with higher betweenness centrality obtain and provide more liquidity during times of distress
- Banks with higher betweenness centrality pay a lower price on their interbank borrowing

Detailed data allow unbiased identification

- Use loan-level regressions controlling for demand
- Simplified bank balance sheet $D_{i,t} + B_{i,t} = L_{ij,t}$
- Diff-in-diff setup with restriction on banks that borrow from at least two lenders controlling for borrower fixed-effects:

$$\Delta L_{ij} = \beta_j + \beta_1 \Delta D_i + \epsilon_{ij} \tag{1}$$

- Access to interbank deposits $D_i \equiv \alpha \text{Network Position}_i$
- And similar for extensive margin
- Crucial for identification: unanticipated interbank deposit shock

Interbank network structure affects pricing of loans

Support of Main Hypothesis

- Intermediation spread in pre-Lehman period: $\sim$ 90bp
- Banks that experience one standard deviation increase in betweenness centrality increase intermediation spread by $\sim$ 30bp
- In line with experimental evidence on trading in networks

Supporting Hypotheses

- 10% increase in betweenness $\leftrightarrow$ 3.5% more borrowing (bank-level)
- 10% increase in betweenness $\leftrightarrow$ 9% more lending (bank-level)
- 10% increase in betweenness $\leftrightarrow$ 3.5% lower spread

Discussion and Conclusion

- Extensive liquidity supply by the ESCB following Lehman event substituted part of the euro area overnight interbank market
- The resulting change in interbank network structure reduced bargaining power of betweenness central banks
- Betweenness central banks make smaller intermediation spreads, which affects their profitability

- Our paper relates the global structure of the interbank network with local liquidity re-allocation

What Do We Know Now That The Dust Has Settled?: Systemic Risk

Andrew W. Lo, MIT

September 29, 2016

MIT GCFP | GOLUB CENTER FOR FINANCE AND POLICY

Progress Since The Crisis

Statistic	July 2009	July 2016
Unemployment[1]	9.5%	4.9%
GDP Growth[2]	–1.0%	1.1%
Housing Starts[3]	581,000	1,189,000
Inflation[3]	–1.0%	1.0%
10 U.S. 10-Year Treasury[4]	3.67%	1.49%
Fed Balance Sheet[5]	$2,074,822MM	$4,472,202MM
U.S. Dollar Index[6]	76.4384	90.8579
Systemic Risk	???	???

[1]June 2006 and 2016; [2]2009Q1 and 2016Q1; [3]June 2009 and 2016; [4]17 July 2009 and 18 July 2016; [5]15 July 2009 and 13 July 2016; [6]15 July 2009 and 15 July 2016.

Macroprudential Policy Intervention

- Risk management involves pain
  - Raise capital, reduce leverage, cut exposures, put on hedge, buy insurance, slow/reverse growth of business unit(s)
- Taking resources away from a currently profitable activity
- Why??

Macroprudential Policy Intervention

- Motivation: to avoid even greater future pain
- A new (and more compelling) narrative is needed
- That’s the role of systemic risk measures

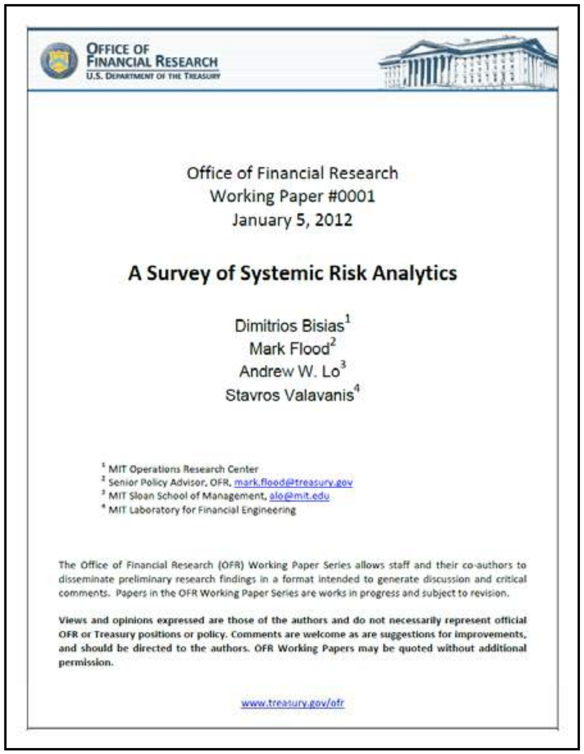
Measuring Systemic Risk

Some General Observations

- No single measure is likely to be sufficient
- Existing measures may become obsolete (Lucas critique)
- New measures will need to be developed
- Academic research and collaboration with industry and government is critical
- Industry can't/won't do this (farmers vs. the National Weather Service)

Let A Thousand Flowers Bloom

Survey of Systemic Risk Measures (over 30!)



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U.S. DEPARTMENT OF THE TREASURY

Office of Financial Research
Working Paper #0001
January 5, 2012

A Survey of Systemic Risk Analytics

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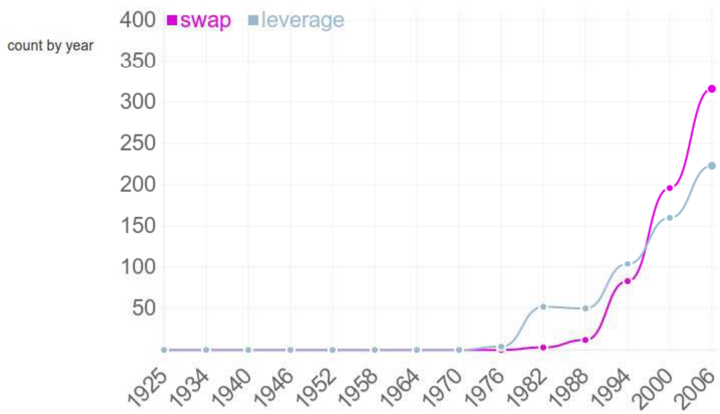
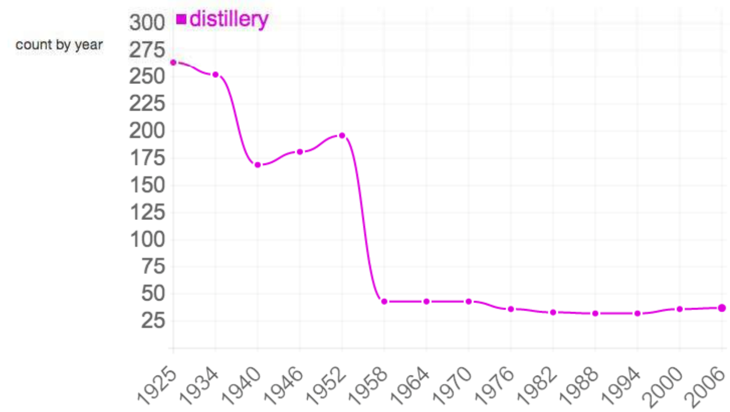
www.treasury.gov/ofr

https://financialresearch.gov/working-papers/files/OFRwp0001_BisiasFloodLoValavanis_MatlabCode-v0_3.zip

Hanley and Hoberg

- Text-mining for topics/risks in 10-K's of 500 banks!





- ➢ Before vs. after Sarbanes-Oxley (1994-2001, 2003-2014)
- ➢ Cluster analysis of topics (systematic vs. idiosyncratic)
- ➢ Overall sentiment of 10-K (measuring culture)

Nyman, Gregory, Kapadia, Ormerod, Tuckett, Smith

- Text-mining for sentiment in BoE market summaries, broker reports, and Reuters newsfeeds
- Conviction Narrative Theory; “excitement” vs. “anxiety”
- ➢ Other measures of market sentiment (put/call ratios)
- ➢ Asymmetric HOO/RSS and the “Peltzman Effect”
- ➢ Consensus measures and countercyclical buffers

Nyman, Gregory, Kapadia, Ormerod, Tuckett, Smith

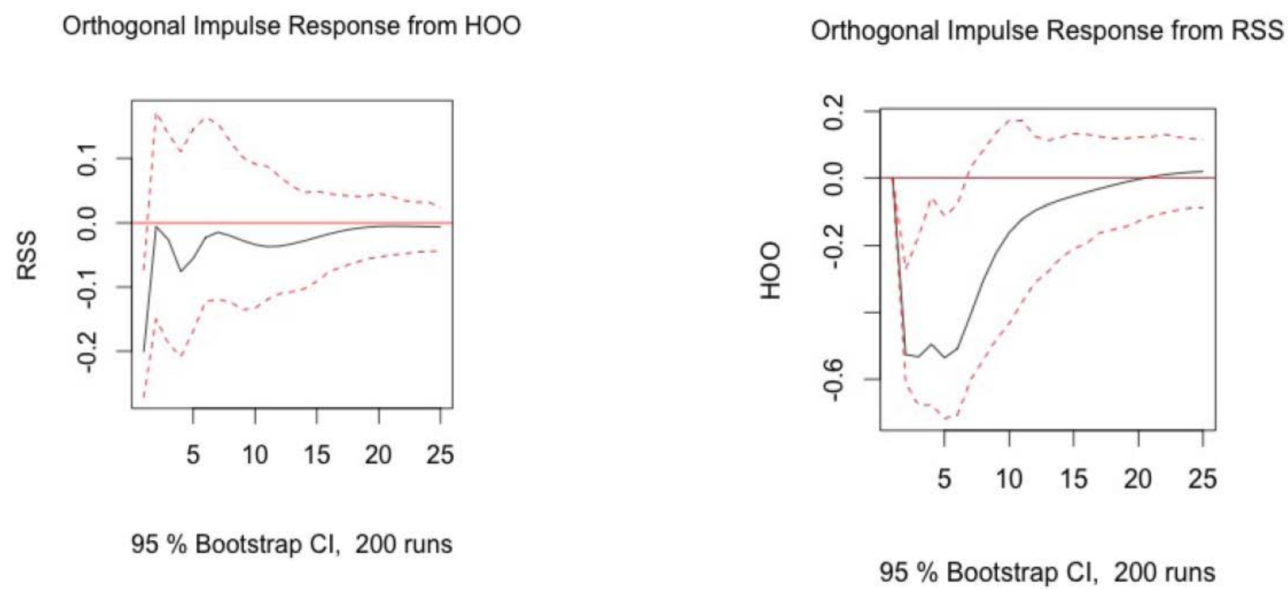
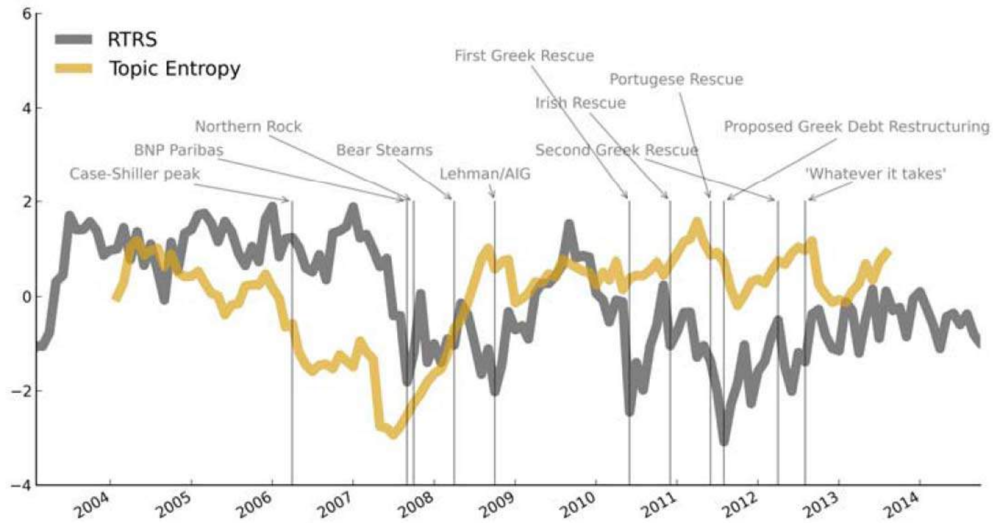


Figure 10: Impact of one standard deviation shocks of uncertainty on RSS (left) and vice versa (right)

- Asymmetry suggests overconfidence $\Rightarrow$ booms

Nyman, Gregory, Kapadia, Ormerod, Tuckett, Smith



- What does consensus look like between 1996 and 2006? Can we measure polarity? How can regulators use consensus to construct countercyclical policies?

Gabrieli and Georg

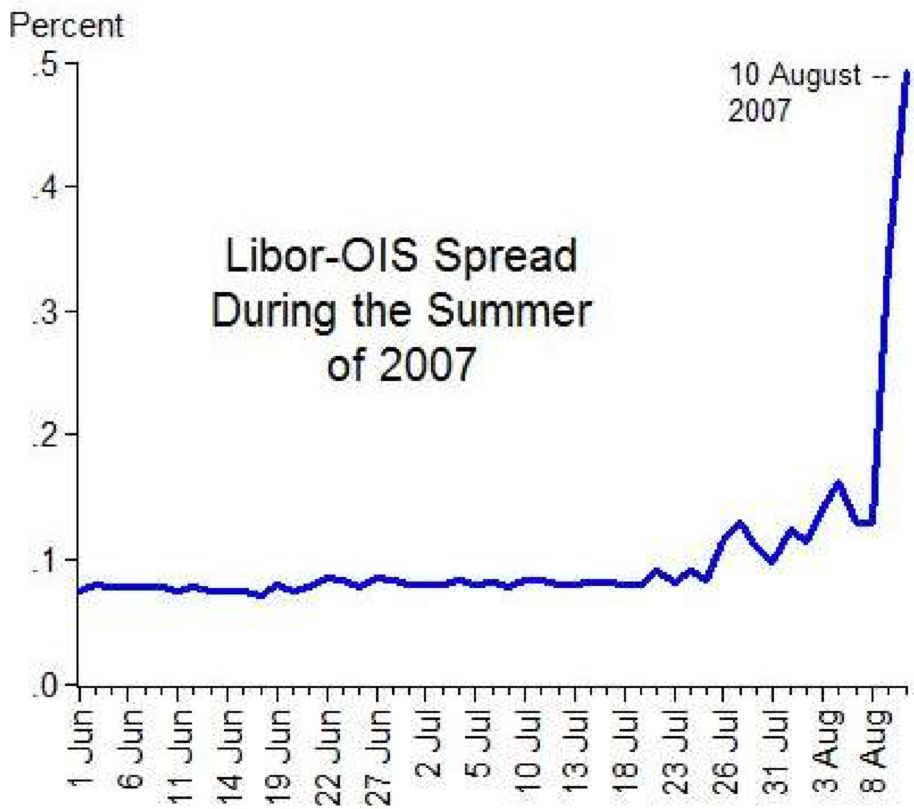
- Network model of interbank loans from July 4 to October 30, 2008
- Linear regressions relating measures of connectedness and importance to liquidity provision and access

➢ For early-warning signals, how about 2007 data?

➢ What about network topology and vulnerabilities?

➢ Can the dynamics of contagion be estimated?

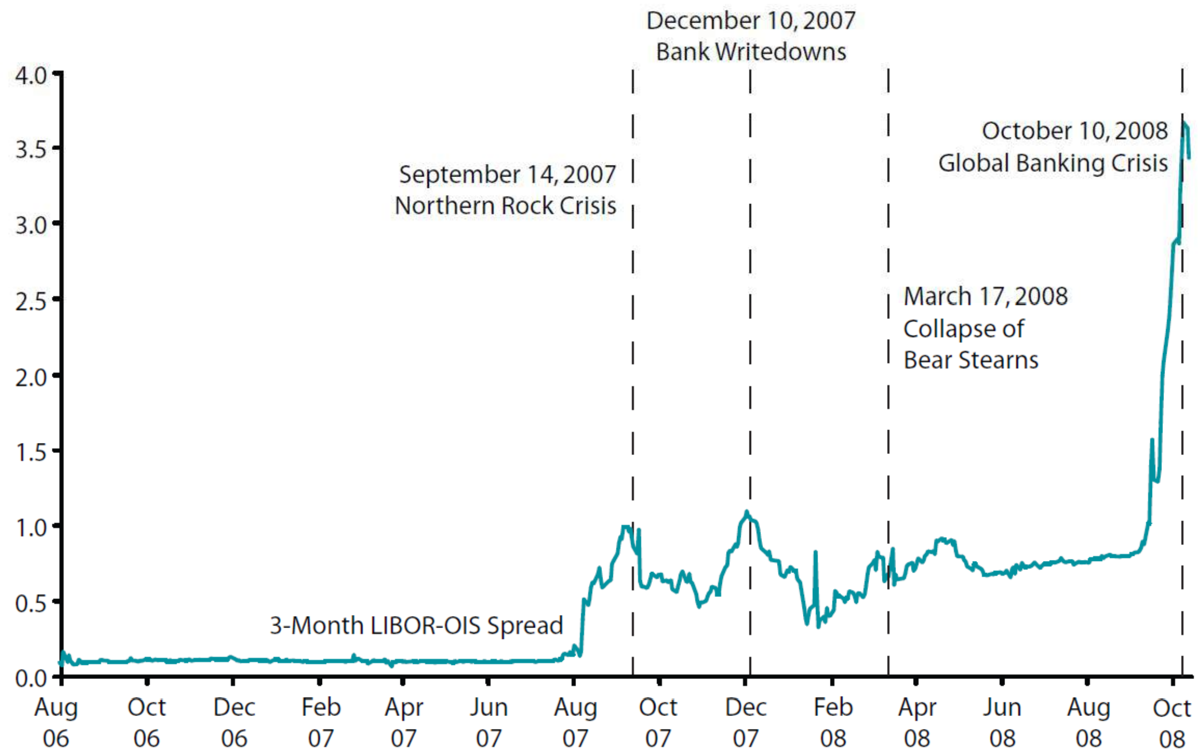
Gabrieliy and Georg



Source: John B. Taylor

Gabrieli and Georg

3-Month LIBOR/OIS Spread
August 2006 to October 2008

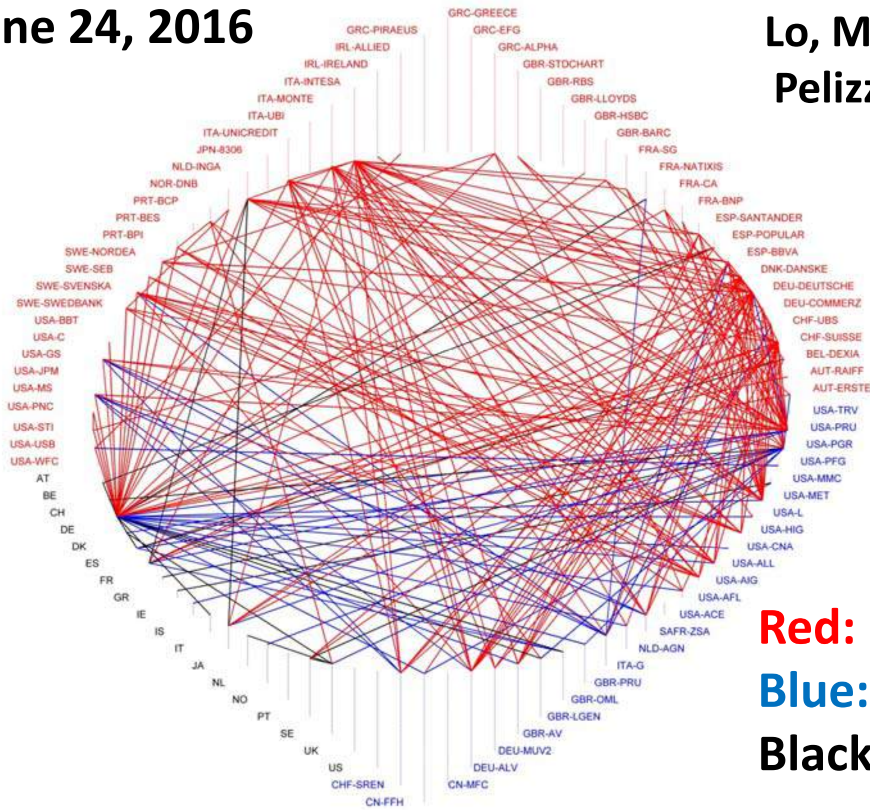


Source: Sengupta and Tam (2008, St. Louis Fed)

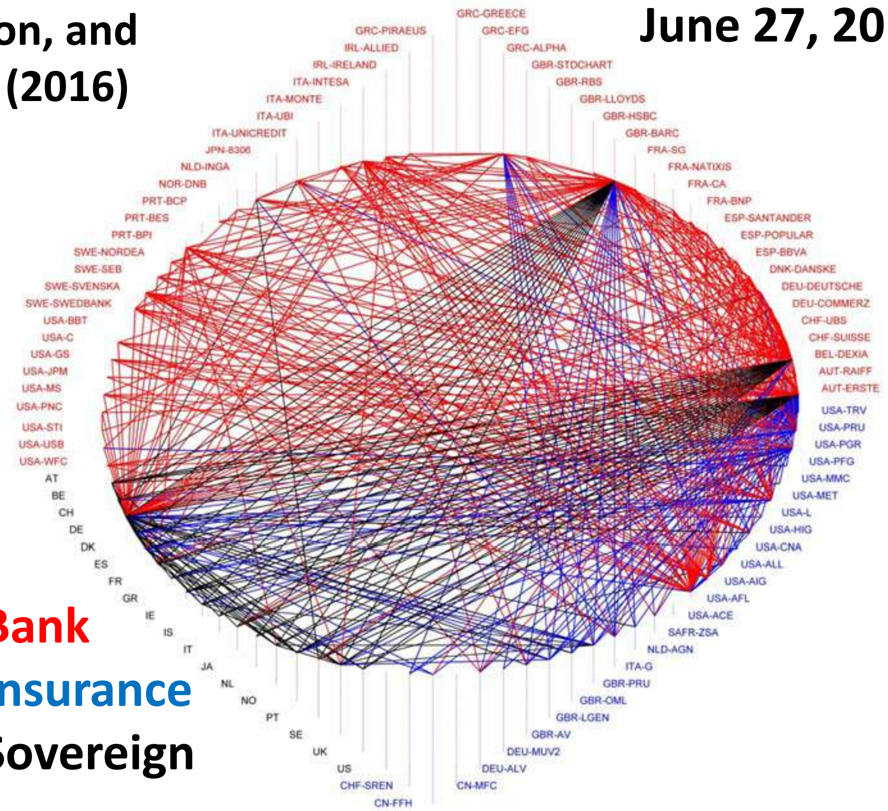
Gabrieli and Georg

Billio, Getmansky, Gray, Lo, Merton, and Pelizzon (2016)

June 24, 2016



June 27, 2016



Red: Bank
Blue: Insurance
Black: Sovereign

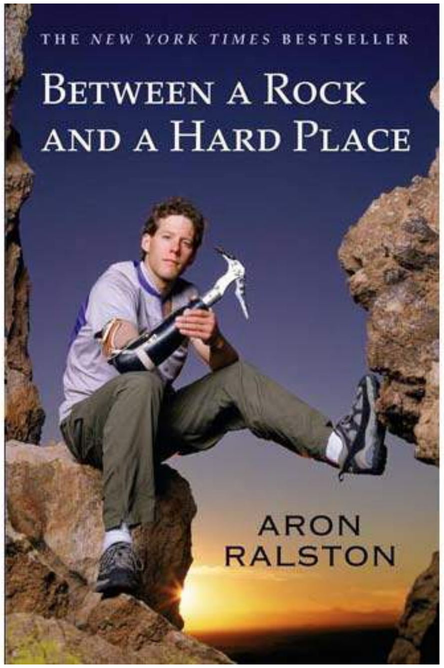
Conclusion

- Financial markets are highly dynamic
- Risks vary over time, circumstances, strategies
- Financial stability is, therefore, also dynamic
- Regulation should adapt in tandem and account for human behavior (Lucas critique + behavioral critique)
- You can't manage what you don't measure
- Proven systemic risk measures can offer **narrative**

Conclusion

Example: Aron Lee Ralston, 4/26/03

- Hiking on 4/26/03 in Blue John Canyon, Utah
- Trapped for 127 hours
- Finally escaped by amputating his own right forearm
- How??
- A different **narrative**!



Conclusion

MIT GCFP

Example: Aron Lee Ralston, 4/26/03

A blond three-year-old boy in a red polo shirt comes running across a sunlit hardwood floor in what I somehow know is my future home. By the same intuitive perception, I know the boy is my own. I bend to scoop him into my left arm, using my handless right arm to balance him, and we laugh together as I swing him up to my shoulder… Then, with a shock, the vision blinks out. I'm back in the canyon, echoes of his joyful sounds resonating in my mind, creating a subconscious reassurance that somehow I will survive this entrapment. Despite having already come to accept that I will die where I stand before help arrives, now I believe I will live.

That belief, that boy, changes everything for me.

Conclusion

Example: Aron Lee Ralston, 4/26/03

- In 2003, Ralston was was not engaged, married, and had no children
- Ralston married in August 2009
- Son Leo was born in 2010

Thank You!