Systemwide Commonalities in Market Liquidity

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What is liquidity?
• Good question!
  – Vast research literature
• Ultimate focus is contract settlement
  – Can I “get to cash” to meet my obligations?

Why do we care?
• Liquidity is crucial to market functioning
  – Most obligations are denominated in cash
• Illiquidity is a common feature of market stress
  – Symptomatic: both cause and effect
Why it’s challenging

- **Latent**
  - We care most about illiquidity (when liquidity vanishes)
  - Often unobserved until it’s too late

- **Nonlinear**
  - We care most about liquidating large positions
  - Small fluctuations are not a good guide for large events

- **Emergent**
  - We care most about aggregate liquidity conditions
  - The whole is not the sum of the parts: liquidity begets liquidity
Some orders of magnitude

• **Corporate equities**
  – 5,000+ individual firms traded
  – High-frequency trading common (ca. μS frequency)

• **Corporate bonds**
  – Ca. 100,000 individual issues traded
  – Weekly average trading frequency more typical

• **Exchange-traded futures**
  – 1,000s of distinct contracts (underlying x maturity)
  – Trading frequency is diverse
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
Examples of Market Liquidity Measures

Market liquidity – financial equities (SIC6)
Jan 1986 – Mar 2014

Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis
Market Microstructure Invariance

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

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

Where:
• \( \bar{\sigma} \) = normalized, expected volatility (betting volatility)
• \( \bar{W} \) = normalized “trading activity” \( \propto \) price \times volume \times volatility
• \( X \) = order size
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

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

Mixed Price-Impact States


Global financial crisis
• 8/2007: BNP and quant funds
• 2/2008: Bear Stearns failure
• 7/2008: Fannie/Freddie failure
• 9/2008: Lehman Bros. failure
• 3/2009: Federal Reserve stress tests

European sovereign debt crisis
• 8/2011: S&P downgrades U.S.
• 9/2011: Occupy Wall St. begins
• 10/2011: Eurozone intervention
• 11/2011: International intervention

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

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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 = 56%, versus Naive Hit Rate = 33%

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>T-Stat (mean/std)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>State 2</td>
<td>State 3</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.51</td>
<td>-0.97</td>
</tr>
<tr>
<td>WTI</td>
<td>0.60</td>
<td>-0.21</td>
</tr>
<tr>
<td>3-mo. Repo Rate</td>
<td>0.53</td>
<td>-0.48</td>
</tr>
<tr>
<td>TED Spread</td>
<td>0.44</td>
<td>-0.05</td>
</tr>
<tr>
<td>5-year Breakeven Inflation</td>
<td>-0.02</td>
<td>-0.04</td>
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<tr>
<td>VIX</td>
<td>0.41</td>
<td>0.01</td>
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<tr>
<td>S&amp;P500 Price/Book</td>
<td>0.40</td>
<td>-0.14</td>
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<tr>
<td>Dow Jones Real Estate Index</td>
<td>-0.86</td>
<td>0.02</td>
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<tr>
<td>Moody’s BAA Index</td>
<td>-0.48</td>
<td>0.28</td>
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<tr>
<td>LIBOR–OIS Spread</td>
<td>-0.54</td>
<td>0.17</td>
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<tr>
<td>DXY Dollar Index</td>
<td>-0.21</td>
<td>-0.39</td>
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<tr>
<td>10yr–2yr Yield Spread</td>
<td>0.22</td>
<td>-0.43</td>
</tr>
</tbody>
</table>

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

What would the model have predicted in 2007-2008?

Method:

- Freeze Probit coefficients in June 2007
- 15-trading-day forecast of state probabilities – forecasts converge on one state
- Models predict low liquidity, starting in August 2007

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

Thanks!