FEDERAL RESERVE BANK *of* CLEVELAND

Contributions to Financial Stability

Measuring and Forecasting Financial Stress

SAFE: An early warning system for systemic banking risk

2013 Financial Stability Conference

Financial Stability Analysis: Using the Tools, Finding the Data

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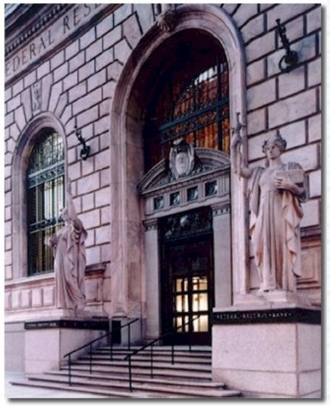


Agenda

1. **Early warning of systemic stress**
   - Measure of systemic conditions
     - Identifying systemic stress
   - Set of factors to explain this measure
     - Forecasting systemic stress

2. **Data**
   - Confidential supervisory data adds value to public data

3. **Uses in supervisory process**
   - Across time
     - Identification of stress
     - Monitoring of stress
     - Alerting of stress
   - Across institutions
     - Contributions to stress
     - Adverse exposures
     - Macroprudential vs. microprudential issues

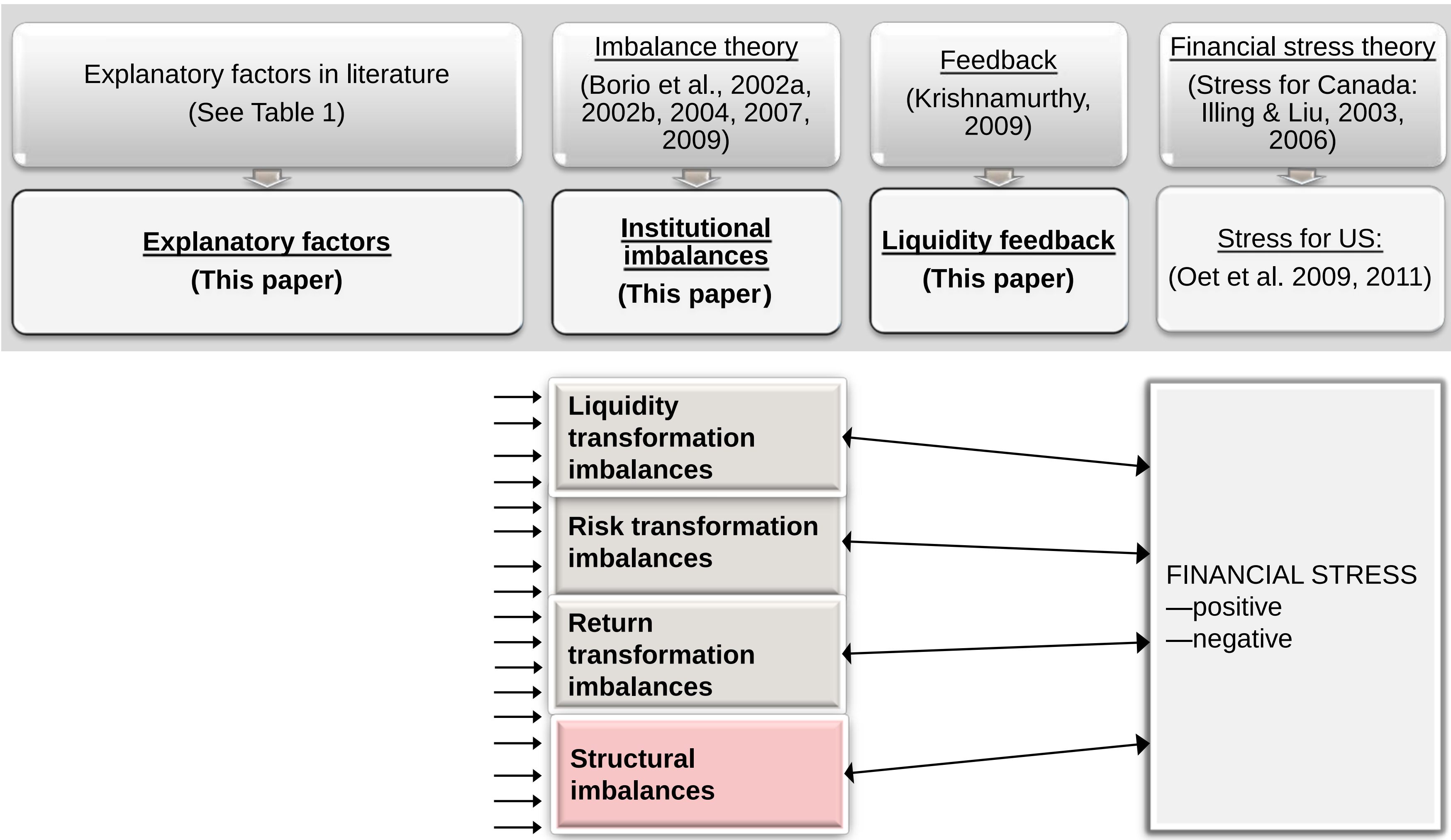
Introduction

- Systemic risk leading to financial crisis
  - Economic imbalances
    - Shock
      - Adverse feedback loop
        - No self-correcting mechanism
          - Financial market fails to function normally
            - Spillover to the real economy

Group of Ten, 2001, BIS

- Develop an early-warning system for systemic risk identification that provides supervisors time to prevent or mitigate a potential financial crisis

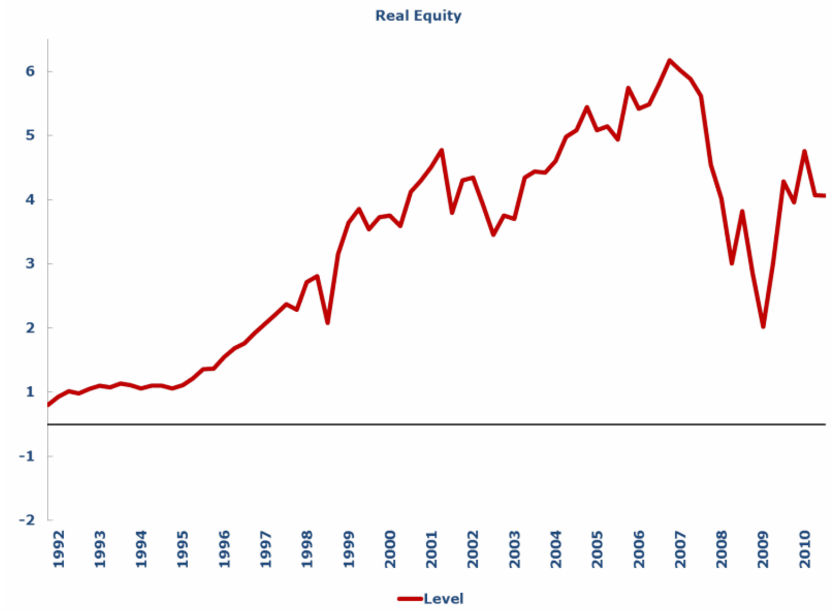
Conceptual model

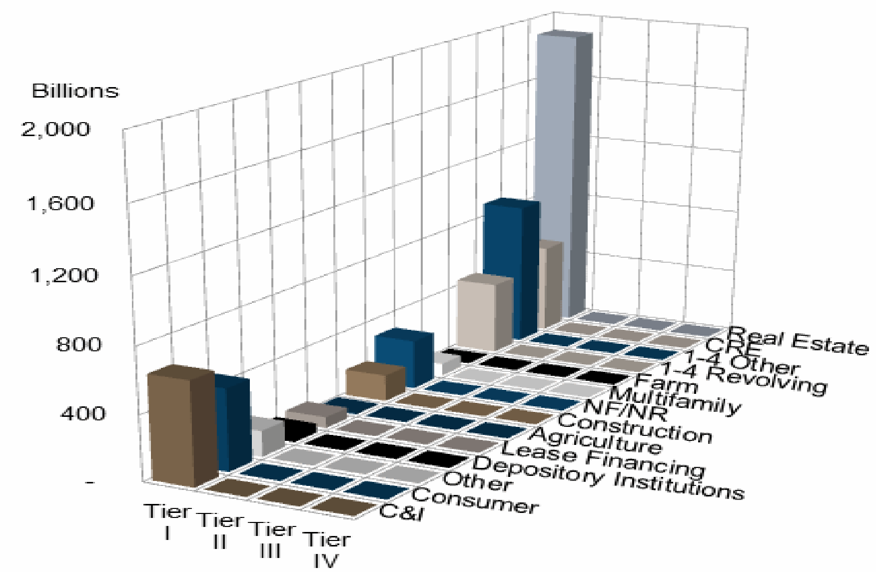


Observations

- Accumulated imbalances above long term means are highly correlated to stress episodes across time

- Structurally, financial system is highly heterogeneous by exposure concentrations across institutions





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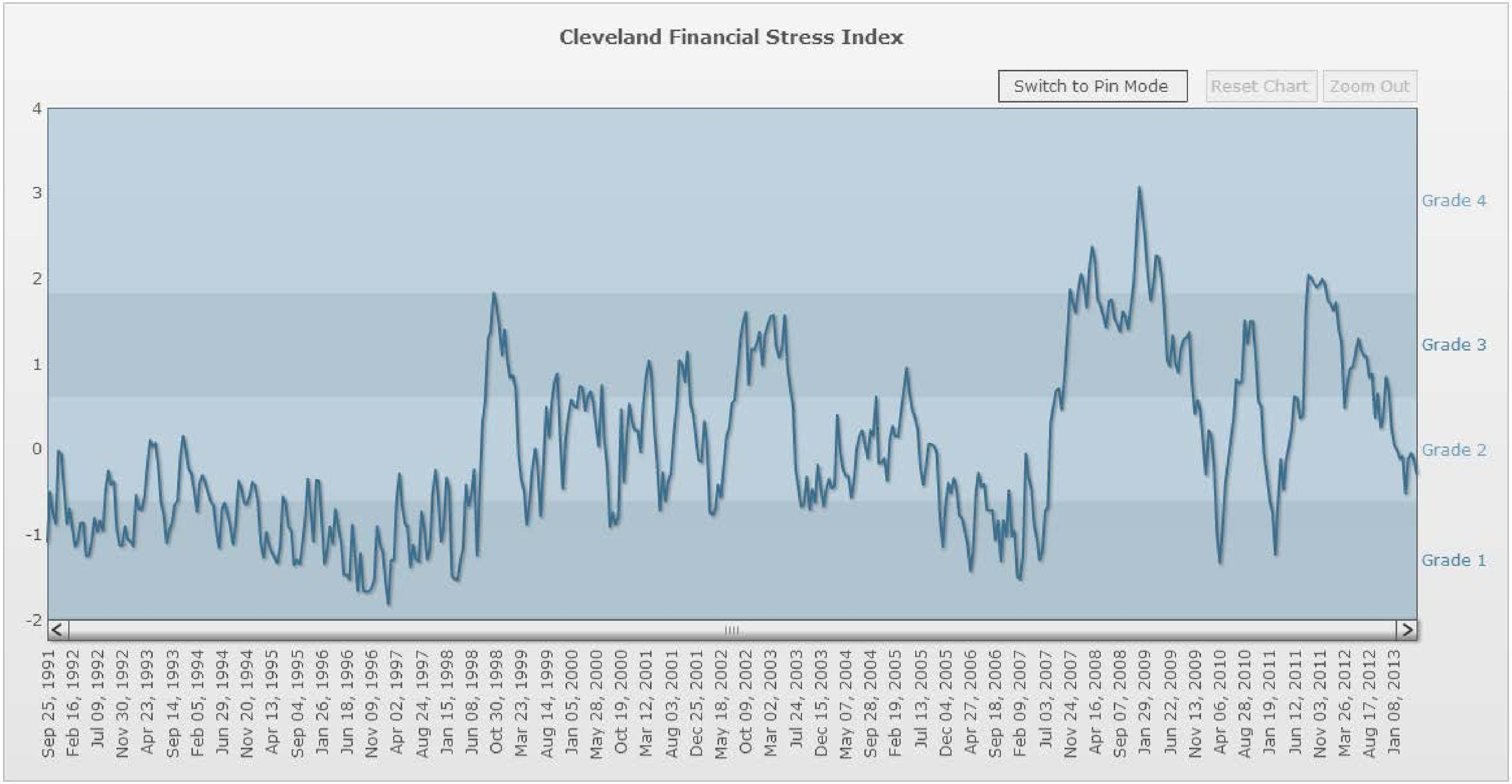
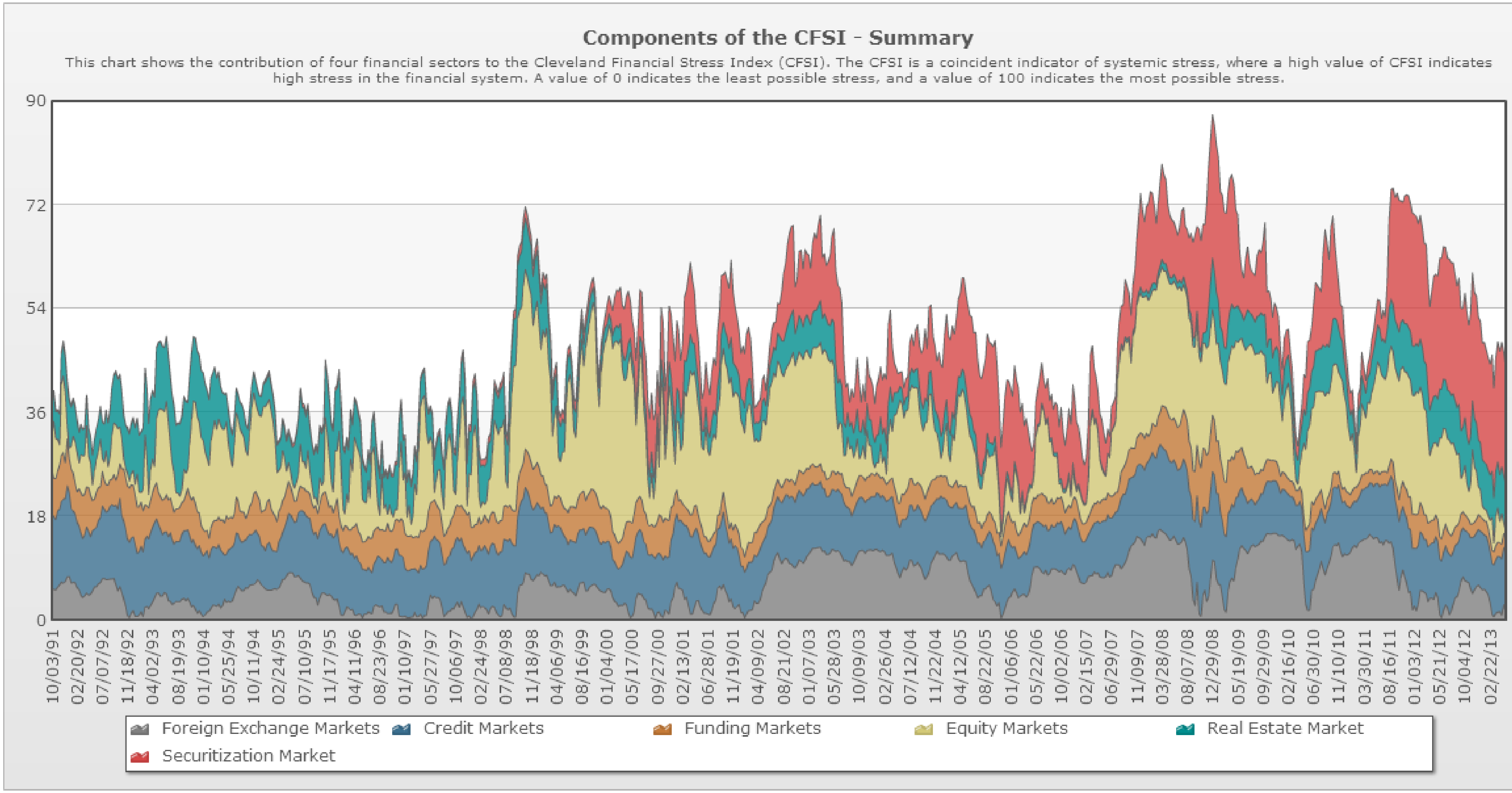
CFSI — measure of US financial stress



- Available daily from http://www.clevelandfed.org/research/data/financial_stress_index/

CFSI — measure of US financial stress



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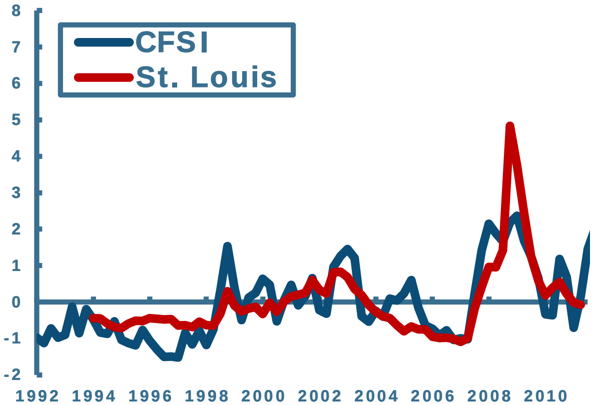
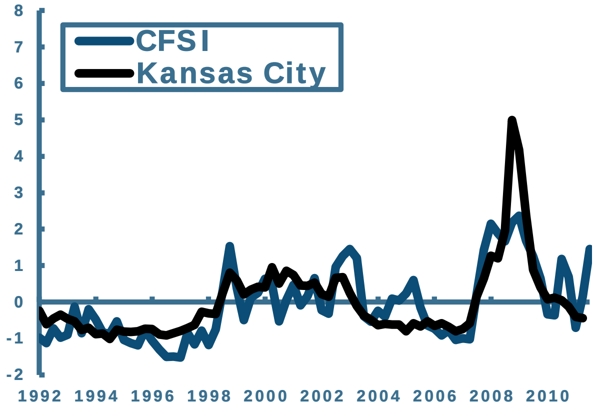
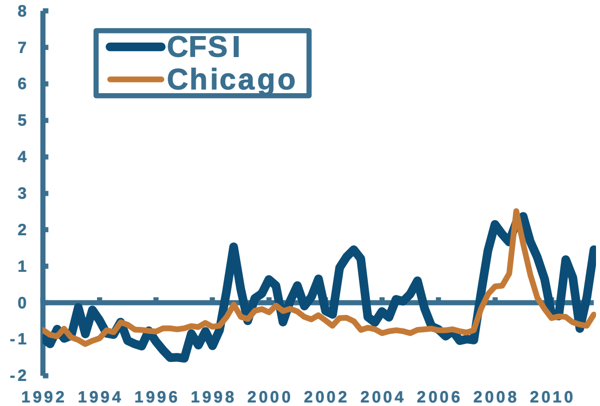
US Financial stress indexes in 2008… and in 2010



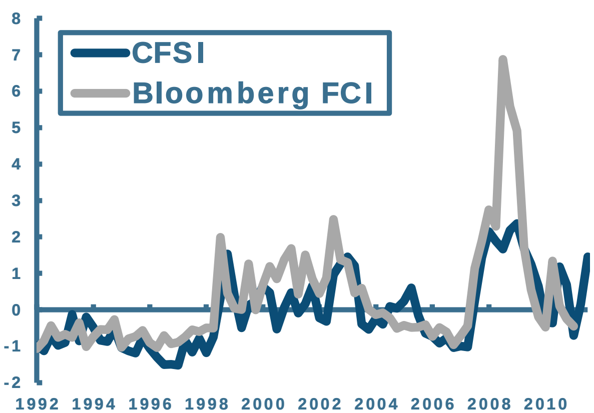
Sources: Oet, Bianco, Gramlich, and Ong (2012); Federal Reserve Bank of St. Louis



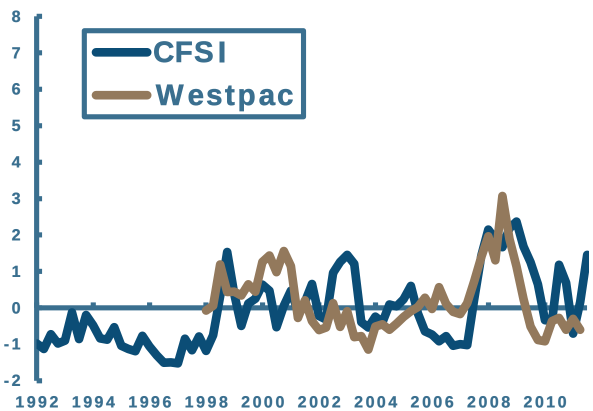
Sources: Oet, Bianco, Gramlich, and Ong (2012); Federal Reserve Bank of Kansas City



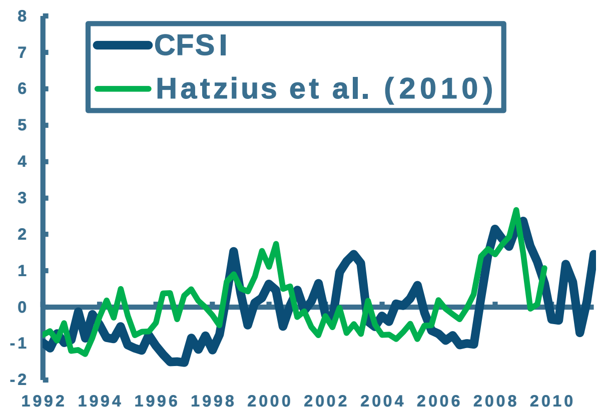
Sources: Oet, Bianco, Gramlich, and Ong (2012); Federal Reserve Bank of Chicago



Sources: Oet, Bianco, Gramlich, and Ong (2012); Bloomberg



Sources: Oet, Bianco, Gramlich, and Ong (2012); Bloomberg



Sources: Oet, Eiben, Bianco, Gramlich, and Ong (2012); Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010)

Note: Values are quarterly averages.

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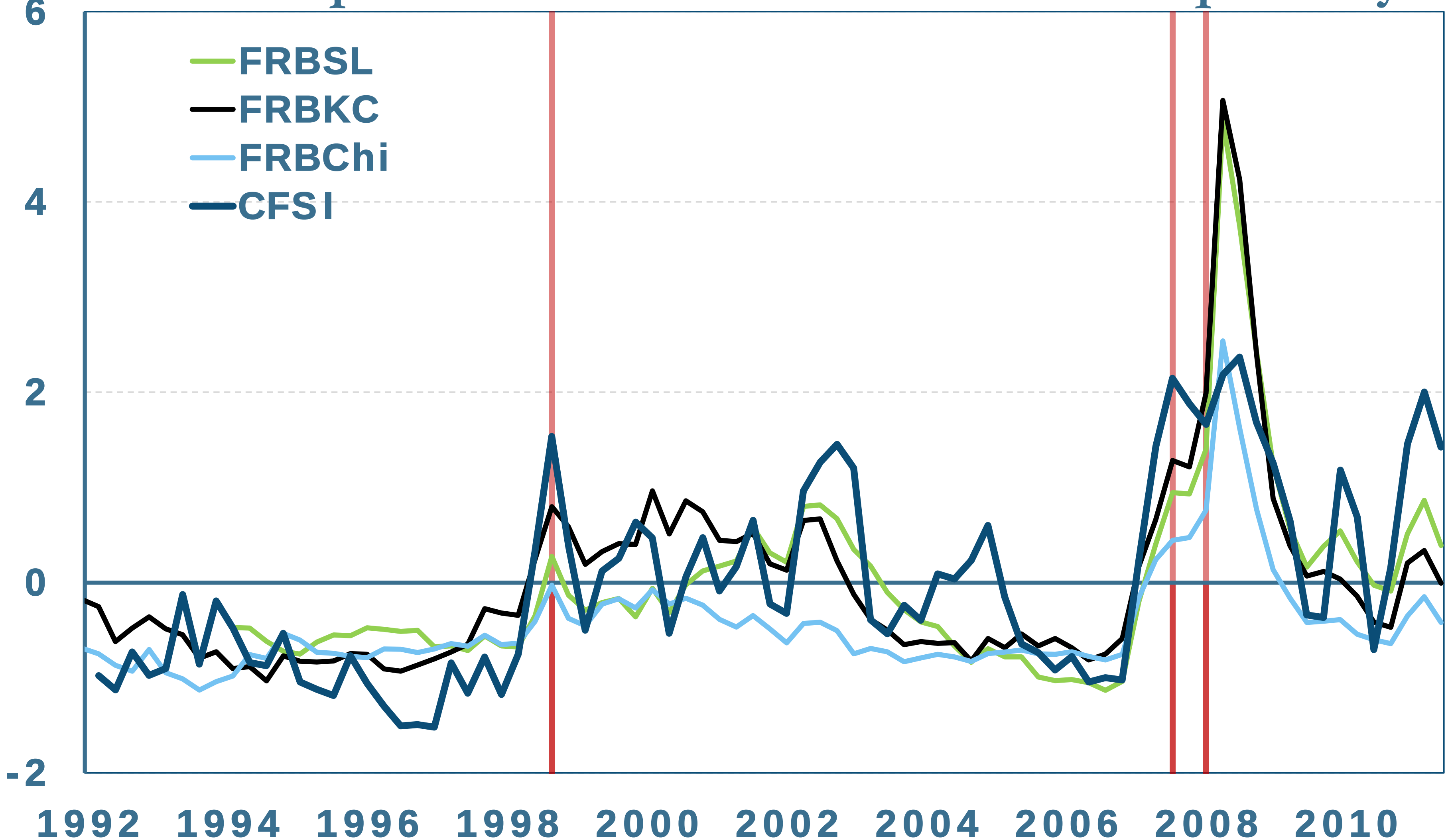
CFSI comparison with alternative indexes - quarterly



Source: Federal Reserve Bank of Cleveland; Federal Reserve Bank of Chicago; Federal Reserve Bank of Kansas City; Federal Reserve Bank of St. Louis

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Development of dependent variable series

- Quarterly financial stress series ($CFSIq_t$)
  - what is the precedent set by the indicator's value
  - how much that precedent matters

- Mathematically:

$$Y_t = CFSIq_t = \sum_j \left[w_{jt} * \int_{-\infty}^{z_{jt}} f(z_{jt}) dz_{jt} \right] * 100$$

  - where the z_{jt} term is the value of indicator j at time t,
  - the integration term is the CDF of indicator j,
  - the w_{jt} term is the weight given to indicator j in the FSI at time t.

- A key technical challenge is the potential for false alarms
  - Overcome by appropriate choice of the weighting methodology

Imbalances

- Methodology uses Z-scores to express imbalances
  - Imbalance $\underline{X_t}$ is defined as deviation of explanatory variable X_t from its mean
  - $\underline{X_t}$ is constructed as standardized imbalance of X_t

$$\underline{X_t} = \frac{X_t - \mu^x{}_t}{\sigma^x{}_t}$$

    - where X_t is a deflated explanatory variable
    - $\mu^x{}_t$ is cumulative mean of the explanatory indicator known as of time t, and $\sigma^x{}_t$ is its cumulative standard deviation
  - The $\underline{X_t}$ imbalance shows potential for stress

Model

- Each SAFE model is an optimal lag linear regression model

$$Y_t = \beta_0 + \beta_{RET}\underline{X_{RET,t-n_{RSK}}} + \beta_{RSK}\underline{X_{RSK,t-n_{RSK}}} + \beta_{LIQ}\underline{X_{LIQ,t-n_{LIQ}}} + \beta_{STR}\underline{X_{STR,t-n_{STR}}} + u_t$$

where the dependent variable Y_t is constructed separately as a series of systemic stress in the U.S. financial markets, and the independent variables $\underline{X_{i,lagged\ t}}$ are return, risk, liquidity, and structural characteristics of the asset class exposures of the top twenty-five US BHCs

Design

- A hazard inherent for all ex ante models is that the model uncertainty may lead to wrong policy choices

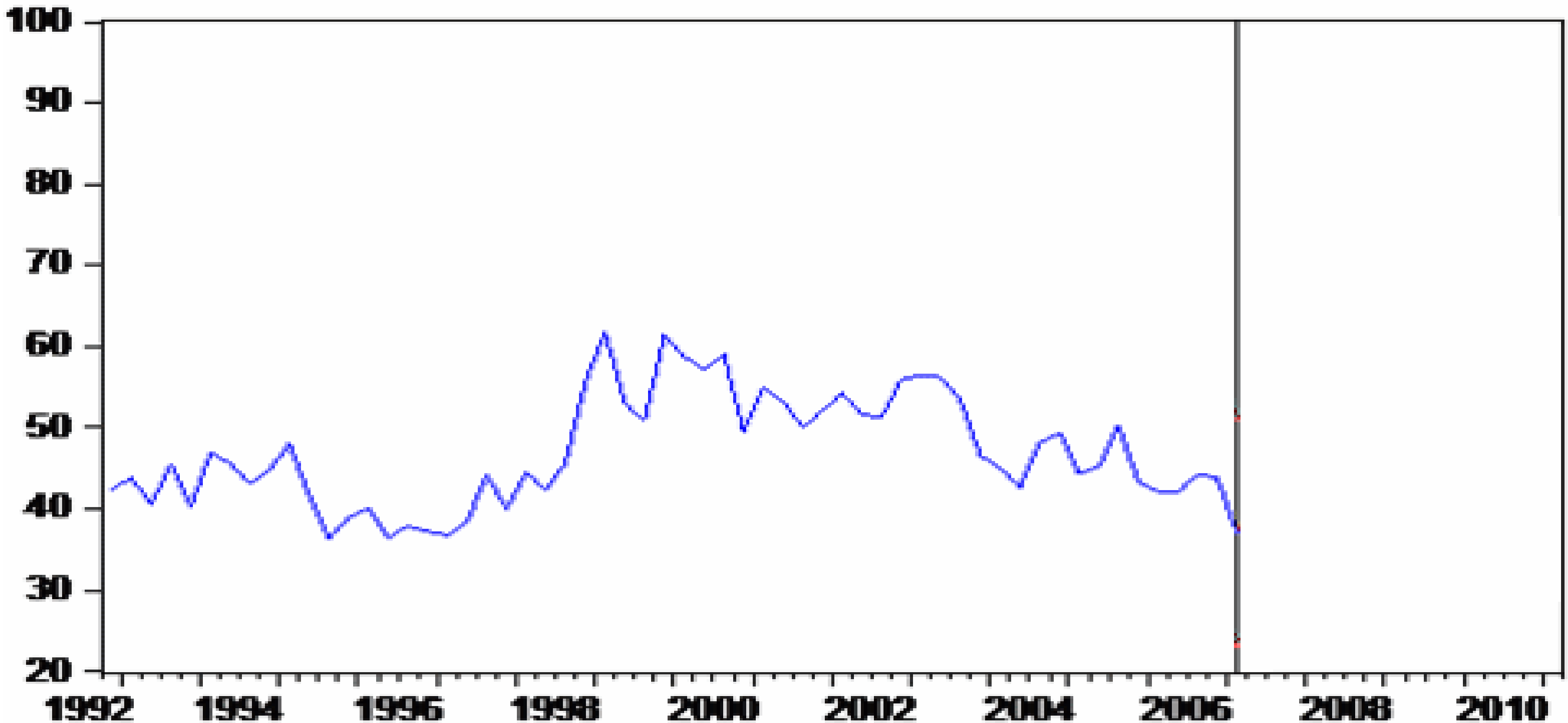
- To mitigate this risk, SAFE develops two perspectives
  - medium term advanced warning specifications, suitable for ex ante policy action
    - long-lag models: lags 6-12
  - short term model specifications for verification and adjustment of supervisory actions
    - short-lag models: lags 2-12

- Model Checks and Balances
  - LL models provide a minimum of 6 quarters warning
  - SL models provide a minimum of 2 quarters warning

Benchmark model

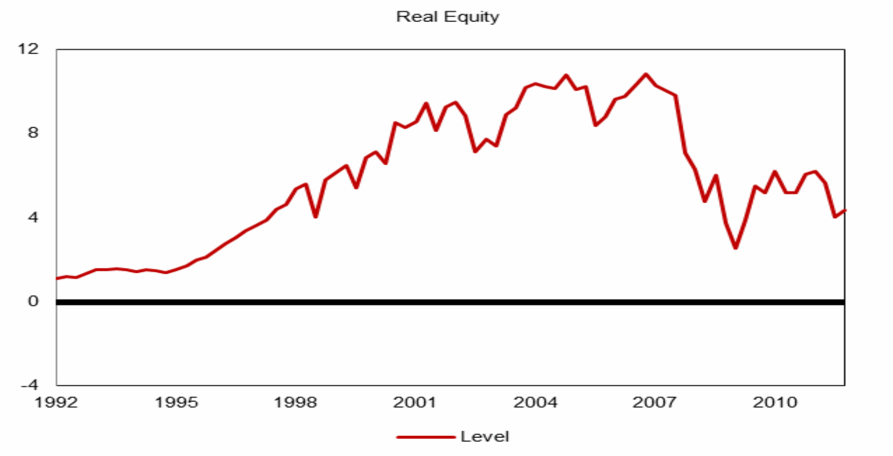
- Expect stress to be related to past stress

$$\widehat{FSI} = 7.85 + 0.60FSI_{-1} + 0.24FSI_{-4}$$

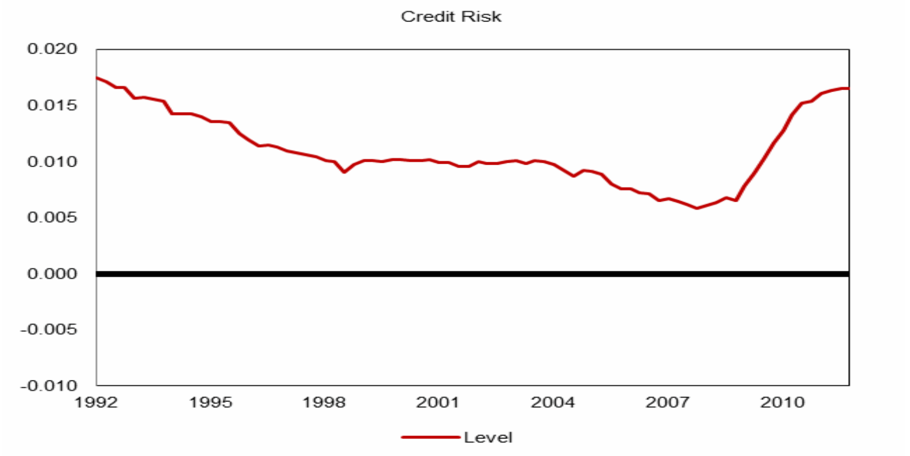


Simple candidate base model

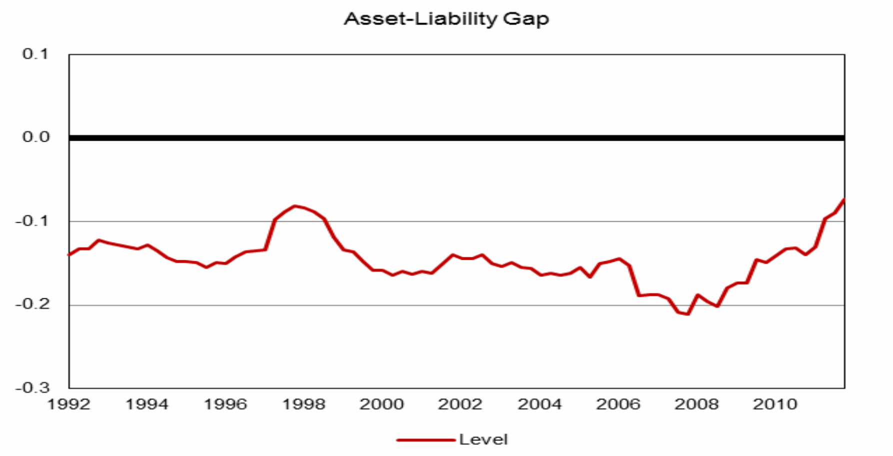
RETURN — **Equity +**



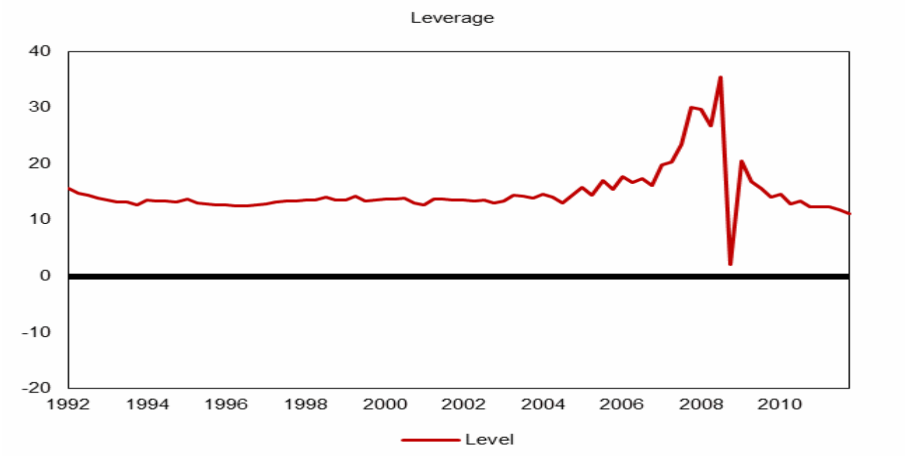
RISK — **Credit Risk Capital –**



LIQUIDITY — **AL Mismatch +**



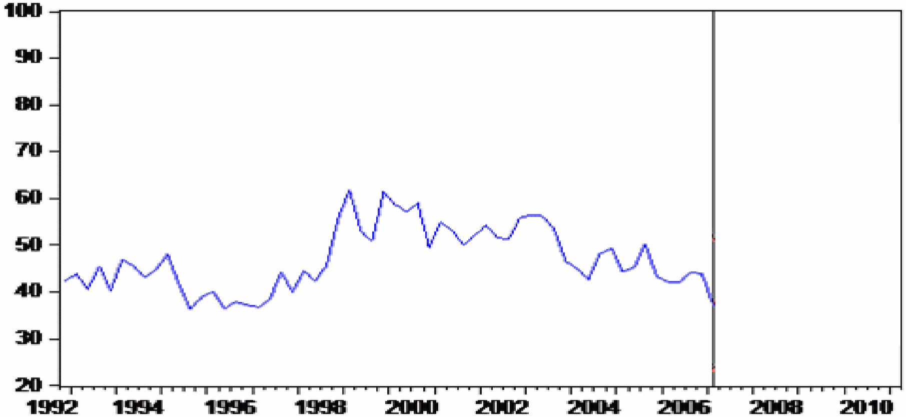
STRUCTURE — **Leverage +**



From simple to complex: short- and long-lag

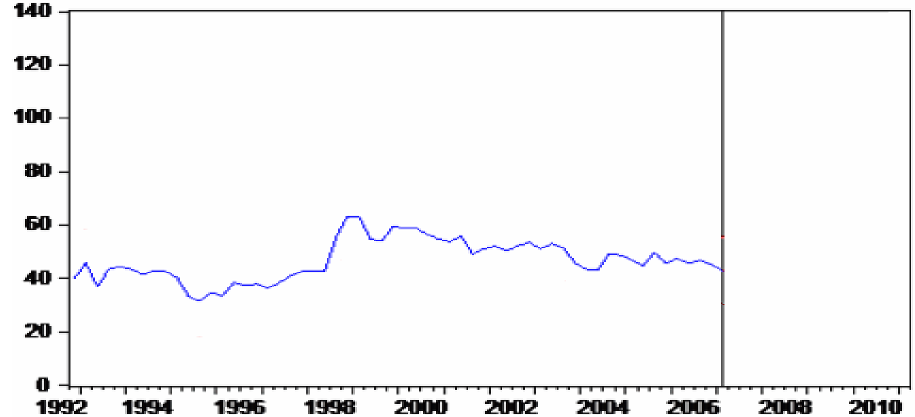
Form Benchmark Model

$$\widehat{FSI} = 7.85 + 0.60FSI_{-1} + 0.24FSI_{-4}$$



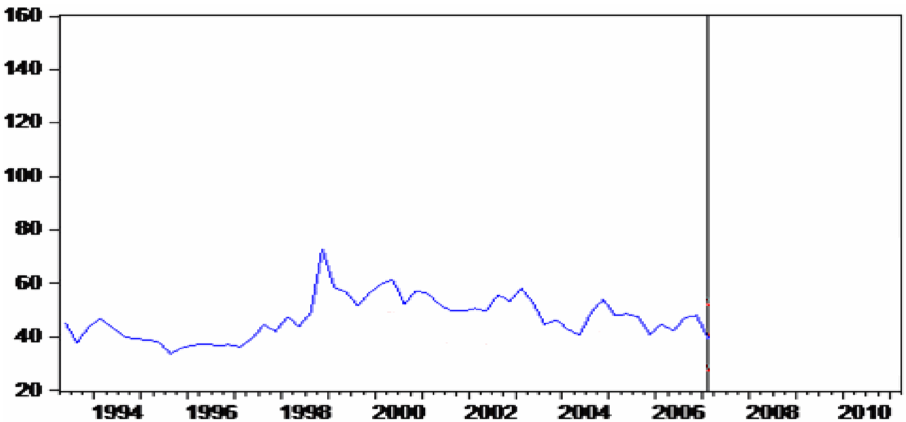
Form Candidate Base Model

$$\widehat{FSI} = 36.58 + 0.35FSI_{-1} + 1.70GT\_AL3_{-5} + 7.04GT\_LEVN_{-9} + 2.34\Delta PMKTCP_{-5} - 12.62\Delta CRCAP\_NV_{-11}$$



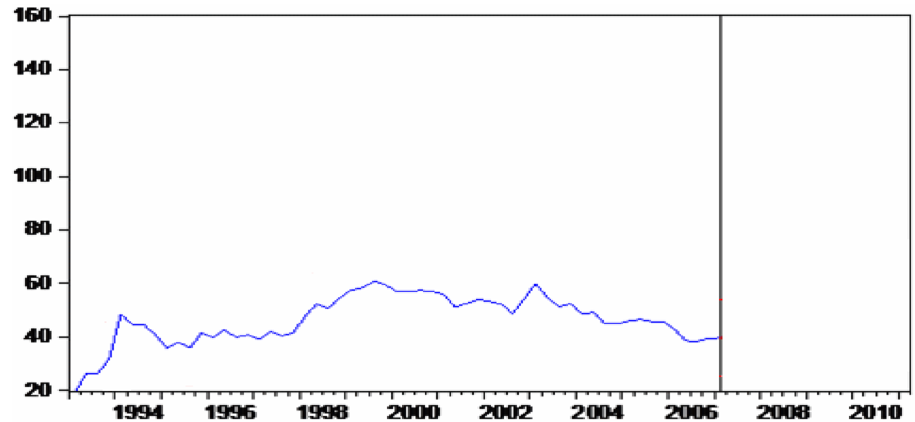
Form Short-Lag Benchmark Model

$$\widehat{FSI} = 38.77 + 0.40FSI_{-1} + 2.06\Delta HFX4_{-6} + 8.65\Delta HEQ5_{-8} + 8.15GT\_LEVN_{-5} - 2.94\Delta EQLGDW3_{-7} - 4.55CR\_EVSV_{-8}$$



Form Long-Lag Benchmark Model

$$\widehat{FSI} = 37.85 - 9.88GT\_ALG3_{-9} + 2.29EDF_{-11} - 2.24CR\_EVNV_{-6} + 4.55GT\_HIB_{-8} + 11.20GT\_LEVN_{-7}$$



Results: short-lag and long-lag

- Short-lag models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBSERVATIONS	61	61	61	61	61	61	61	61
R-SQUARED	0.733	0.824	0.817	0.803	0.784	0.783	0.774	0.780
AIC (OLS)	6.224	5.901	5.921	5.973	6.076	6.082	6.080	6.057
SC (OLS)	6.536	6.489	6.441	6.423	6.560	6.566	6.492	6.438

- **In-sample**
  4Q:1991–1Q:2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Combination
RMSE	13.86	20.74	13.07	16.13	15.83	21.47	11.49	16.67	17.14
MAPE	18.68	26.36	16.87	21.96	19.17	27.37	18.82	21.09	23.06
Theil U	0.150	0.231	0.138	0.178	0.173	0.246	0.117	0.185	0.185

- **Out-of-sample**
  2Q:2007–4Q:2012

- Long-lag models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OBSERVATIONS	62	62	62	62	62	62	62	62
R-SQUARED	0.799	0.813	0.829	0.861	0.808	0.740	0.798	0.814
AIC (OLS)	5.973	5.933	5.854	5.639	5.938	6.219	5.976	5.916
SC (OLS)	6.419	6.482	6.437	6.188	6.418	6.631	6.422	6.431

- **In-sample**
  4Q:1991–1Q:2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Combination
RMSE	27.99	30.36	23.04	24.68	28.47	27.21	29.28	30.20	28.00
MAPE	29.89	33.57	25.20	24.88	29.94	29.35	31.91	33.08	30.34
Theil U	0.231	0.256	0.178	0.197	0.235	0.223	0.244	0.254	0.230

- **Out-of-sample**
  2Q:2007–4Q:2012

Forecast combinations

- Employ regression to resolve relative importance of each model
- Clarify significance of variables out-of-sample

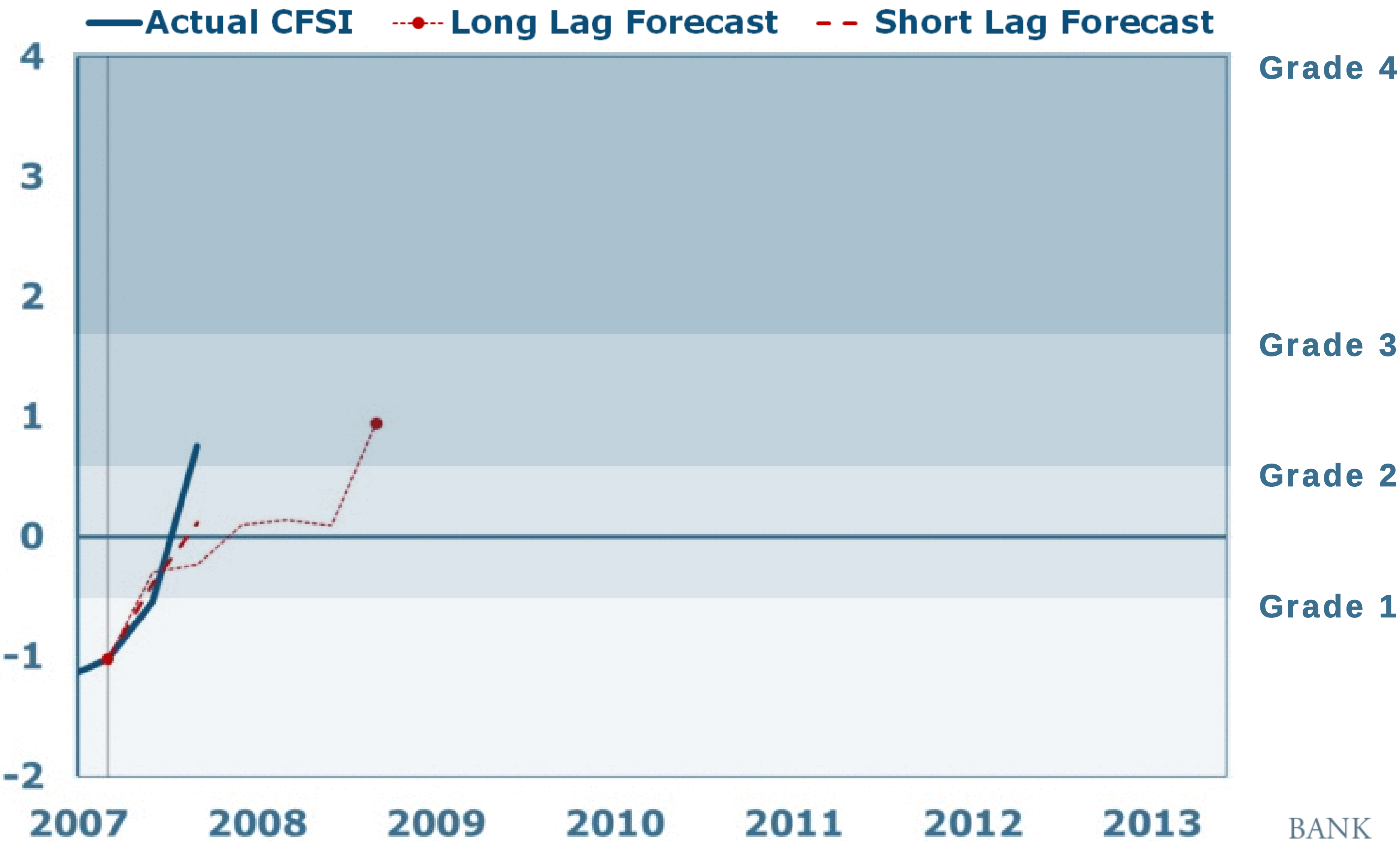
  - Short-lag forecast combination

$$CFSI_t = w_1 SL1_t + w_2 SL2_t + w_3 SL3_t + w_4 SL4_t + w_5 SL5_t + w_6 SL6_t + w_7 SL7_t + (1 - w_1 - w_2 - w_3 - w_4 - w_5 - w_6 - w_7) SL8_t + \varepsilon_t$$

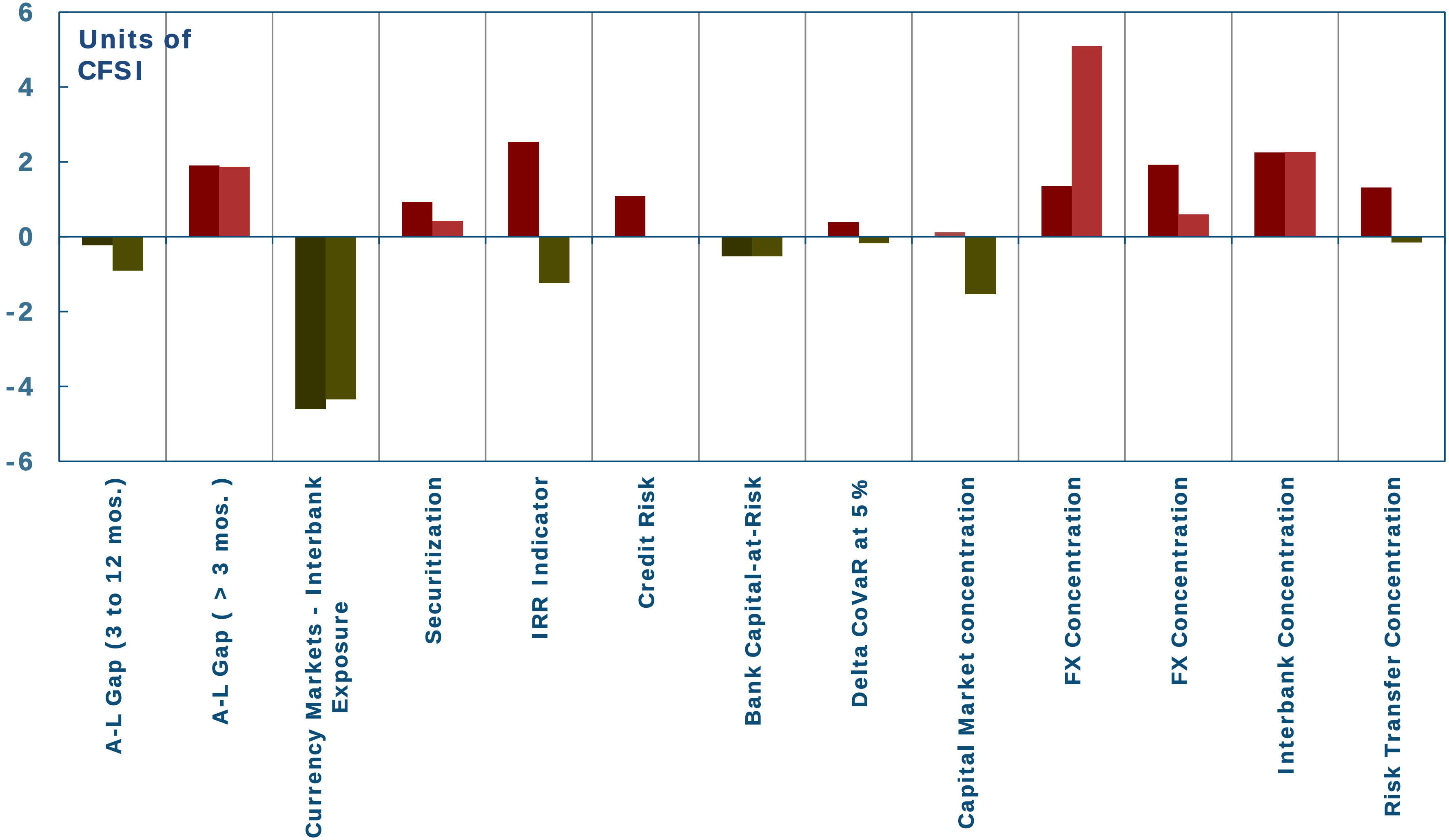
  - Long-lag forecast combination

$$CFSI_t = w_1 LL1_t + w_2 LL2_t + w_3 LL3_t + w_4 LL4_t + w_5 LL5_t + w_6 LL6_t + w_7 LL7_t + (1 - w_1 - w_2 - w_3 - w_4 - w_5 - w_6 - w_7) LL8_t + \varepsilon_t$$

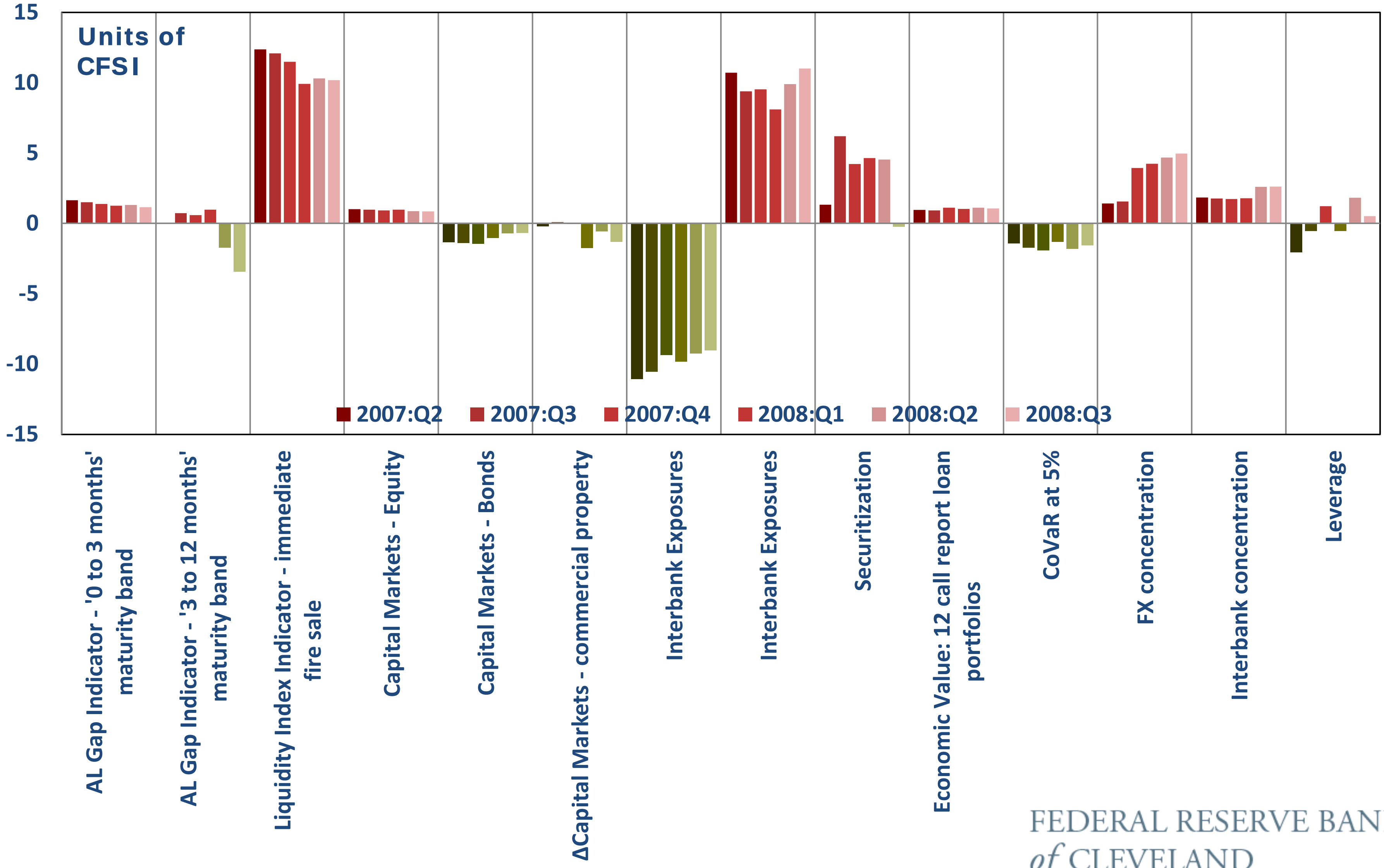
How accurate were SAFE forecasts in real time?



Short-lag stress drivers — 2Q: 2007



Long-lag stress drivers — 2Q: 2007



Explanatory data sources

- Explanatory Data -86 quarterly data panels from March 1991 to March 2013, top Tier top 100 BHCs, aggregated top 25 BHCs, specified using 62 in-sample quarters

Return Imbalances	Liquidity Imbalances	Risk Imbalances	Structure Imbalances
- FRS – FDR micro data - CRSP - S&P Case-Schiller data - MIT CRE data	- FRS – FDR micro data - Moody's	- FRS – FDR micro data - Moody's	- FRS – FDR micro data - CRSP - FRS - CoVaR model - FRS - Flow of Funds
† FRS – X-Country data	†† FRS - IRR FOCUS †† FRS - BankCaR †† FRS – SABR/SEER †† FRBC –SCAP-haircut †† FRBC – LFM	†† FRS - IRR FOCUS †† FRS - BankCaR †† FRS –CAMELS †† FRS-SABR/SEER †† FRBC –SCAP-haircut †† FRBC – LFM	† FRS – X-Country data

Clear row indicates public data.
Shaded row indicates supervisory data.
† - Confidential supervisory data (category 1).
†† - Constructed supervisory data (category 2).

Confidential supervisory and public data

- There are three broad categories of explanatory data.
  - Institution-specific data internal to the Federal Reserve System
  - Undisclosed Federal Reserve models and their output
    - These models may use either publicly available data or FRS data
  - Data from the public domain
    - These include raw data from the public domain as well as output from publicly available models that utilizes data from the public domain.
- Our approach defines confidential supervisory data as FRS internal data and the undisclosed output of FRS models.

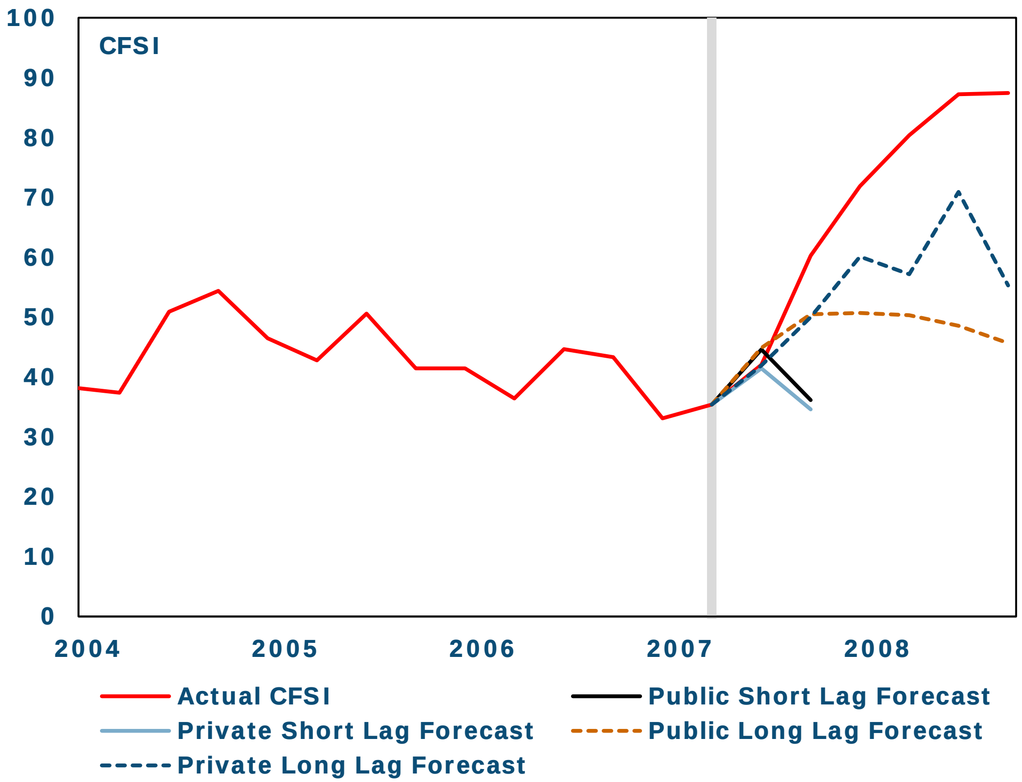
Measures	FRS Series	Proportion FRS
Total	33	50.0%
RET Measures	1	10.0%
RSK Measures	28	82.4%
LIQ Measures	3	42.9%
STR Measures	1	7.1%

Does confidential supervisory data add value?

- To test, we remove all FRS variables from the model suggestion stage and re-specify the optimal model.
  - Many of the public series from our original model are preserved
  - Risk series are most depleted by loss of confidential data

- Summary of Findings
  - FRS models fit the in-sample period more tightly
  - FRS models provides a more accurate forecast by all observed metrics

- Conclusions
  - Both model sets catch the increase in stress during 2Q 2007. Confidential models do better in explaining the ongoing crisis. Public models miss the subprime episode all together.
  - This demonstrates the importance and usefulness of confidential data in the creation of an Early Warning System.



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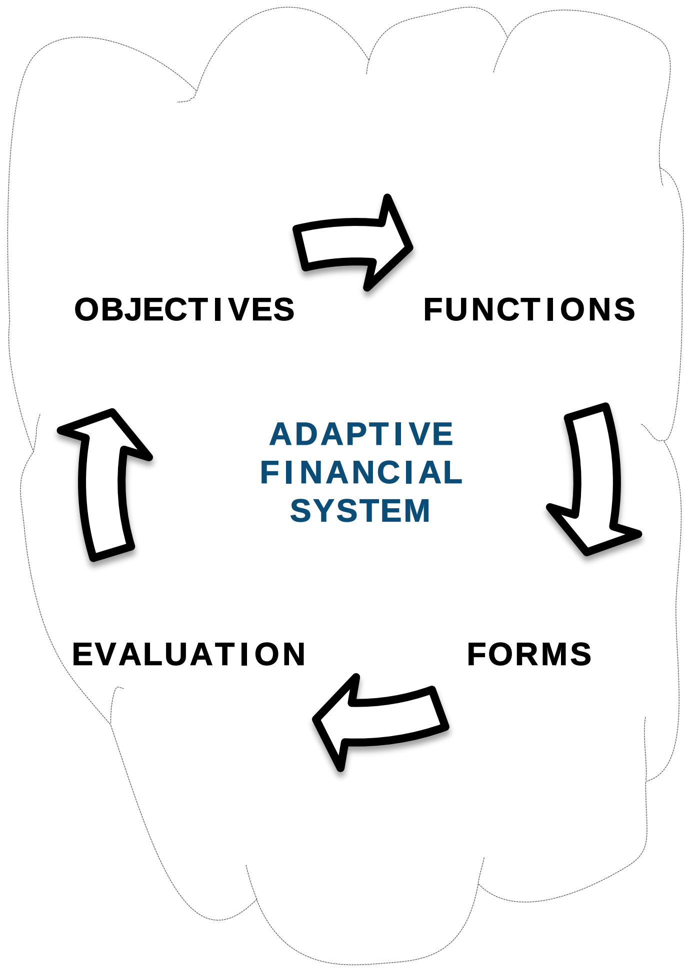
Using the tools: the challenges

OBJECTIVES
- T| Time dimension of policy objectives
- X| Cross-sectional dimension of policy objectives

FUNCTIONS
- Identification of systemic conditions
- Forward-looking
- Forecasting
- Identification of systemic imbalances
- Distinguish excessive exposures
- Sensitivity to systemic risk posed



EVALUATION
- Expected loss calculations
- Model uncertainty aversion
- Local robustness analysis
- Robustness with multiple models

FORMS
- **Early warning systems**
- Asset price models
- Stress testing
- Microprudential feeds

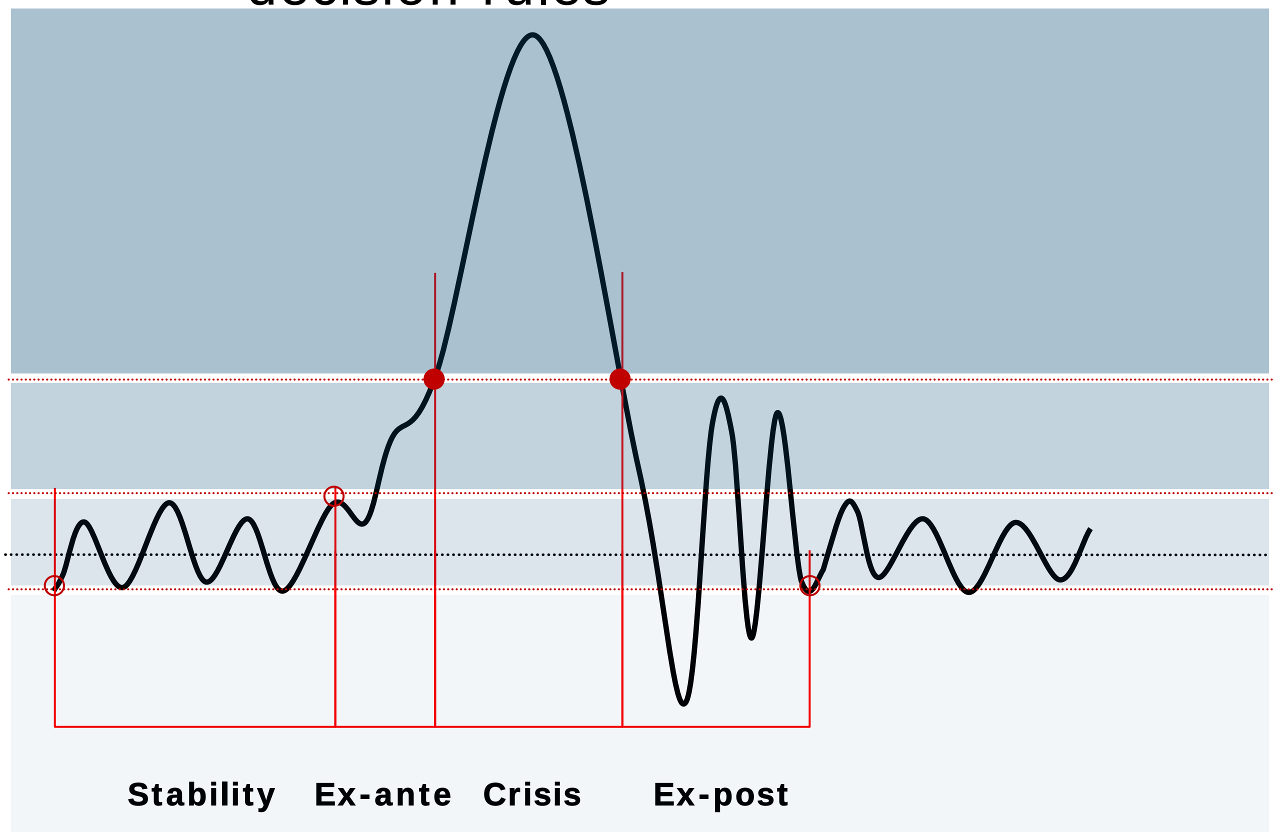
Uses in supervisory process

- Uses across time
  - Forecast thresholds
  - Stress alerts
  - Migration matrices
- Uses across institutions
  - Stress contributions
  - Targets and limits
  - Tiered parity
  - Macroprudential / microprudential issues

Time dimension

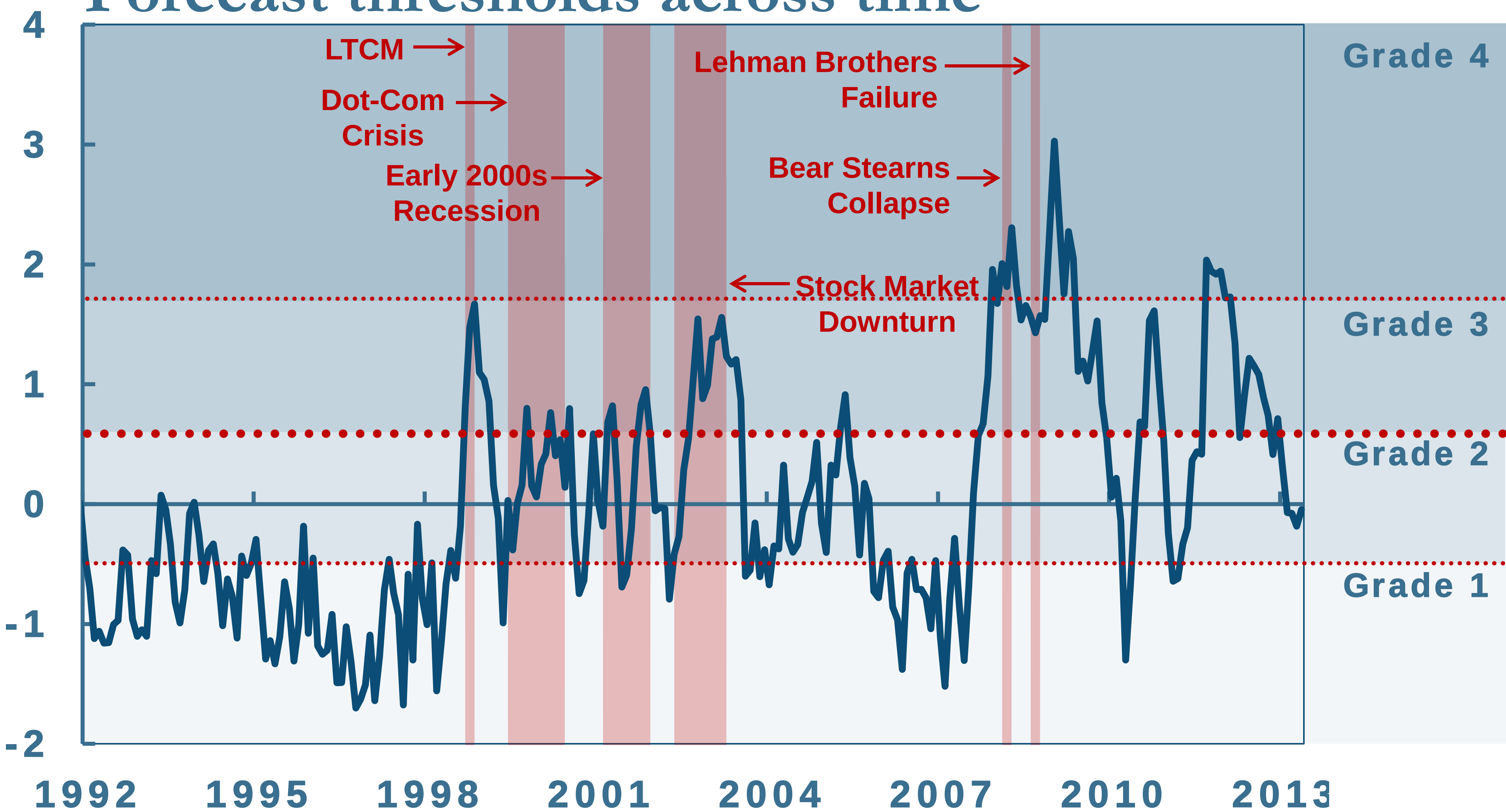
Policymakers' decision is assisted by establishing

- stress thresholds and
- decision rules



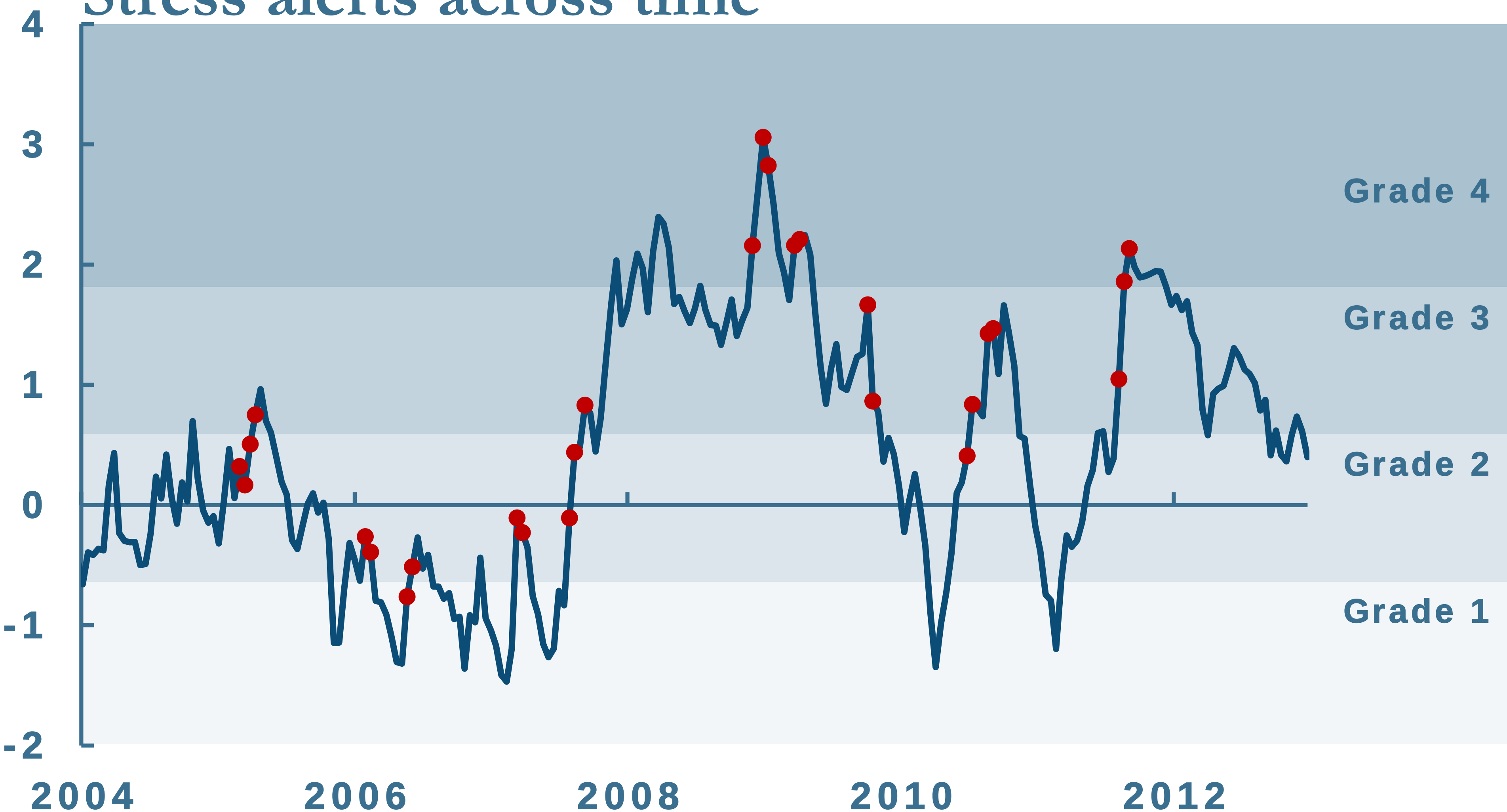
- When forecast of stress exceeds the target level of stress, the policymakers can weigh the economic costs of regulatory action against economic costs of a shock
- When forecasts of stress fall short of target action level, EWS supports markets' ability to self-resolve the particular level of stress

Forecast thresholds across time



Source: Federal Reserve Bank of Cleveland.

Stress alerts across time



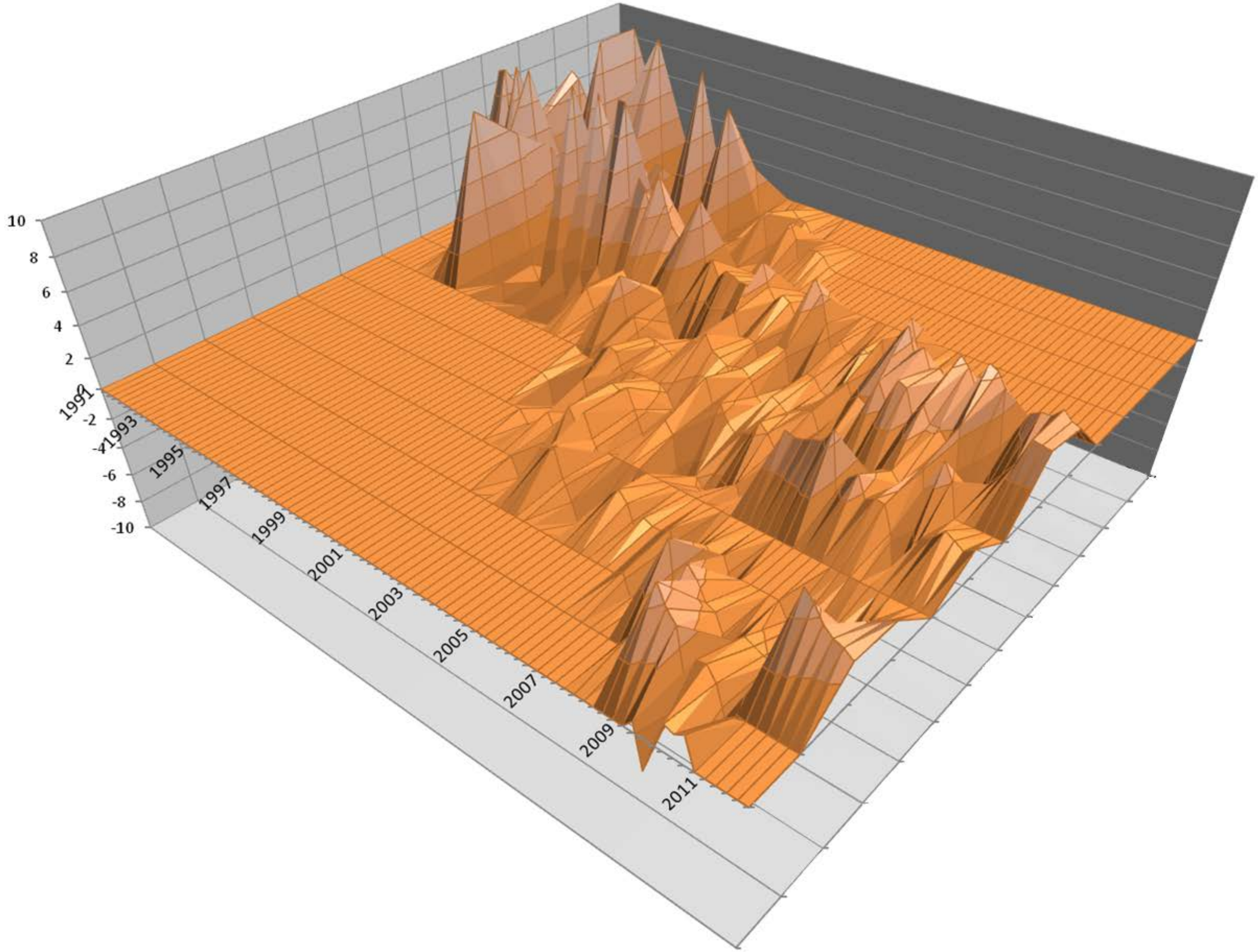
Source: Oet, Bianco, Gramlich, and Ong (2012).

Migration matrices across time

- Leverage change (std) needed for stress migration

	Grade 1	Grade 2	Grade 3	Grade 4
Grade 1	0	2.3	5.1	7.4
Grade 2	(2.3)	0	2.3	4.6
Grade 3	(5.1)	(2.3)	0	2.3
Grade 4	(7.4)	(4.6)	(2.3)	0

Stress contributions across top 5 institutions



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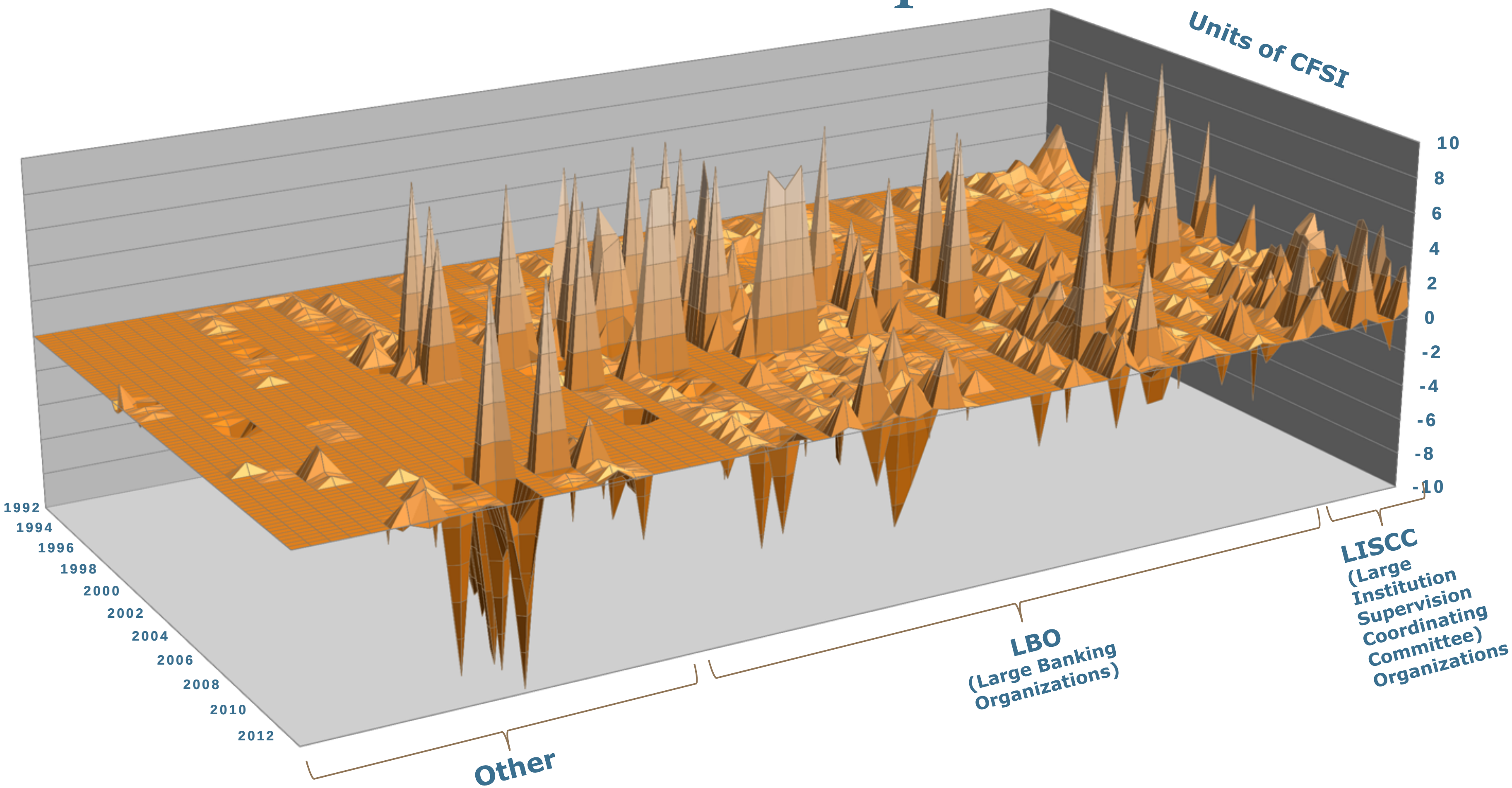
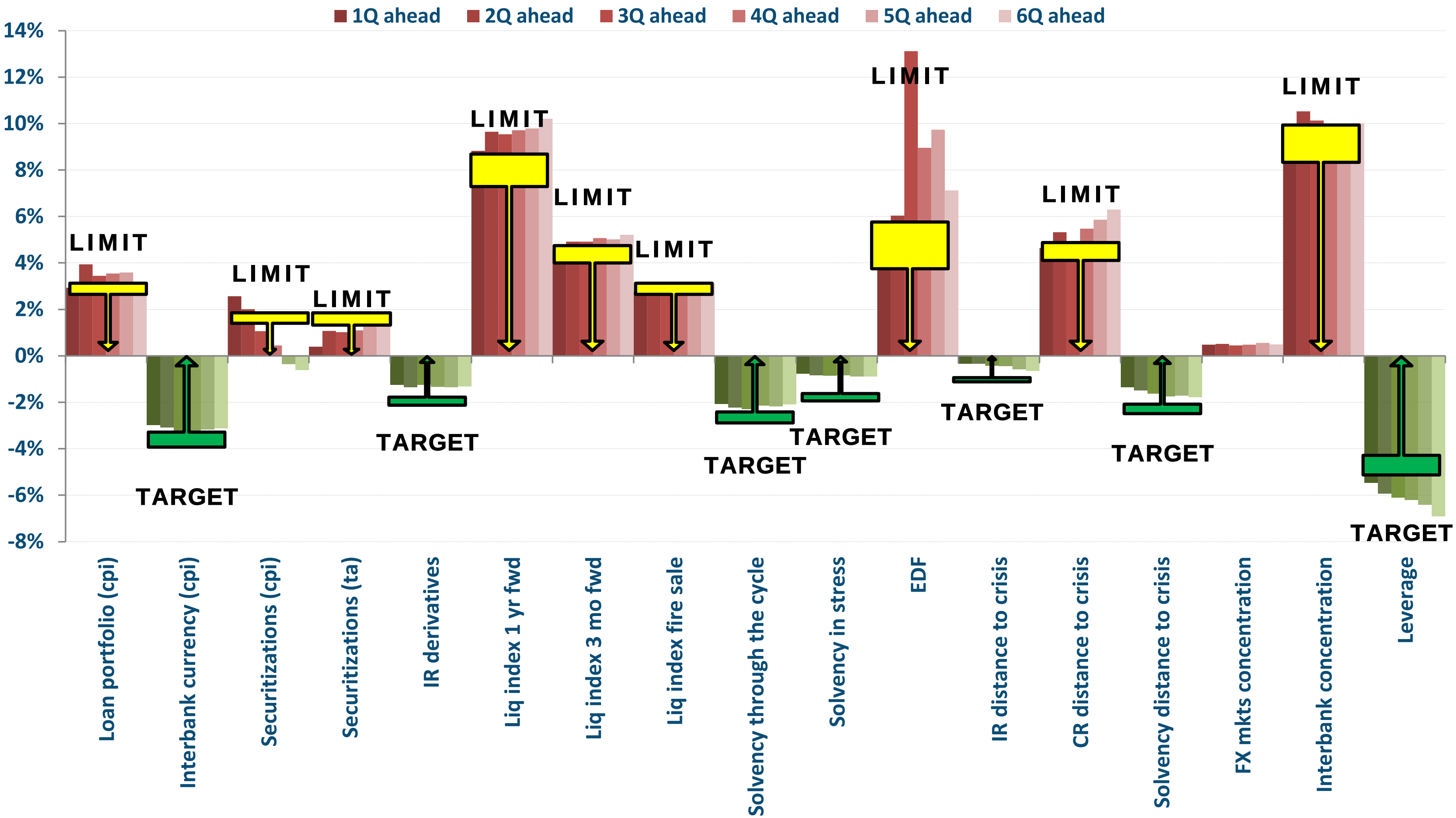
Stress contributions across top 25 institutions



Potential targets and limits across institutions



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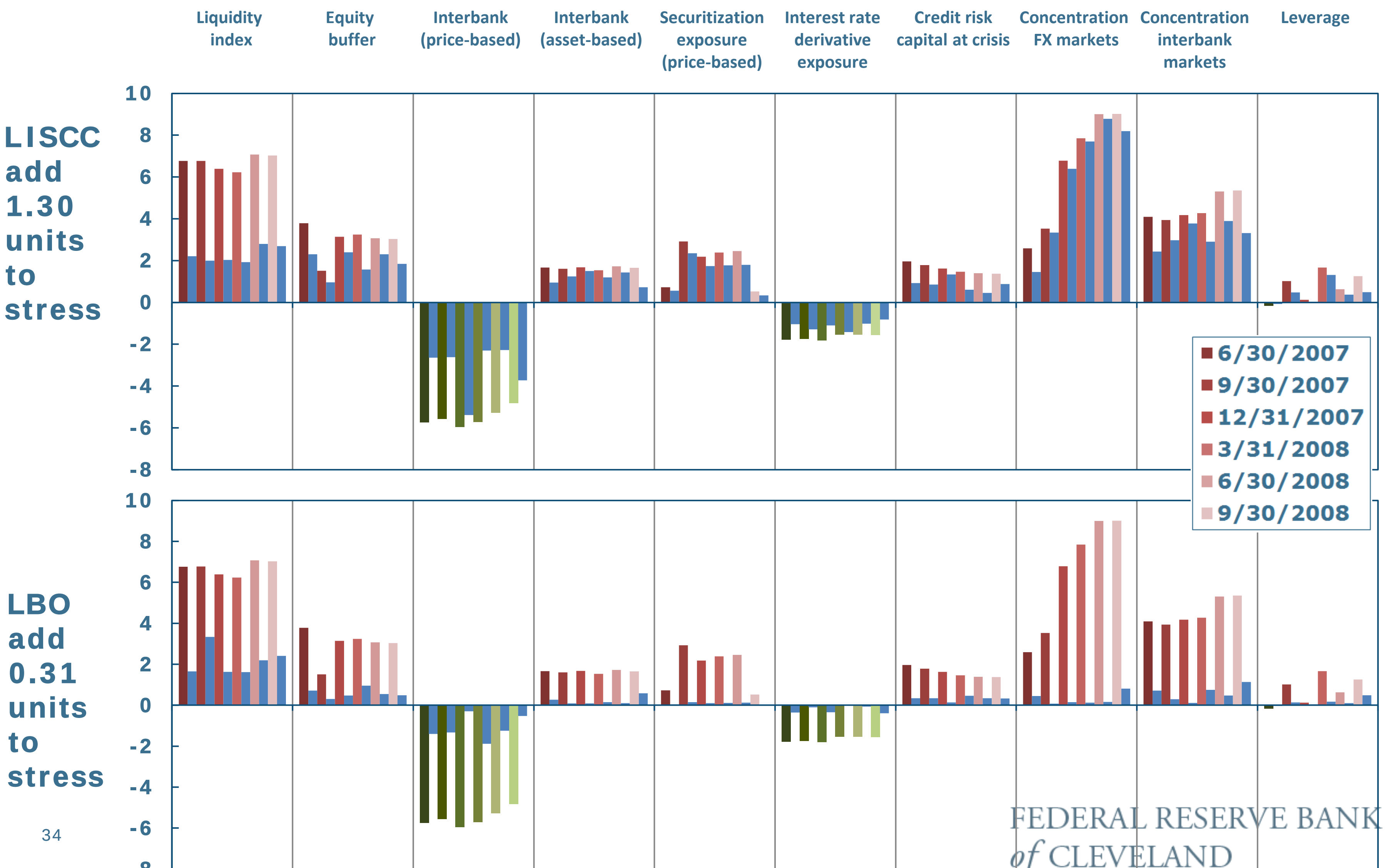
Tiered parity supervision across institutions



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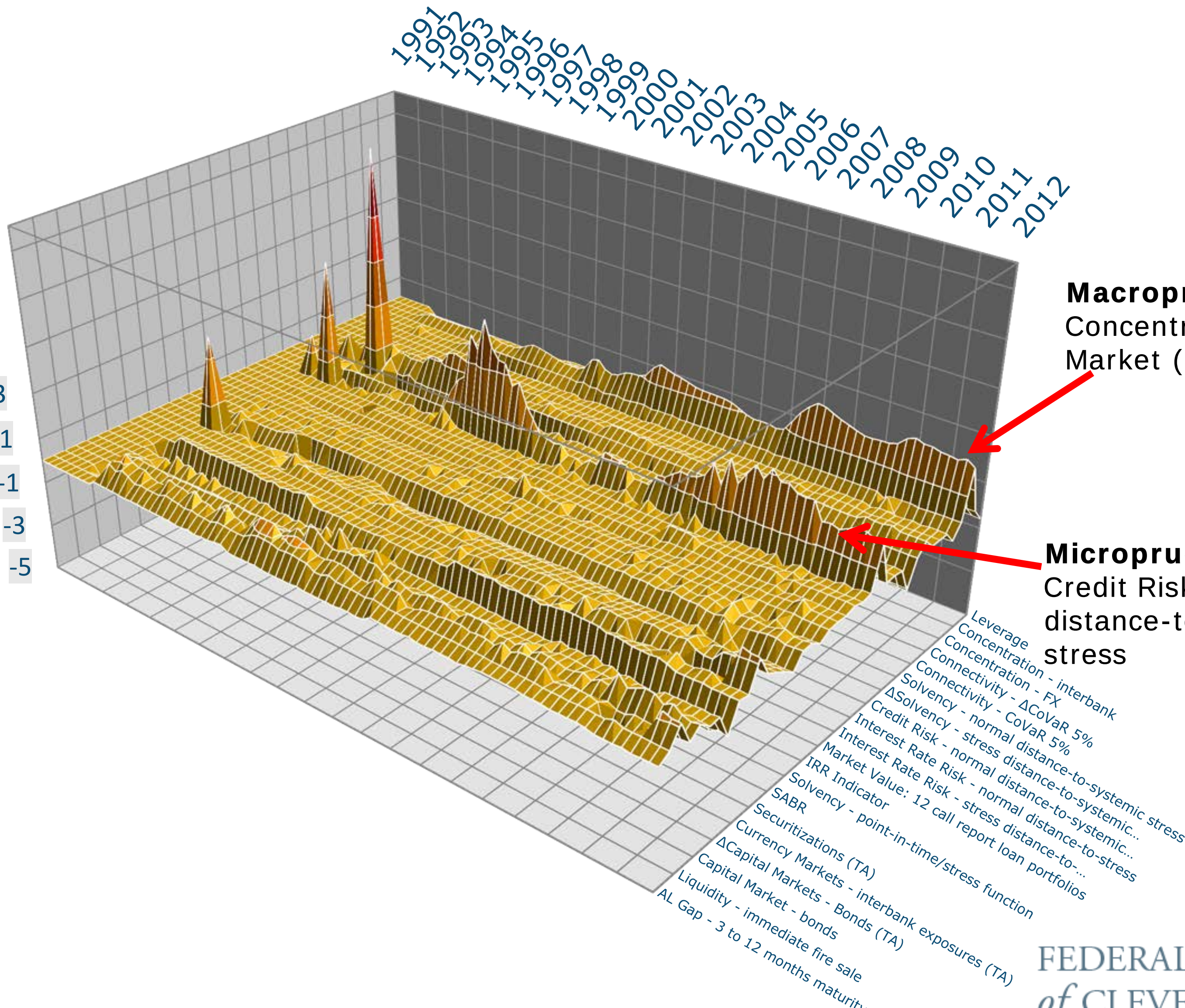
Macroprudential and microprudential issues across institutions



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Conclusion: SAFE Early Warning System

- Three main contributions
  - significant association between institutional imbalances, system structure, and financial market stress
  - evidence of value of confidential supervisory data from comparisons of public and confidential SAFE models
  - supervisory uses in two dimensions
    - across time: improved identification of emerging systemic stress
    - across institutions: improved identification of adverse common exposures

- SAFE substantiates macroprudential policy choices to supplement the fundamental institution-specific microprudential practices

Discussion

- Q&A

- Thank you for your attention

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