OFFICE OF FINANCIAL RESEARCH

Systemwide Commonalities in Market Liquidity

Mark Flood *– Office of Financial Research (OFR)*

Joint work with:

John Liechty *– OFR, Penn State U.*

Tom Piontek *– OFR*

Market Risk: Understanding & Managing Tail Events

Cambridge Centre for Risk Studies and Oxford Economics

Cambridge Judge Business School, UK, Dec 8th, 2015

Disclaimer

Views and opinions expressed are those of the authors and do not necessarily represent official OFR or Treasury positions or policy.

Views expressed in this presentation are those of the speaker(s) and not necessarily of the Office of Financial Research.

Liquidity Measurement

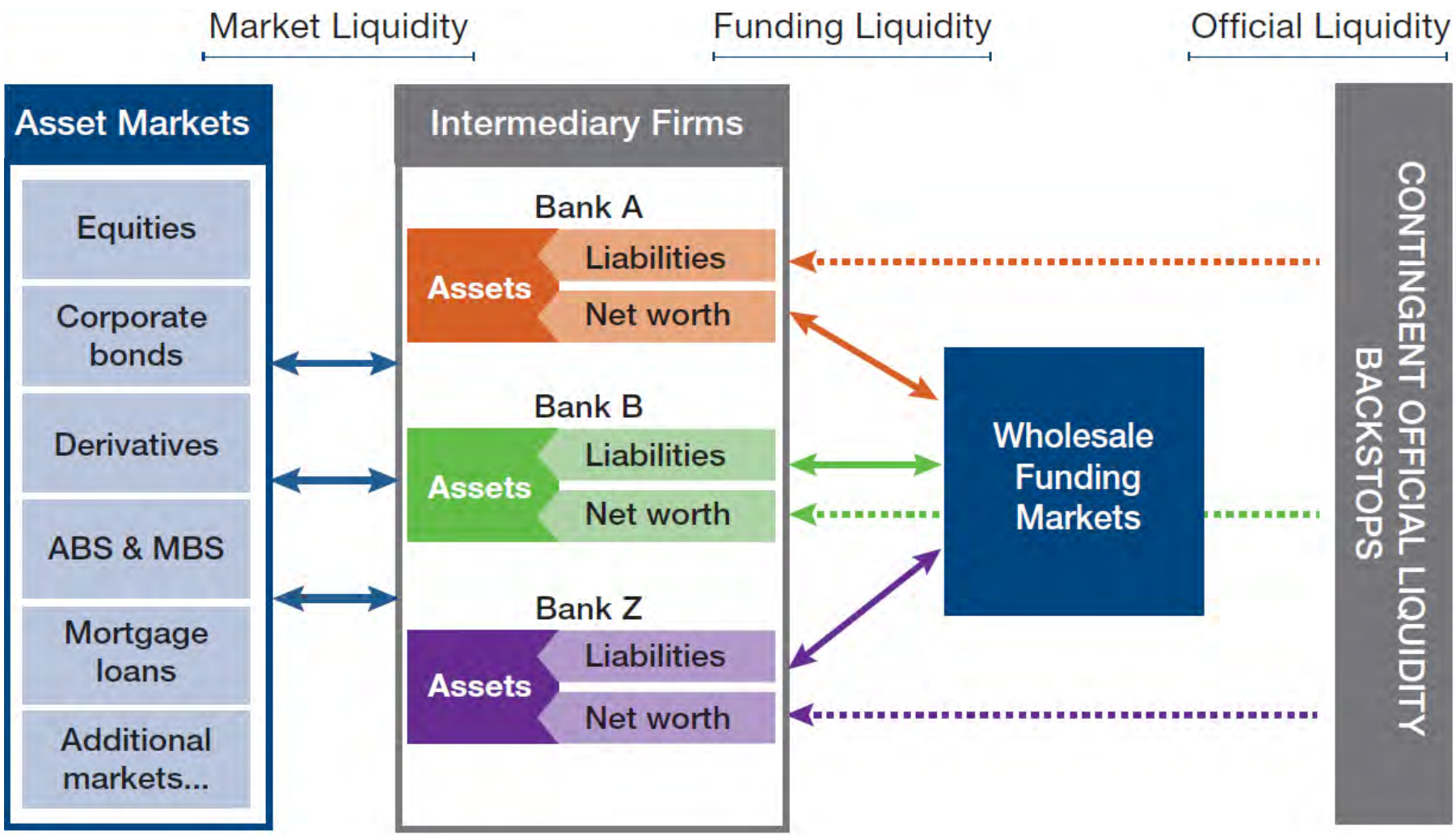
Why we care

- **Liquidity is crucial to market functioning**
  - "getting to cash" for contract settlement
- **Illiquidity is a common feature of market stress**
- **Vast research literature**

Why it's challenging

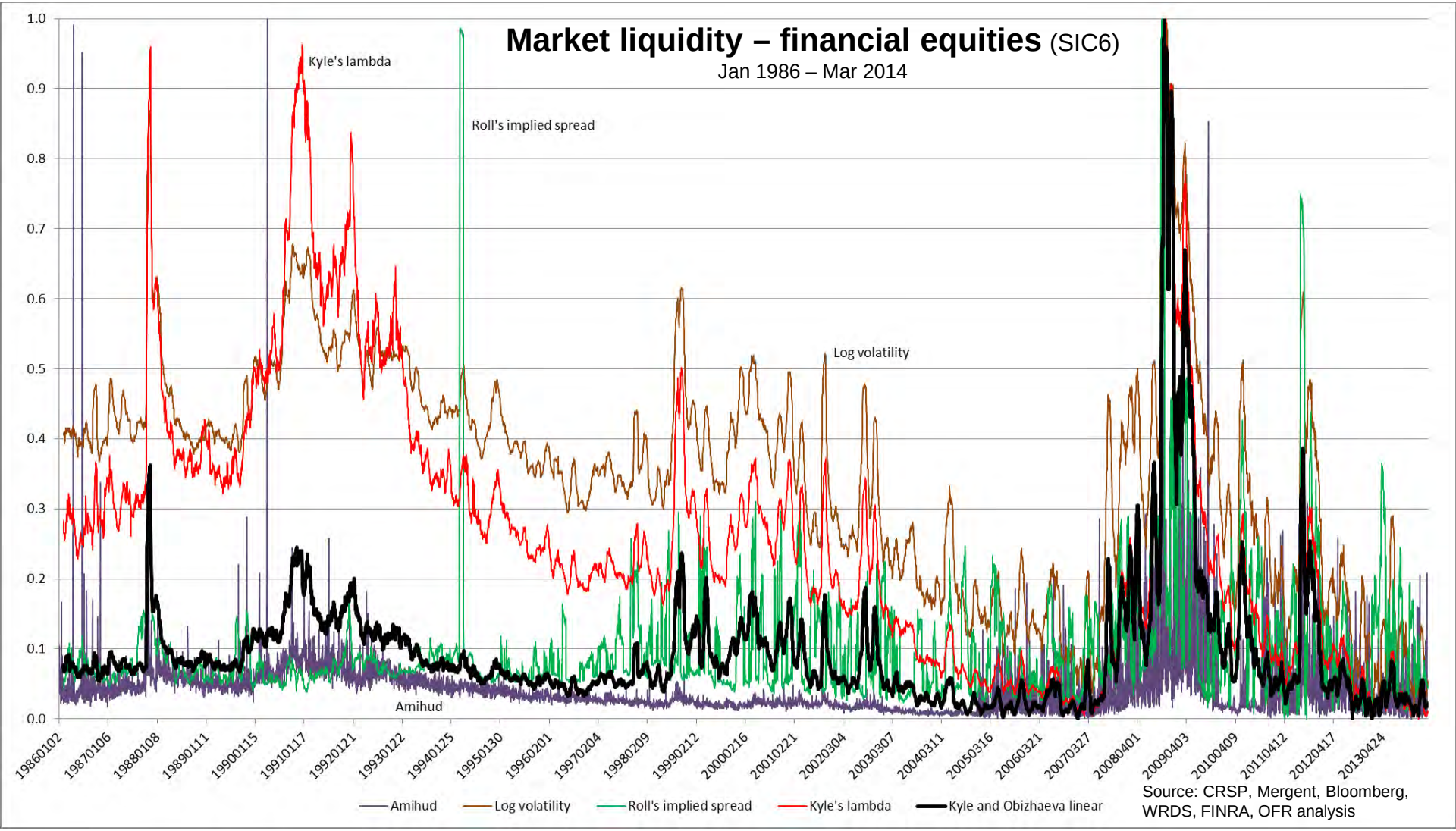
- **Latent – illiquidity often unobserved until it's too late**
- **Nonlinear – small fluctuations may not be a good guide for large events**
- **Emergent – the whole is not the sum of the parts**

Market and Funding Liquidity



Source: OFR analysis

Examples of Market Liquidity Measures



Liquidity Measurement Requirements

Table 2: Five Market Liquidity Measures for Financial Equities

Jan. 1986 – Mar. 2014

	AMIH	LVOL	ROLL	KLAM	INVL
Mean	0.04330	0.35720	0.10243	0.26807	0.09706
Std. deviation	0.04803	0.16116	0.09747	0.19360	0.10050
Skewness	7.37033	0.26863	4.94018	1.09850	4.30274
Kurtosis	101.59150	0.52763	35.01501	1.23800	25.59540
Num. observations	7121	7121	7121	7121	7121

Sources: CRSP, WRDS, OFR Analysis

Feasibility

- Data inputs need to be available to calculate measure

Timeliness

- It should be practical to update the metric at least daily

Comparability

- Metric should have same general statistical characteristics for all markets

Granularity

- The measurement should be resolvable to the level of the individual markets

Market Microstructure Invariance

- Kyle and Obizhaeva (2014)

  "Market Microstructure Invariants: Theory and Empirical Tests"

- Daily measure
- Works for many markets ("invariant")
- The calibrated price-impact trading cost, C(X), in basis points:

$$C(X) = \bar{\sigma}\left[\kappa_0 \bar{W}^{-1/3} + \kappa_1 \bar{W}^{1/3} \frac{X}{\bar{V}}\right]$$

Where:

- $\bar{\sigma}$ = normalized, expected volatility (betting volatility)
- $\bar{W}$ = normalized "trading activity" $\propto$ price x volume x volatility
- X = order size

Interpreting Market Microstructure Invariance

- "Business time" in local markets is paced by "betting" activity – a Poisson process

Trading cost, *C*, as a response function to trading impulse, *X*

First-order volatility effect

3/2 power to normalize to business time

Normalized trading impulse

$$C(X) = \bar{\sigma}\left[\kappa_0 \bar{W}^{-1/3} + \kappa_1 \bar{W}^{1/3} \frac{X}{\bar{V}}\right]$$

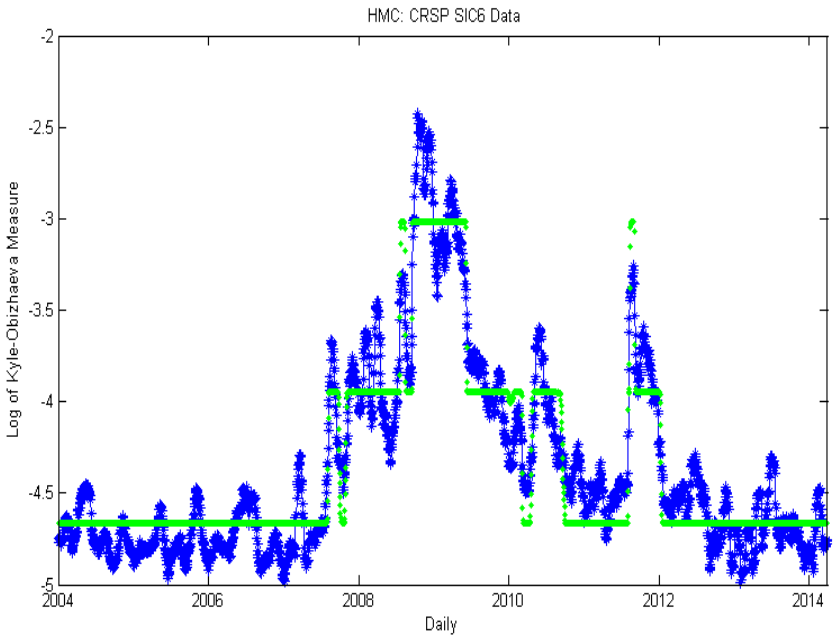
Bid-ask spread component

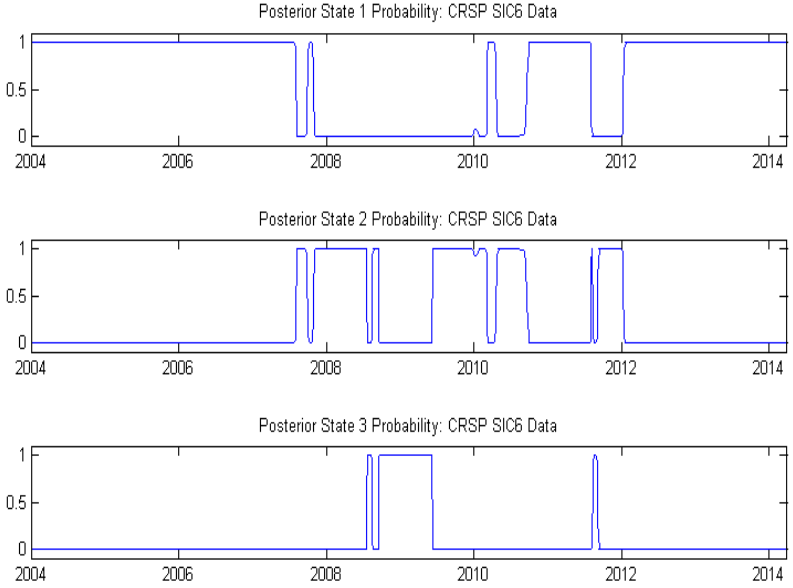
Market impact component

Latent Liquidity Structure

Hidden Markov Chain for observed liquidity

- For each market, estimates a "latent" or unobserved level of liquidity
- Bayesian Hierarchical Model; Inference using Markov Chain Monte Carlo
- Detected three distinct liquidity states (levels of the price impact measures)
- Estimated level of liquidity for each state and probability of being in a state



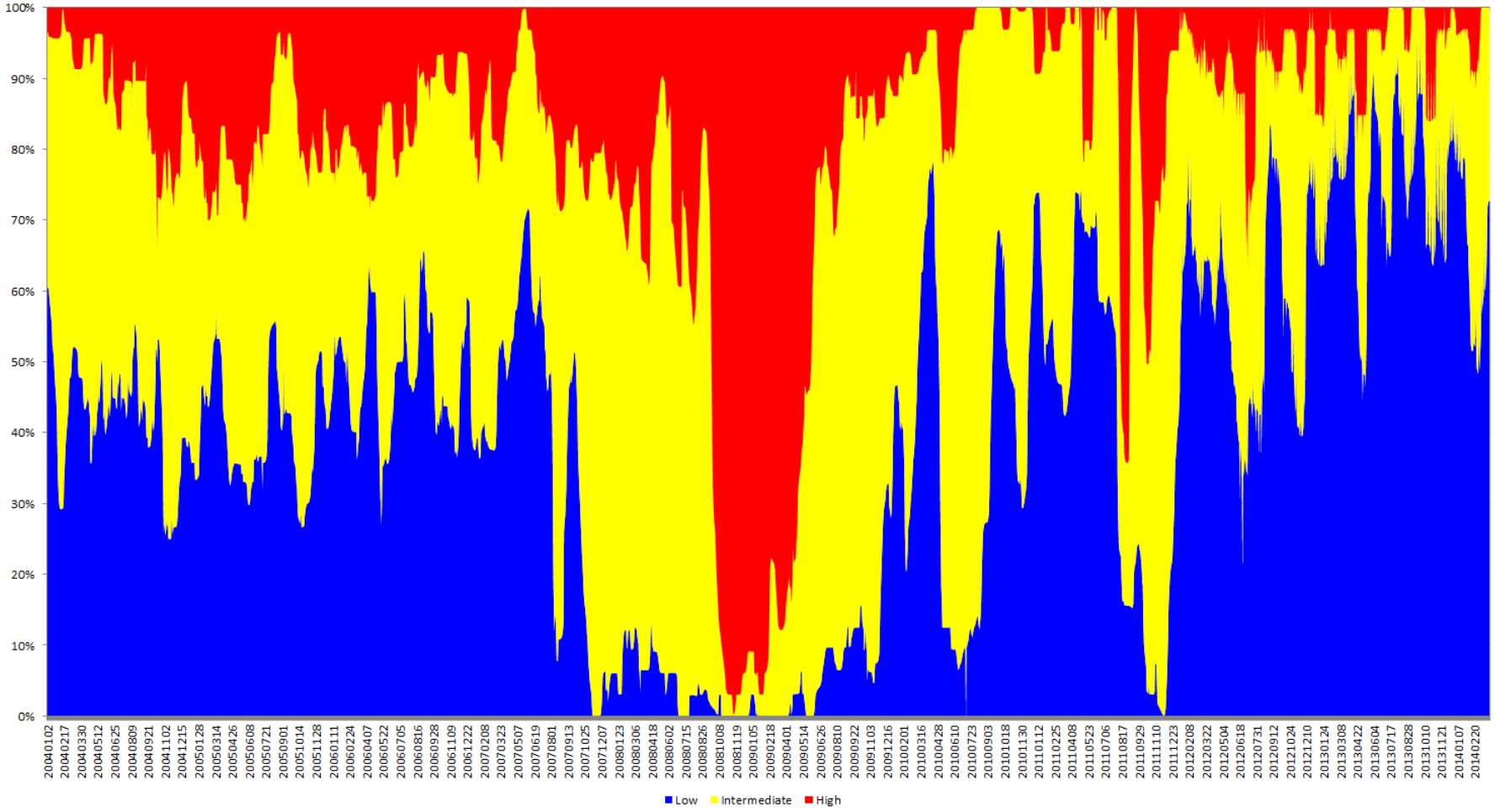


Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Estimated Liquidity States

Average Estimated State Probabilities

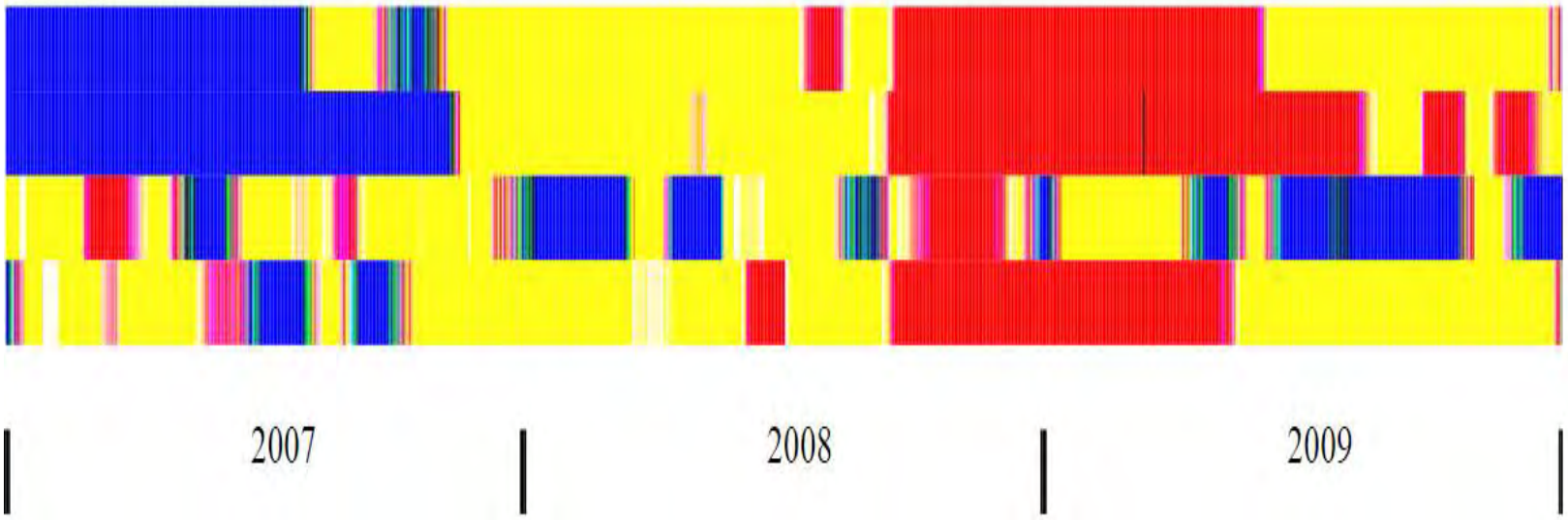
(Hidden Markov Chains, 33 series, Apr. 2004 – Mar. 2014)



Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Mixed Price-Impact States

4 Markets, Daily, 2007 – 2009

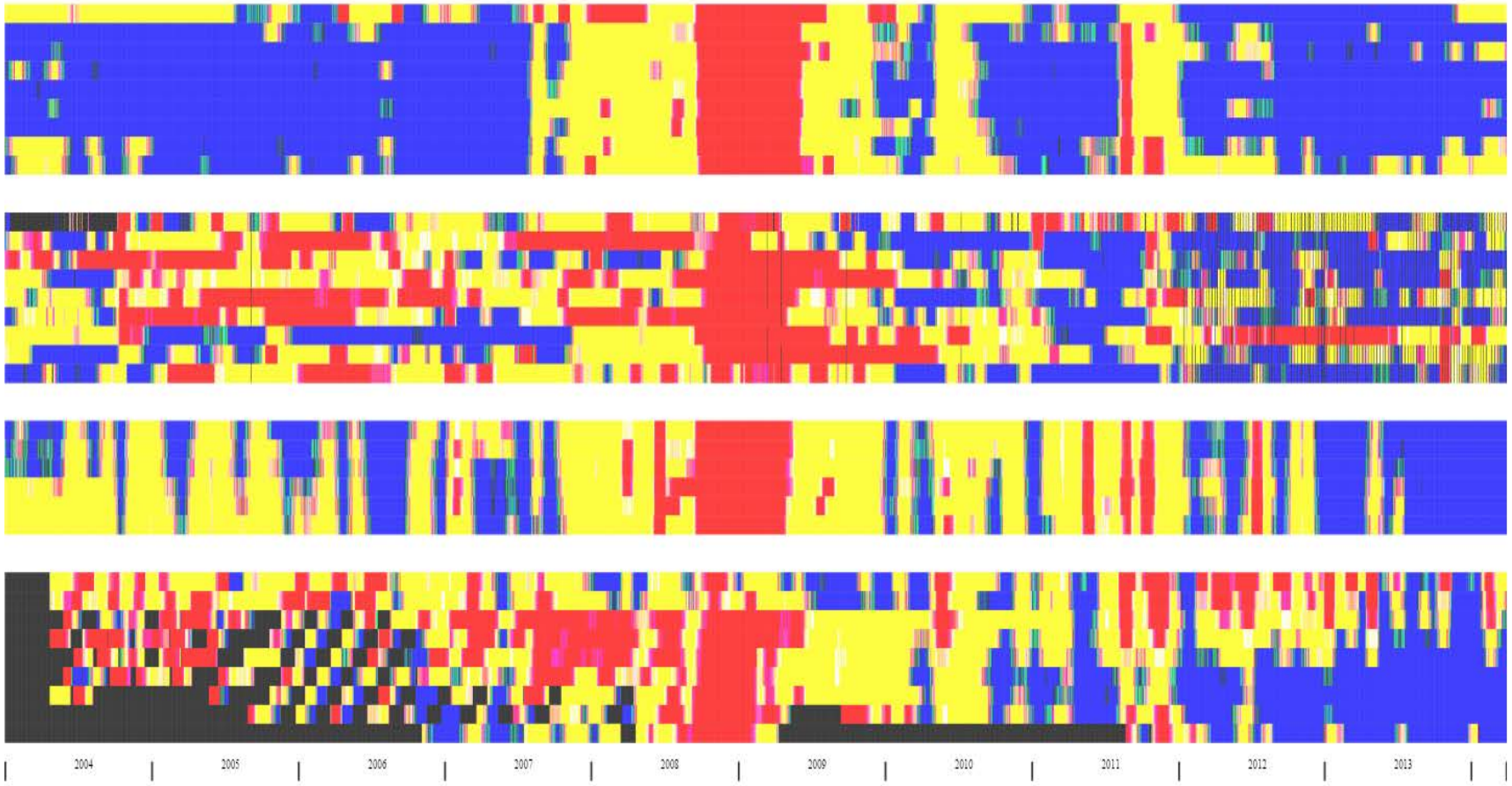


Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Big Heat Map

Mixed Price-Impact States

4 Markets, Daily, 2004 – 2014

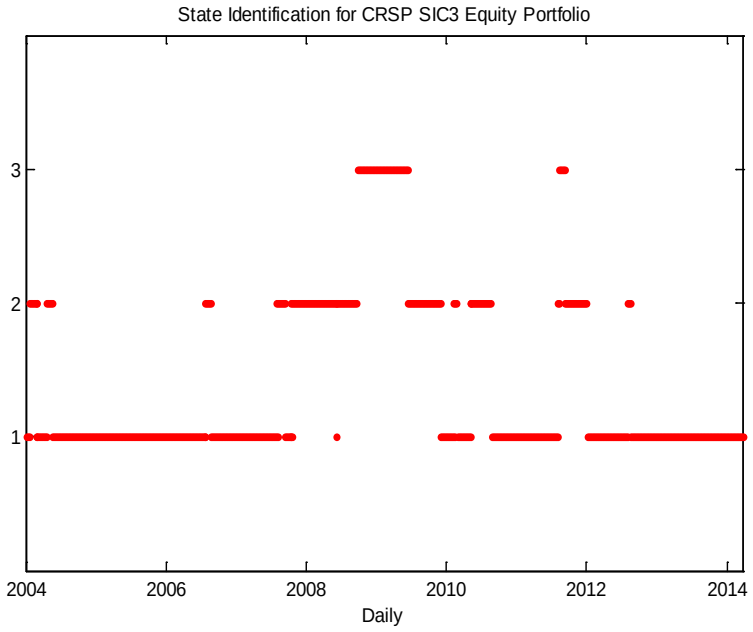


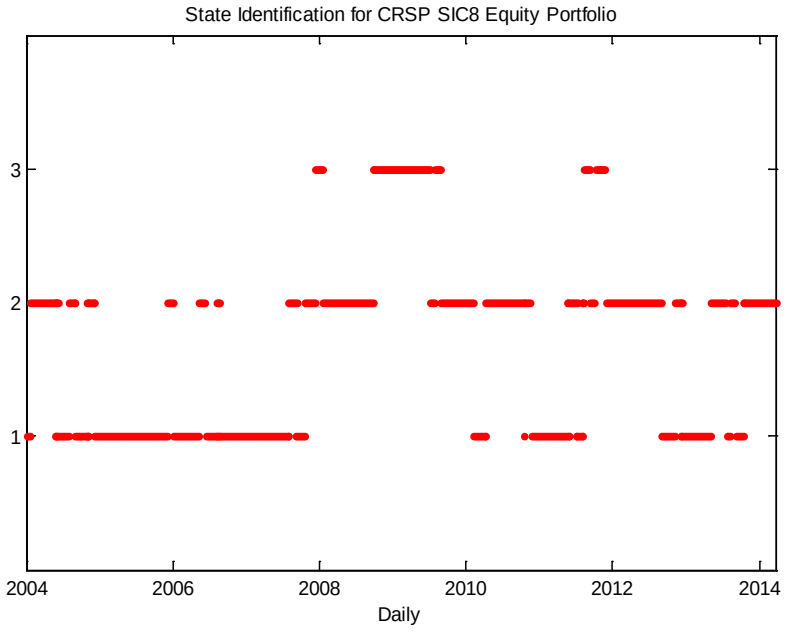
Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Hierarchical Model

What is driving the hidden Markov models?

- Relating financial/economic summaries to changes in latent liquidity states
- Multivariate (multiple markets) filtered Hidden Markov Chain model
  - Treat as a choice problem:
    - Choice of estimated liquidity state for each market/date
  - Fit a Multinomial Probit model to predict the choice





Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Hierarchical Model

What is driving the hidden Markov models?

- **Eleven financial market summary indicators to predict each latent state**
- **Equity (CRSP) and bond (TRACE) liquidities – here as first principal components**
  - MCMC Average Hit Rate = 67%, versus Naive Hit Rate = 33%

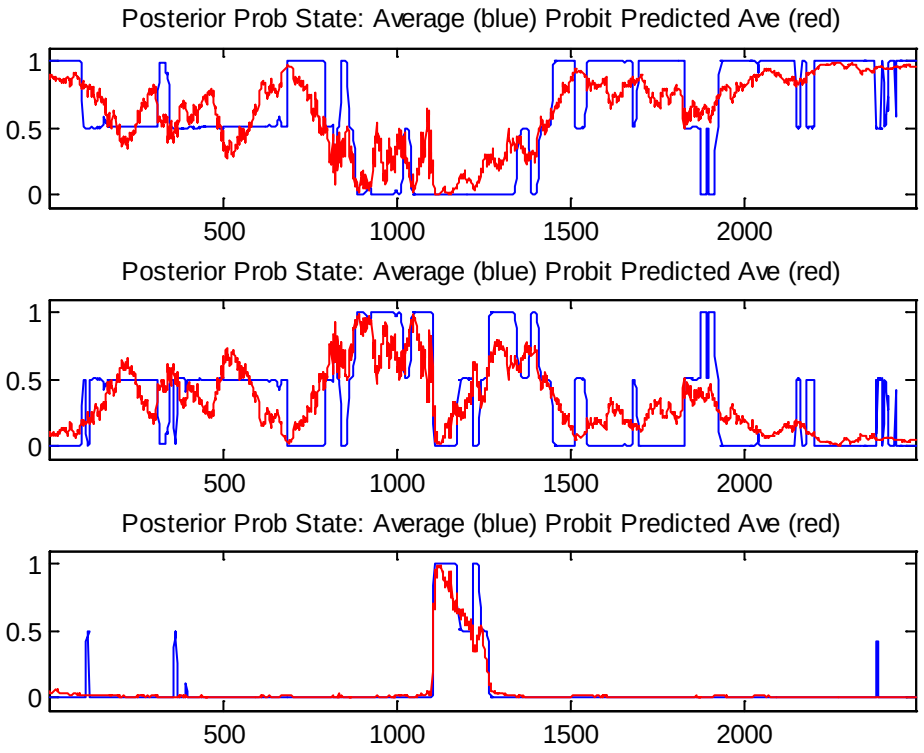
Variable	Coefficient		T-Stat (mean/std)	
	State 2	State 3	State 2	State 3
Intercept	-1.00	-0.94	-34.7	-45.43
WTI	0.37	-0.16	13.00	-4.02
3-mo. Repo Rate	0.76	-0.25	11.41	-19.15
TED Spread	0.51	-0.22	5.35	-12.46
5-year Breakeven Inflation	0.07	-0.06	3.62	-6.02
VIX	-0.12	0.02	-4.30	1.93
S&P500 Price/Book	-0.01	0.08	-0.29	3.43
Dow Jones Real Estate Index	-1.31	0.07	-19.18	2.31
Moody's BAA Index	-0.10	0.20	-1.78	12.76
LIBOR–OIS Spread	-0.46	0.38	-4.90	26.32
DXY Dollar Index	-1.08	0.10	-22.18	6.92
10yr–2yr Yield Spread	-0.40	-0.14	-6.80	-7.57

Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Hierarchical Model

Probit fit of market summary variables to liquidity states

- **Average latent liquidity states**
- **Predicted state from fitted Probit model**



State 1 (high liquidity)

- Avg. posterior probability of state
- Probit predicted (avg.) probability

State 2 (intermediate liquidity)

- Avg. posterior probability of state
- Probit predicted (avg.) probability

State 3 (low liquidity)

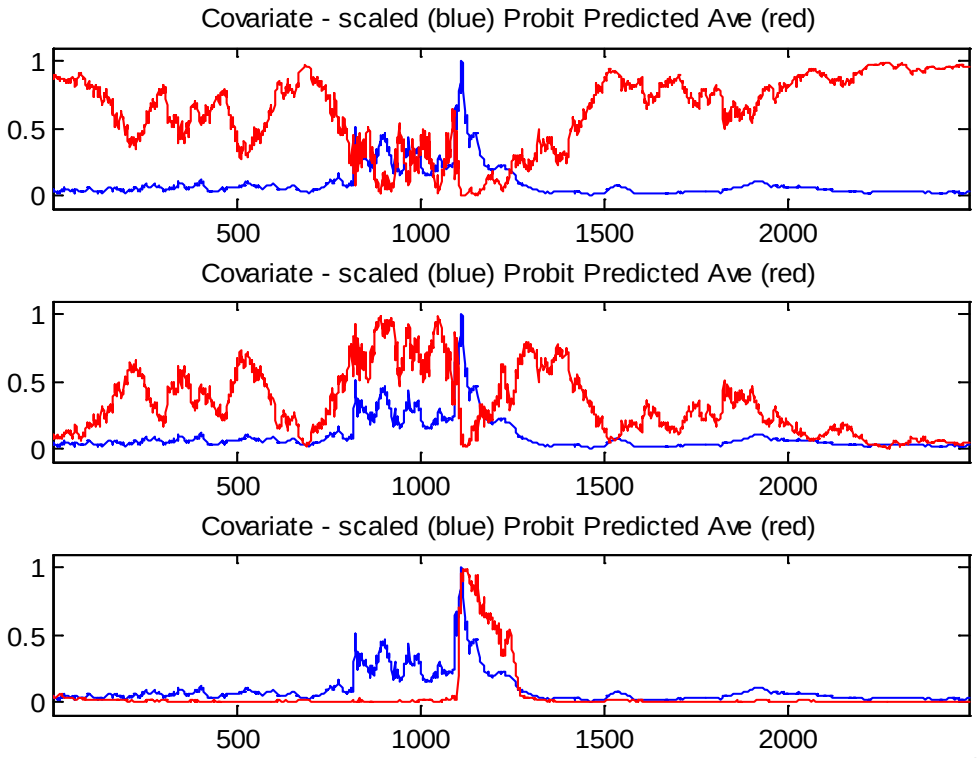
- Avg. posterior probability of state
- Probit predicted (avg.) probability

Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Hierarchical Model

Interpreting the Probit results – case of the TED spread

- TED spread jumps in 2007, peaks after Lehman
- Probit over-predicts the probability of State 3, due to policy response



State 1 (high liquidity)

- TED spread (scaled)
- Probit predicted (avg.) probability

State 2 (intermediate liquidity)

- TED spread (scaled)
- Probit predicted (avg.) probability

State 3 (low liquidity)

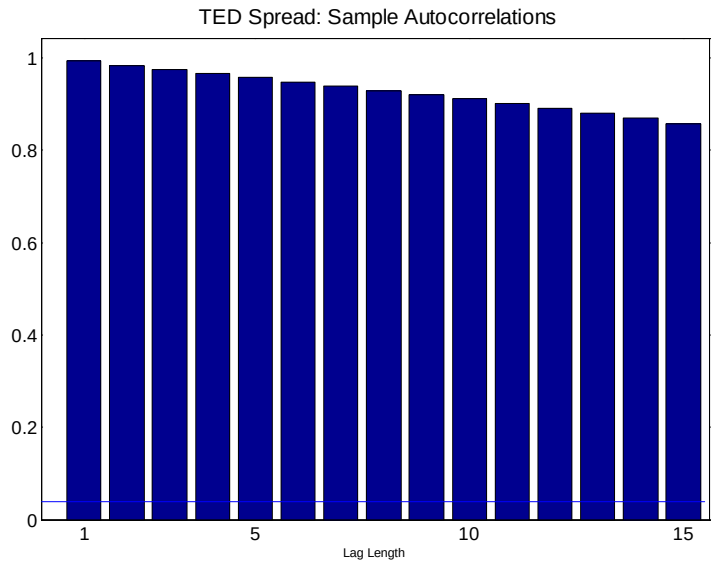
- TED spread (scaled)
- Probit predicted (avg.) probability

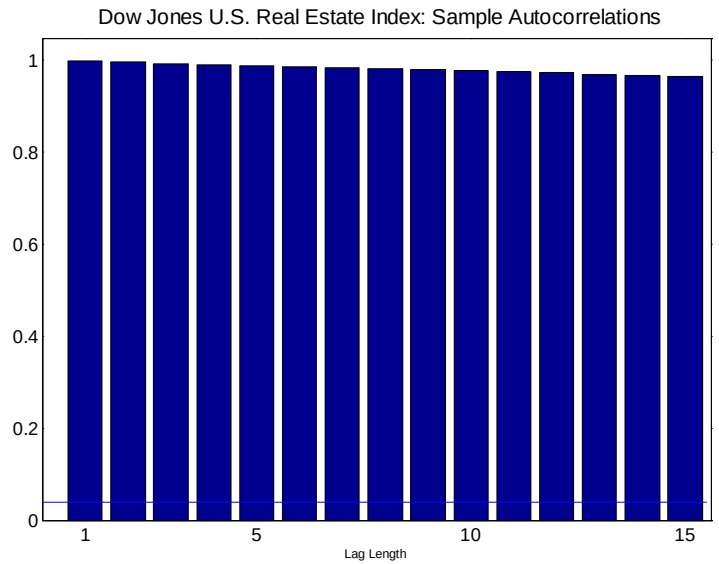
Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Predicting Liquidity Regimes

Can the Probit model predict the liquidity state?

- What do lagged (not current) summary variables say about liquidity state?
- Strong persistence in financial/economic summary variables
  - Shown in autocorrelation functions – summary variables enter in levels
  - Two examples: TED spread and Dow Jones Real Estate Index



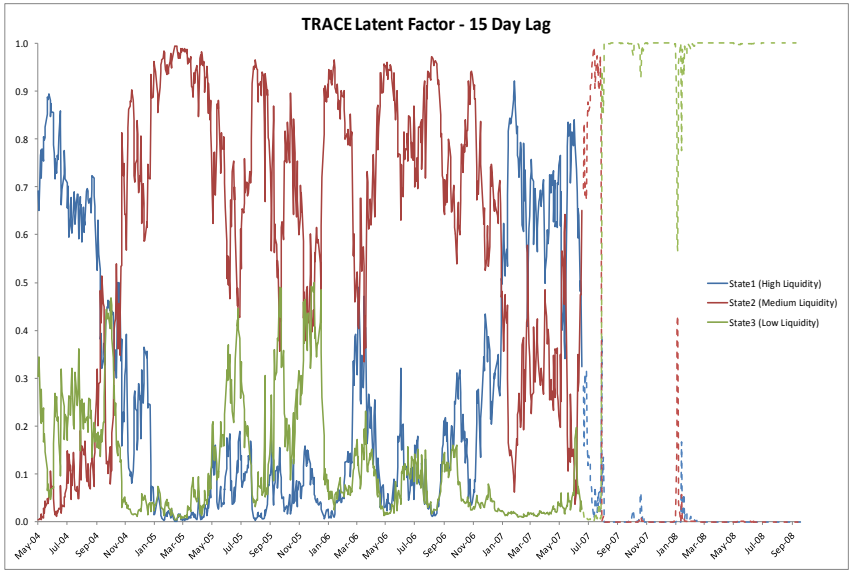


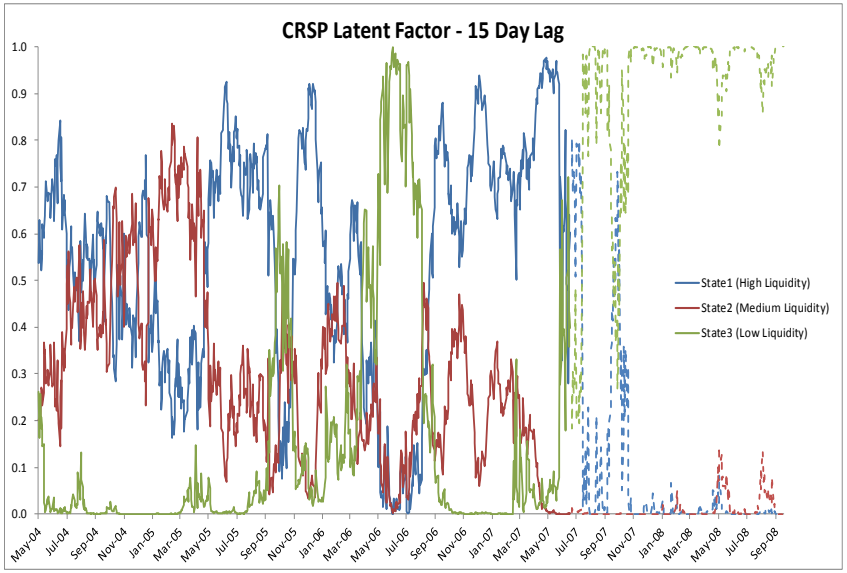
Source: Mergent, Bloomberg, OFR analysis

Predicting Liquidity Regimes (Probit fit Mar 2004 – Jun 2007)

What would the model have predicted in 2007-2008?

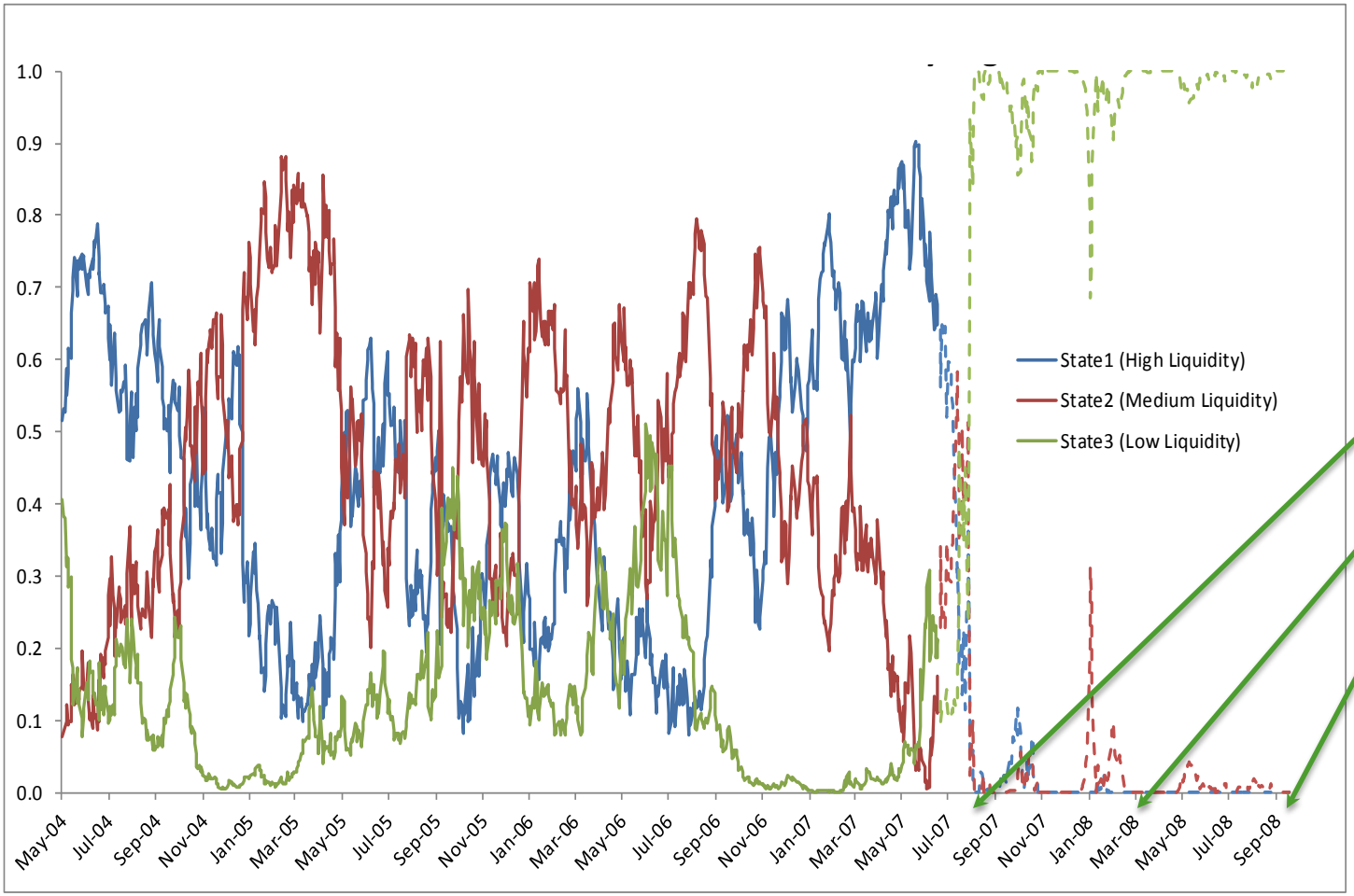
- **Freeze Probit coefficients in June 2007**
- **15-trading-day forecast of state probabilities**
  - **Forecasts at this horizon tend to converge on a single state**
- **Models predict low liquidity, starting in August 2007**





Source: CRSP, WRDS, OFR analysis

Combining equity and bond market liquidity



Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis

Gratitude

Thanks!