# Diagnosing the Financial System
# Financial Conditions and Financial Stress

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[1]The views herein are our own and do not necessarily represent those of the Federal Reserve Bank of Chicago or the Federal Reserve System.

1. Constructing an Index of Financial Conditions
   - Motivation
   - Methodology
   - Indicators
2. Monitoring financial stability
   - Motivation
   - Methodology
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## Ideal Properties of a Financial Conditions Index

A Summary Statistic for Financial Conditions

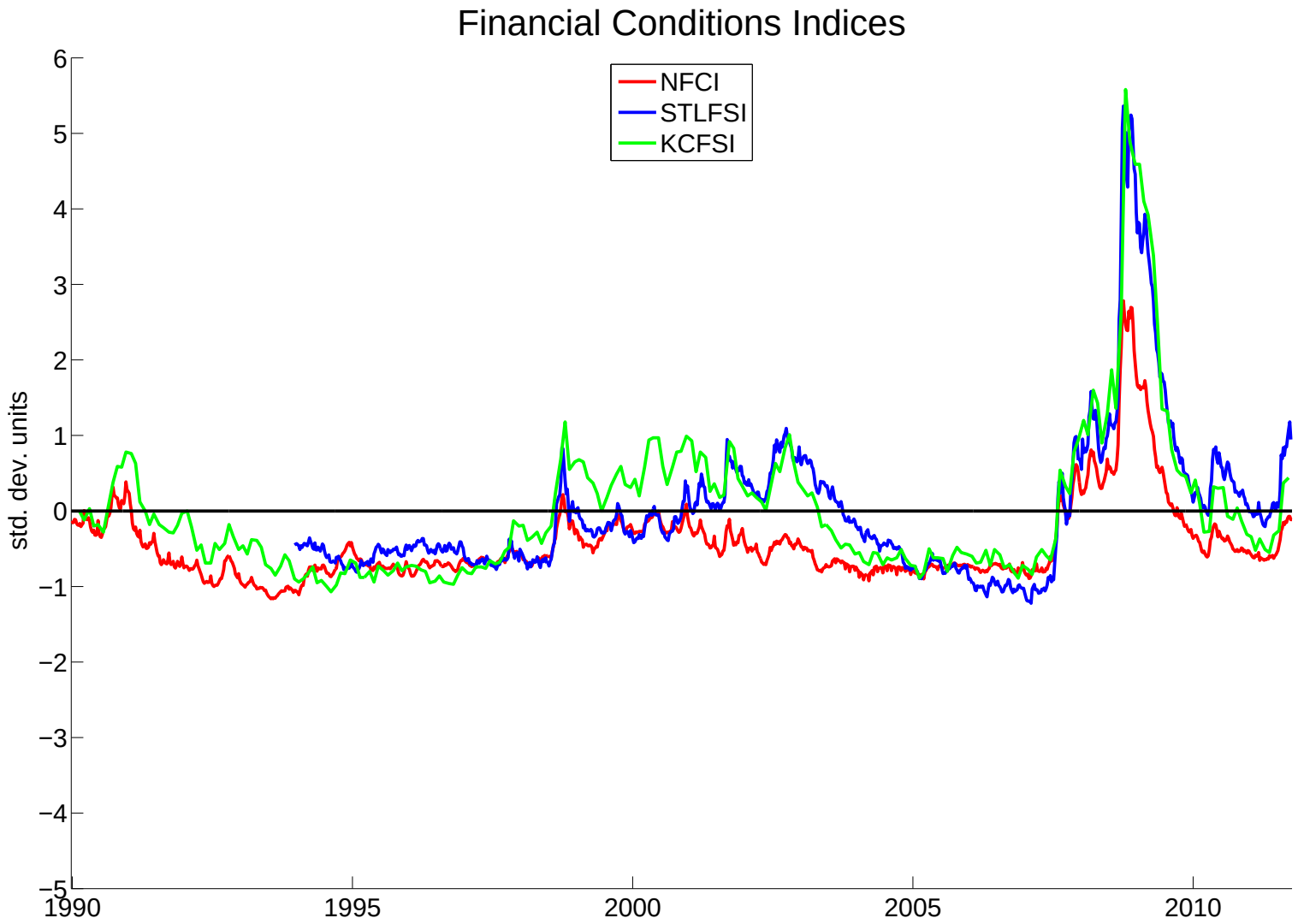
- Broad coverage of the financial system (Large $\widehat{N}$)
- A rich time-series history (Large $\widehat{T}$)
- Systemic importance weights (Cross-sectional $\rho$)
- Captures short and medium-run dynamics (Dynamic $\rho$)
- Frequent observation (High frequency index)
- Able to handle many data types (Mixed frequency data)

Recent proliferation of such indexes for the U.S., but few meet the above criteria in multiple dimensions

| Index | # of Indicators | Frequency of Indicators | Frequency of Index | First Period | Estimation method |
|---|---|---|---|---|---|
| NFCI | 100 | Mixed | Weekly | 1973W1 | Dynamic Factor |
| Matheson (IMF) | 30 | Monthly | Monthly | 1994M1 | Dynamic Factor |
| Hatzius et. al. | 40 | Quarterly | Quarterly | 1970Q1 | PCA |
| KCFSI | 11 | Monthly | Monthly | 1990M2 | PCA |
| STLFSI | 18 | Weekly | Weekly | 1993W52 | PCA |

Meeting one dimension often leads to problems in others, i.e. broad coverage and real-time inference due to revisions

NFCI meets all of them with small historical revision errors (typically 0.1 standard deviations or less)


Financial Conditions Indices
NFCI
STLFSI
KCFSI
std. dev. units
6
5
4
3
2
1
0
−1
−2
−3
−4
−5
1990
1995
2000
2005
2010

## National Financial Conditions Index (NFCI)

1. A weighted average of unbalanced panel of mixed frequency data
   - 25 Quarterly, 34 Monthly, and 41 Weekly variables
2. Captures a single common dynamic factor among the 100 indicators
   - Spreads (+), Volatility (+), Volumes (-), Leverage (-)
   - Increasing Risk and Uncertainty, Decreasing Liquidity and Leverage
3. Interpretation:
   - Positive value = "Tight" conditions
   - Negative value = "Loose" conditions
   - Degree measured in standard deviations from historical mean

## Estimating the NFCI

Our methodology is a synthesis of three different statistical methods:

1. PCA (Stock & Watson, 2002) "cross sectional averaging"
2. Dynamic Factor (Doz, Giannone & Reichlin (2006)) "time averaging"
3. Harvey accumulator (adapted by Aruoba, Diebold & Scotti (2009)) to deal with temporal aggregation/missing observations

EM algorithm of Shumway & Stoffer (1982) and Watson & Engle (1983) is used to tie all three together

## The EM algorithm

The panel of time series of financial variables, $Y_{it}$, is explained linearly by a latent factor, $F_t$, with dynamics of finite order ($p^\star = 15$):

$$y_t = Z\alpha_t + \epsilon_t \quad (1)$$

$$\alpha_{t+1} = T\alpha_t + \eta_t \quad (2)$$

where $\alpha_{t-i} = [F_{t-i}]$ for $i = 0, 1, \ldots, p^\star$, and $y_t = [Y_{it}]$ for $i = 1, \ldots, \hat{N}$ and $\epsilon_t \sim N(0, H)$ and $\eta_t \sim N(0, Q)$.[2]

OLS on PCA estimate of $F_t$ used to initialize system
Red estimates maximize log-likelihood with respect to blue (E)
Blue estimates maximize log-likelihood conditional on observed data (M)

[2] We assume $H$ is a diagonal matrix and use the normalization restriction of Doz, Giannone & Reichlin (2006) on $Q$.

Two extensions to the Kalman filter and smoother are needed:

1. Concentrate out missing values in (1) (Durbin & Koopman, 2001)
2. Add Harvey accumulators to (2) (Harvey, 1989)

*Example: Variables that represent sums over weekly base frequency*

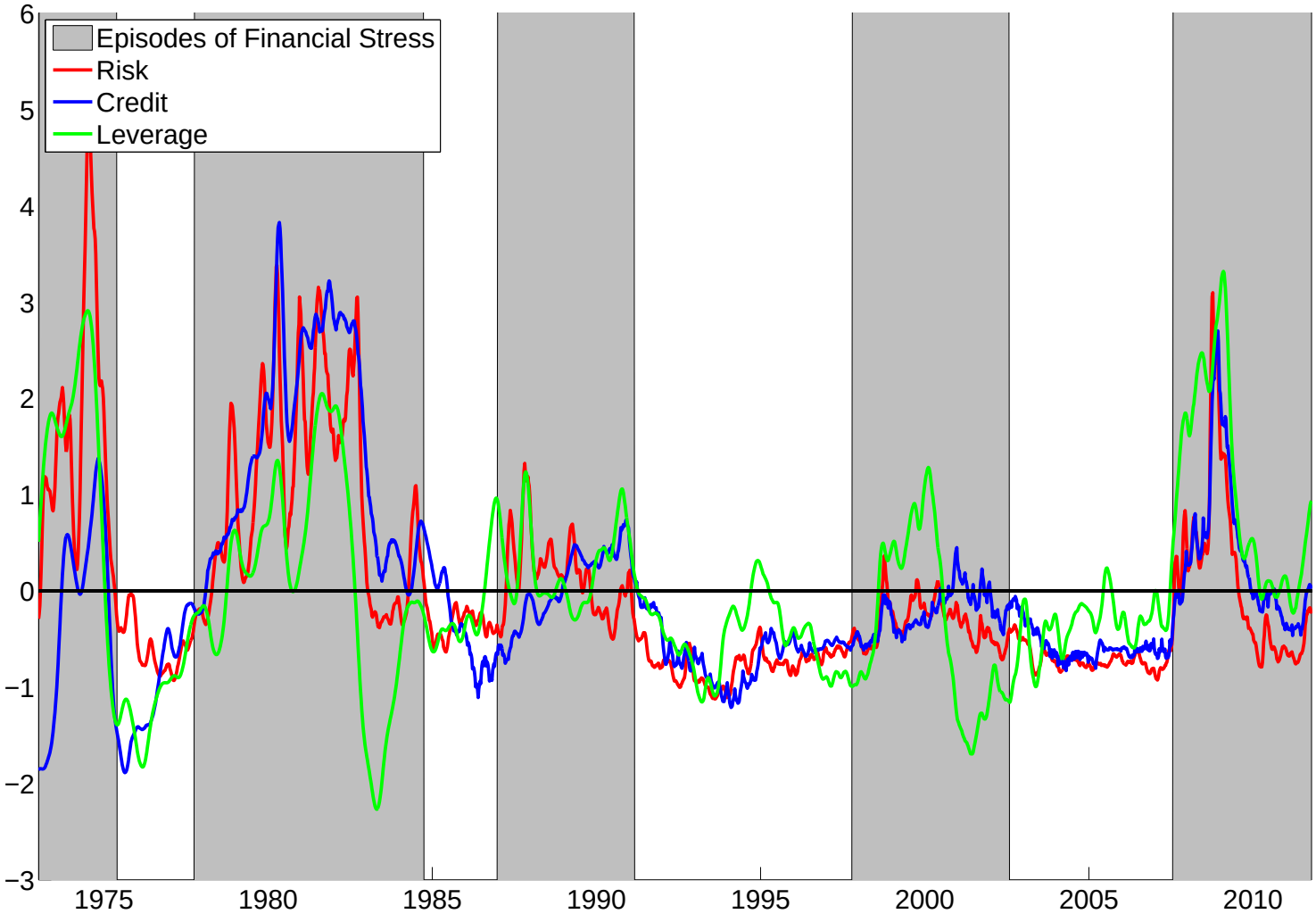
An "accumulator" that represents the cumulative sum of the past realizations of the latent factor $\alpha_{t-i}$ for all $i$ weeks in the lower frequency. These variables load on to the accumulator instead.

$$
\begin{aligned}
S_t &= s_t S_{t-1} + \alpha_t \\
s_t &= \begin{cases} 0 & \text{if } t \text{ is the first week of the month or quarter} \\ 1 & \text{otherwise} \end{cases}
\end{aligned}
$$

## Limitations of the NFCI

1. Weights are constant over time
   - Shift in weight toward money market variables post-84
     - 30% full sample vs. 50% post-84
     - Almost all taken from banking variables
   - Lower index baseline mean and variance post-84
     - Mostly due to lower volatility of economic conditions
2. Coverage of the financial system changes over time
   - 1973: 25% coverage 1987: 50% coverage
   - Growth in importance of the shadow banking system evident
3. A 1-Factor Model
   - Multi-factor model may be better fit – but difficult to implement
   - Consider subindexes instead: Risk, Credit, and Leverage

| Market | Indicator w/ the Greatest Weight in the NFCI |
|---|---|
| Repurchase Agreements | Total Repo Market Volume |
| Treasuries | 2-year Interest Rate Swap/Treasury yield spread |
| Commercial Paper | 1-month Nonfinancial commercial paper A2P2/AA credit spread |
| Interbank Lending | 3-month TED spread (LIBOR-Treasury) |
| Corporate Bonds | Merrill Lynch High Yield/Moody's Baa corporate bond yield spread |
| Securitized Debt | Citigroup Global Markets ABS/5-year Treasury yield spread |
| Stock Markets | CBOE S&P 500 Volatility Index (VIX) |
| Municipal Bonds | Bond Market Association Municipal Swap/20-year Treasury yield spread |
| Collateral Prices | MIT Center for Real Estate Transactions-Based Commercial Property Price Index |
| Consumer Credit Conditions | Senior Loan Officer Opinion Survey: Tightening Standards on RRE Loans |
| Banking System Conditions | Credit Derivatives Research Counterparty Risk Index |
| Shadow Bank Assets and Liabilities | Total Agency and GSE Assets/Nominal GDP |
| Business Credit Conditions | Senior Loan Officer Opinion Survey: Tightening Standards on Small C&I Loans |
| Commercial Bank Assets and Liabilities | Commercial Bank C&I Loans/Total Assets |


Episodes of Financial Stress
Risk
Credit
Leverage
6
5
4
3
2
1
0
−1
−2
−3
1975
1980
1985
1990
1995
2000
2005
2010

## An Application: Monitoring Financial Stability

What constitutes a cautionary level of the NFCI and its subindexes?

We can use the past as a guide similar to the way NBER recessions have been used for business cycle indicators, i.e. Berge and Jorda (2011).

But we don't have formal dates like for recessions, and we need a way to weight costs and benefits of this approach: ROC analysis.

## A Decision Theory Problem

Consider the following problem faced in medical statistics from which ROC analysis hails:

*Given a known incidence of a disease in a population, how likely is it that a positive test result is reflective of a true occurrence in sample?*

Consider the similar problem with respect to monitoring financial stability:

*Given known incidences of financial crises in U.S. history, how likely is it that a reading of the NFCI truly reflects crisis-like conditions?*

Our prior on the incidence of financial crisis is informed by historical studies, e.g. Laeven and Valencia (2008, 2010), Reinhart and Rogoff (2009), etc. We consider three sets of historical crisis dates:

| U.S. Financial Crises | Brave & Butters | Lopez-Salido & Nelson | Laeven & Valencia |
|---|---|---|---|
| International Banking Crisis (1973-1975) | 1973w2 - 1975w21 | 1973 - 1975 | - - |
| Dollar, Banking, and LDC Crises (1977-1984) | 1977w40 - 1984w39 | 1982 - 1984 | - - |
| S&L, Black Monday, and LBO/Junk Bond Collapse (1987-1991) | 1986w53 - 1991w9 | 1988 - 1991 | 1988 |
| Asian Crisis, Russian Default and LTCM, Y2K, Nasdaq Bubble, 9/11 and Enron (1997-2002) | 1997w43 - 2002w31 | - - | - - |
| Subprime Mortgage Crisis and Aftermath (2007-Current) | 2007w31 - Present | 2007 - Present | 2007 - Present |

## Receiver Operator Characteristics (ROC) Analysis

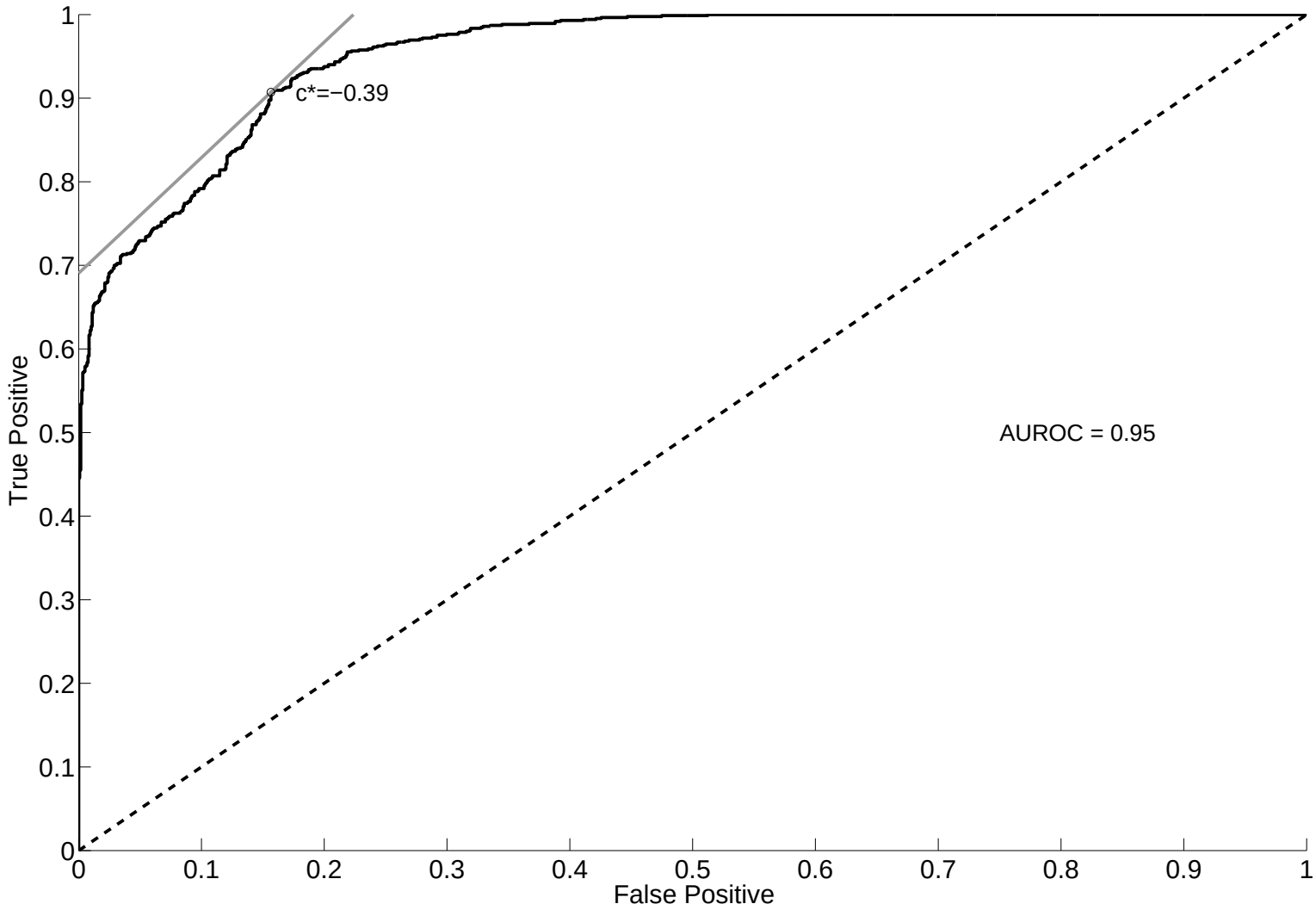
The ROC curve is defined over the range of possible threshold rules $c$:

$$TP(c) = P[F_t \geq c | C_t = 1] \quad (3)$$
$$FP(c) = P[F_t \geq c | C_t = 0] \quad (4)$$

where $F_t$ is the NFCI, and $C_t$ is a binary variable with 1 representing a crisis episode. The Cartesian convention is given as:

$$\{ROC(r), r\}_{r=0}^{1} \quad (5)$$

where $ROC(r) = TP(c)$ and $r = FP(c)$.
We can non-parametrically fit this curve using our crisis dates.


c*=−0.39
AUROC = 0.95
True Positive
False Positive
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

## AUROC at Contemporaneous Forecast Horizon

| | Brave and Butters | Lopez-Salido and Nelson | Laeven and Valencia |
|---|---|---|---|
| **NFCI** | **0.95** | **0.76** | **0.62** |
| Risk | **0.93** | **0.73** | **0.58** |
| Credit | **0.90** | **0.72** | **0.63** |
| Leverage | **0.78** | **0.69** | **0.77** |
| STLFSI | **0.86** | - | - |
| KCFSI | **0.93** | - | - |
| IMF | **0.89** | - | - |

Numbers in bold are statistically significant at standard confidence levels.

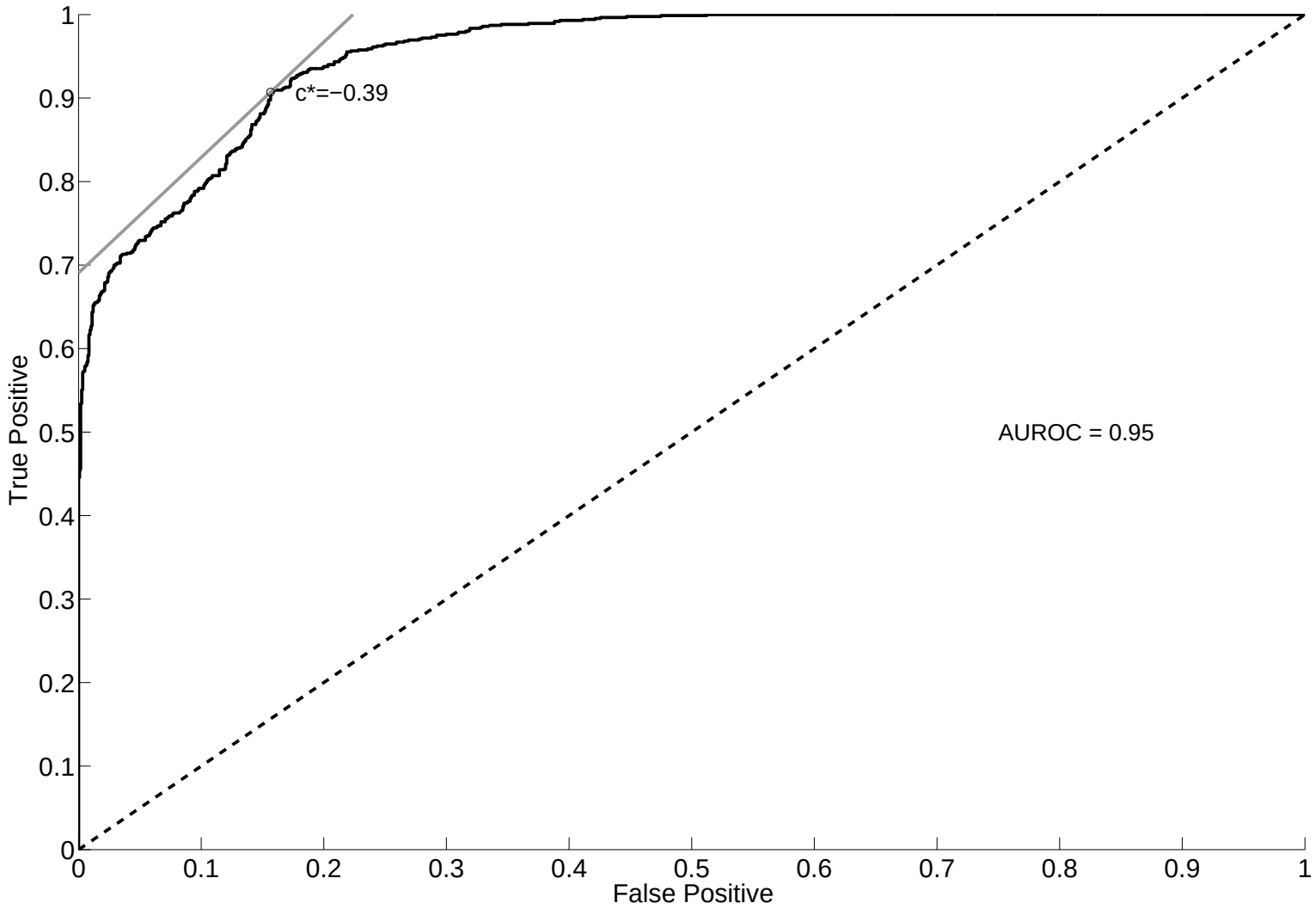
Thresholds, $c^*$, derived from utility function over Type I and II errors:

$$\begin{aligned} U &= U_{11}ROC(r)\pi + U_{01}(1 - ROC(r))\pi + \\ &\quad U_{10}r(1-\pi) + U_{00}(1-r)(1-\pi) \end{aligned} \tag{6}$$

where $U_{ij}$ is the utility associated with the prediction $i$ given that the true state is $j$,and $i, j \in \{0, 1\}$, and $\pi$ is the unconditional probability of observing a crisis episode in the sample. Utility maximization implies:

$$\frac{\mathcal{L}(C_t = 0|F_t)}{\mathcal{L}(C_t = 1|F_t)} \equiv \frac{\partial ROC}{\partial r} = \frac{U_{00} - U_{10}}{U_{11} - U_{01}} \frac{(1-\pi)}{\pi} \tag{7}$$

the point where the likelihood ratio equals the expected marginal rate of substitution between utility of accurate crisis and non-crisis prediction.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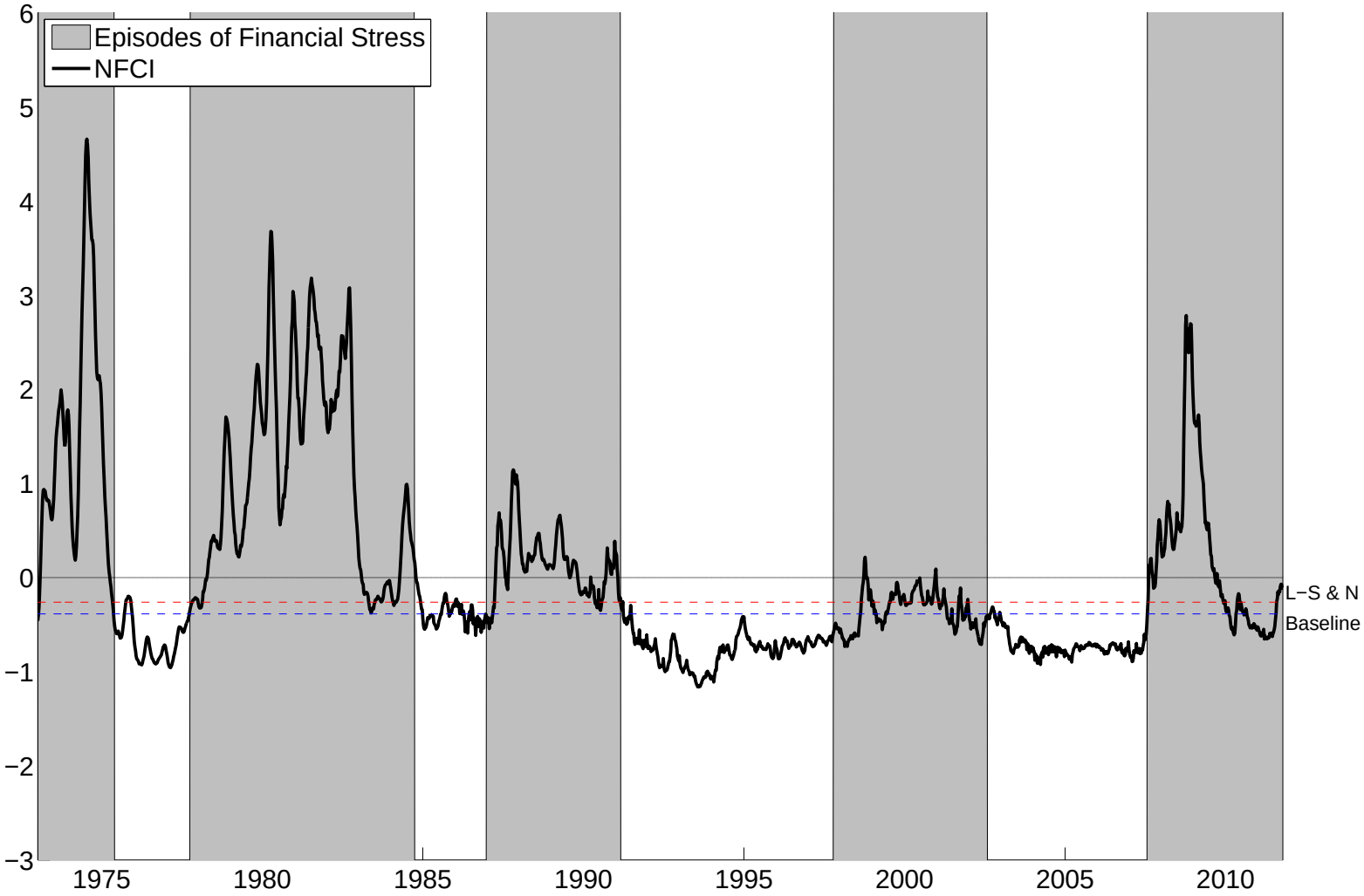
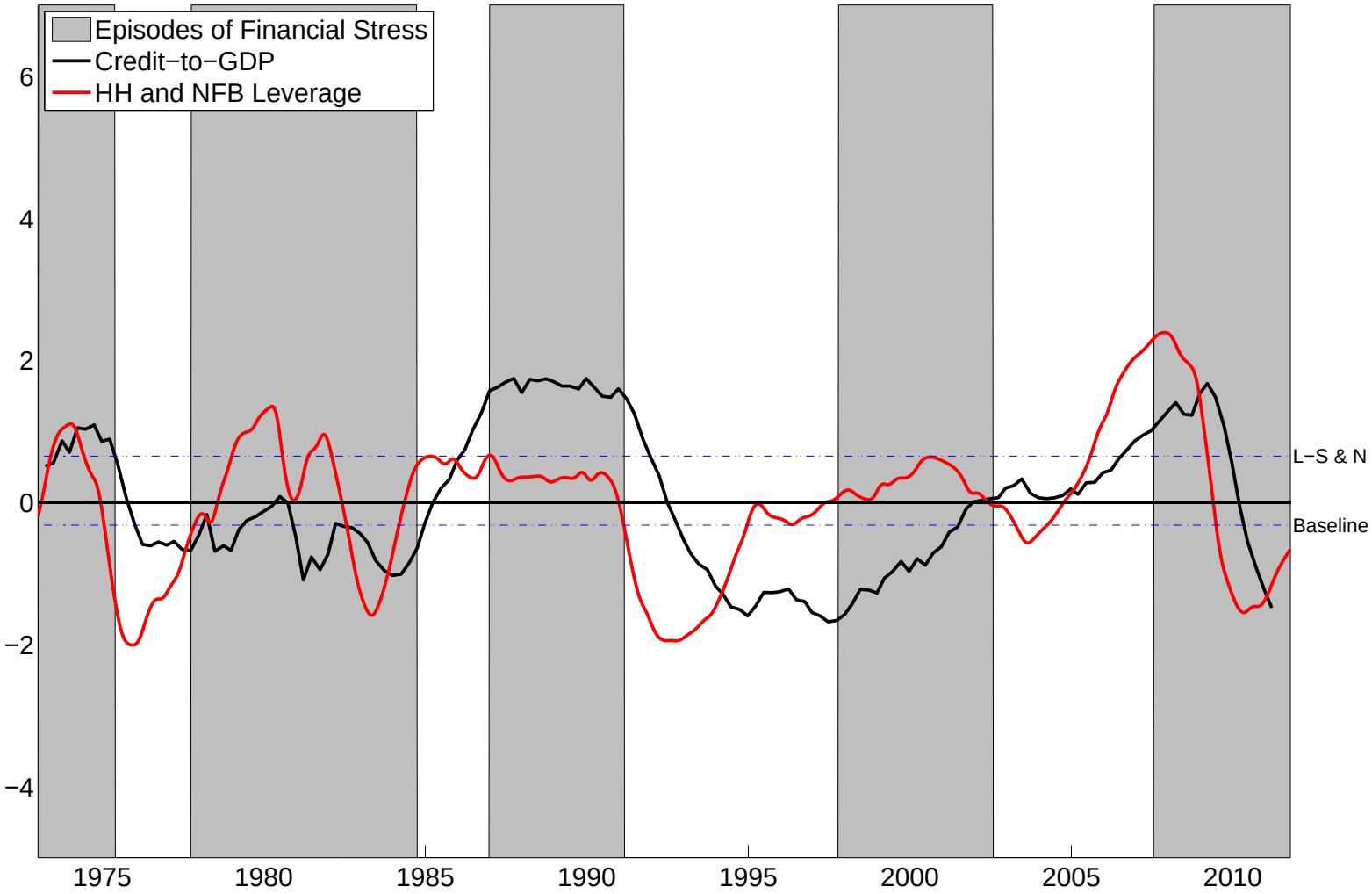
0.6
0.7
0.8
0.9
1


Episodes of Financial Stress
NFCI
6
5
4
3
2
1
0
−1
−2
−3
1975
1980
1985
1990
1995
2000
2005
2010
L−S & N
Baseline

## AUROC at 2-year Ahead Forecast Horizon

| | Brave and Butters | Lopez-Salido and Nelson | Laeven and Valencia |
|---|---|---|---|
| **NFCI** | **0.62** | **0.73** | **0.45** |
| Risk | **0.64** | **0.74** | **0.45** |
| Credit | **0.55** | **0.62** | **0.43** |
| Leverage | **0.66** | **0.79** | **0.68** |
| Credit-to-GDP | 0.48 | **0.83** | **0.82** |
| Nonfin. Leverage | **0.72** | **0.83** | **0.86** |

Numbers in bold are statistically significant at standard confidence levels.


Episodes of Financial Stress
Credit−to−GDP
HH and NFB Leverage
6
4
2
0
−2
−4
1975
1980
1985
1990
1995
2000
2005
2010
L−S & N
Baseline

## Summary: Inferences for Stabilization Policy

1. Worst crises are associated with
   - Deleveraging by financial sector
   - Sudden, sharp reassessments of risk
   - A severe tightening of credit
   - Resulting deleveraging by nonfinancial firms and households
2. Leverage measures play a key role in the credit cycle
   - Adrian and Shin (2010): Financial leverage
   - Bernanke et al (1999): Nonfinancial leverage

# Appendix

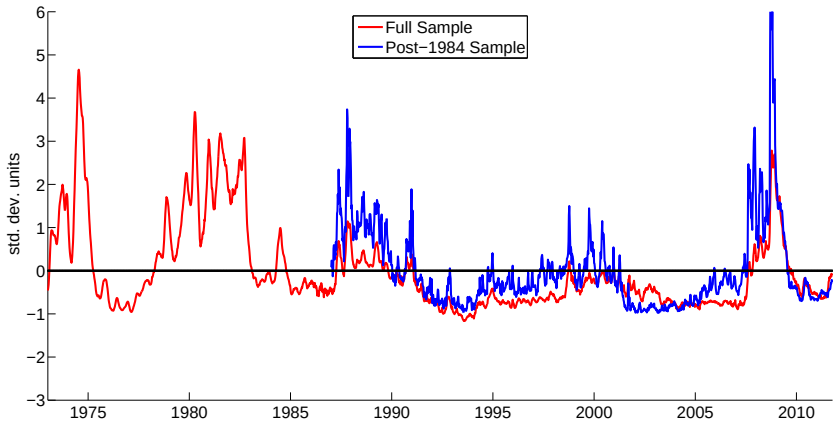
Subindexes can be constructed using the two-step method of Doz, Giannone, and Reichlin (2006)

- Zero out factor loadings for variables not in the subindex
- Run through Kalman smoother once using NFCI state-space parameters and new factor loadings

Like Hatzius et. al. (2010) may also want to consider financial conditions relative to economic conditions

- Regress each indicator on current and lagged CFNAI-MA3 & quarterly PCE inflation
- Match with frequency of indicator in regressions
- For weekly indicators, assume a lag and constant within month values
- Use standardized residuals to estimate factor – "Adjusted NFCI"

## Full and Post-84 Sample NFCI




## Full and Post-84 Sample ANFCI