System-Wide Commonalities in Market Liquidity

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31 Mar 2015
Views and opinions expressed are those of the authors and do not necessarily represent official OFR or Treasury positions or policy.
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

Market Liquidity

Funding Liquidity

Official Liquidity

Asset Markets
- Equities
- Corporate bonds
- Derivatives
- ABS & MBS
- Mortgage loans
- Additional markets...

Intermediary Firms
- Bank A
  - Assets
  - Liabilities
  - Net worth

- Bank B
  - Assets
  - Liabilities
  - Net worth

- Bank Z
  - Assets
  - Liabilities
  - Net worth

Wholesale Funding Markets

Source: OFR analysis

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Examples of Market Liquidity Measures

Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis
Liquidity Measurement Requirements

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
Liquidity Measurement Requirements

All measures are positively correlated
Invariance metric (INVL) is strongly correlated with each of the measures, but not perfect

Table 1: Correlations Among Liquidity Measures for Financial Equities

<table>
<thead>
<tr>
<th></th>
<th>AMIH</th>
<th>LVOL</th>
<th>ROLL</th>
<th>KLAM</th>
<th>INVL</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMIH</td>
<td>1.00</td>
<td>0.39</td>
<td>0.16</td>
<td>0.39</td>
<td>0.42</td>
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<tr>
<td>LVOL</td>
<td>1.00</td>
<td>0.23</td>
<td>0.92</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>ROLL</td>
<td>1.00</td>
<td>0.11</td>
<td>0.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>KLAM</td>
<td>1.00</td>
<td>0.66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NIVL</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sources: CRSP, WRDS, OFR Analysis
Market-level Price Impact Measures

Market Microstructure Invariance

- Kyle and Obizhaeva (2014)
- 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 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

Bid-ask spread component

Market impact component

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


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

Mixed Price-Impact States

CRSP portfolios
SIC 0–8

TRACE corp. bonds SIC 0–8

WTI futures
Mat. 1–6 mos.

VIX futures
Mat. 1–9 mos.

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

What is driving the hidden Markov models?

• How are macro summaries of the financial markets/economy related to changes in the latent liquidity states?

• Using a Multivariate (multiple markets) filtered Hidden Markov Chain model
  – Have estimates of being in each state for every market at each point in time
  – Treat as a choice problem and use a Multinomial Probit model

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

What is driving the hidden Markov models?

- Considered 11 financial market/macro indicators (such as inflation, the yield curve, dollar index, etc.) to predict each latent state.

<table>
<thead>
<tr>
<th>Macro Variable</th>
<th>State 2</th>
<th>State 3</th>
<th>State 2</th>
<th>State 3</th>
<th>State 2</th>
<th>State 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.64**</td>
<td>-1.01**</td>
<td>0.02</td>
<td>0.01</td>
<td>-40.27</td>
<td>-102.11</td>
</tr>
<tr>
<td>VIX®</td>
<td>0.62**</td>
<td>0.26**</td>
<td>0.03</td>
<td>0.02</td>
<td>23.77</td>
<td>15.67</td>
</tr>
<tr>
<td>WTI</td>
<td>0.83**</td>
<td>-0.23**</td>
<td>0.03</td>
<td>0.01</td>
<td>30.65</td>
<td>-16.53</td>
</tr>
<tr>
<td>3m Repo Rate</td>
<td>0.68**</td>
<td>-0.41**</td>
<td>0.02</td>
<td>0.01</td>
<td>38.28</td>
<td>-49.12</td>
</tr>
<tr>
<td>TED Spread</td>
<td>0.49**</td>
<td>-0.09**</td>
<td>0.03</td>
<td>0.01</td>
<td>18.53</td>
<td>-10.98</td>
</tr>
<tr>
<td>Yield Curve (10y–2y)</td>
<td>0.19**</td>
<td>-0.38**</td>
<td>0.02</td>
<td>0.04</td>
<td>9.66</td>
<td>-56.07</td>
</tr>
<tr>
<td>S&amp;P 500 P/B Ratio</td>
<td>0.68**</td>
<td>-0.13**</td>
<td>0.03</td>
<td>0.01</td>
<td>23.85</td>
<td>-9.86</td>
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<tr>
<td>Dow Jones Real Estate Index</td>
<td>-1.17**</td>
<td>0.13**</td>
<td>0.02</td>
<td>0.01</td>
<td>-64.48</td>
<td>11.69</td>
</tr>
<tr>
<td>Moody’s Baa Index</td>
<td>-0.67**</td>
<td>0.47**</td>
<td>0.02</td>
<td>0.01</td>
<td>-43.57</td>
<td>60.83</td>
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<tr>
<td>LIBOR–OIS Spread</td>
<td>-0.64**</td>
<td>0.13**</td>
<td>0.05</td>
<td>0.02</td>
<td>-13.07</td>
<td>7.38</td>
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<td>DXY Dollar Index</td>
<td>-0.39**</td>
<td>-0.37**</td>
<td>0.04</td>
<td>0.01</td>
<td>-10.67</td>
<td>-41.05</td>
</tr>
<tr>
<td>U.S. 5y Breakeven Inflation</td>
<td>-0.03</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
<td>-1.43</td>
<td>0.36</td>
</tr>
</tbody>
</table>

** Significant at a 99% confidence level

MCMC Average Hit Rate = 66%, Naive Hit Rate = 33%

Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis
Predicting Macroeconomic Variables

Can we predict macro variables (and then liquidity)?

- **Hidden liquidity states**
- **Macro drivers of hidden states (predict these, predict liquidity)**

![Graphs showing equities posterior state probabilities](image)

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

What is driving the hidden Markov models?

![Graphs showing VIX-scaled (blue) Probit Predicted Avg (red) over time]

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

What is driving the hidden Markov models?

Source: CRSP, Mergent, Bloomberg, WRDS, FINRA, OFR analysis
Why VAR models do not offer insights

- Distribution of off-diagonal correlations between the 8 equity liquidity time-series
- Reveals high level of multi-collinearity in equity liquidity time-series
Vector Auto Regression Models

Why VAR models do not offer insights

- Factor Model: over 70% of the variation is explained by the first factor
- High multi-collinearity results in all lagged variables predicting all remaining variables
- Future research will explore predictive power of Bayesian Factor model

Source: CRSP, WRDS, OFR analysis
### Vector Auto Regression Models

#### Why VAR models do not offer insights

- High multi-collinearity results in all lagged variables predicting all remaining variables
- Future research will explore predictive power of Bayesian Factor model

<table>
<thead>
<tr>
<th>Independent Variables of VAR(2) Models</th>
<th>Intercept</th>
<th>SIC1</th>
<th>SIC2</th>
<th>SIC3</th>
<th>SIC4</th>
<th>SIC5</th>
<th>SIC6</th>
<th>SIC7</th>
<th>SIC8</th>
</tr>
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<tbody>
<tr>
<td>T-STATS</td>
<td>4.66</td>
<td>4.25</td>
<td>24.70</td>
<td>30.43</td>
<td>2.81</td>
<td>21.04</td>
<td>-16.01</td>
<td>33.98</td>
<td></td>
</tr>
<tr>
<td>SIC1 Lag1</td>
<td>31.63</td>
<td>2.87</td>
<td>5.42</td>
<td>8.90</td>
<td>6.56</td>
<td>8.61</td>
<td>4.72</td>
<td>5.48</td>
<td></td>
</tr>
<tr>
<td>SIC3 Lag1</td>
<td>2.57</td>
<td>9.39</td>
<td>21.03</td>
<td>15.82</td>
<td>9.85</td>
<td>14.63</td>
<td>6.05</td>
<td>14.69</td>
<td></td>
</tr>
<tr>
<td>SIC4 Lag1</td>
<td>3.27</td>
<td>8.30</td>
<td>14.29</td>
<td>20.26</td>
<td>10.13</td>
<td>15.71</td>
<td>5.27</td>
<td>18.78</td>
<td></td>
</tr>
<tr>
<td>SIC5 Lag1</td>
<td>3.75</td>
<td>13.29</td>
<td>12.18</td>
<td>13.77</td>
<td>19.18</td>
<td>13.55</td>
<td>12.50</td>
<td>11.91</td>
<td></td>
</tr>
<tr>
<td>SIC6 Lag1</td>
<td>3.46</td>
<td>6.33</td>
<td>12.80</td>
<td>15.19</td>
<td>8.53</td>
<td>20.57</td>
<td>6.57</td>
<td>14.11</td>
<td></td>
</tr>
<tr>
<td>SIC7 Lag1</td>
<td>4.08</td>
<td>16.48</td>
<td>12.33</td>
<td>11.12</td>
<td>19.43</td>
<td>14.00</td>
<td>28.99</td>
<td>4.89</td>
<td></td>
</tr>
</tbody>
</table>

| SIC1 Lag2                              | 28.40     | 2.26  | 5.05  | 8.30  | 5.63  | 8.04  | 3.80  | 4.92  |
| SIC2 Lag2                              | 1.24      | 19.97 | 13.16 | 12.33 | 14.77 | 10.79 | 11.92 | 8.34  |
| SIC3 Lag2                              | 2.36      | 8.36  | 19.91 | 14.62 | 8.64  | 13.90 | 4.97  | 13.72 |
| SIC4 Lag2                              | 2.94      | 7.21  | 13.39 | 18.88 | 8.87  | 14.87 | 4.13  | 17.72 |
| SIC5 Lag2                              | 3.38      | 11.83 | 11.03 | 12.19 | 17.43 | 12.58 | 11.01 | 10.64 |
| SIC6 Lag2                              | 3.15      | 5.25  | 11.97 | 13.91 | 7.13  | 19.49 | 5.44  | 13.01 |
| SIC7 Lag2                              | 3.60      | 14.63 | 11.01 | 9.10  | 17.46 | 12.49 | 26.82 | 3.22  |
| SIC8 Lag2                              | 2.29      | 5.35  | 13.78 | 19.55 | 8.45  | 16.08 | 1.68  | 22.32 |
Predicting Liquidity Regimes

Can we use the Probit model to predict the liquidity state?

- Endogeneity concerns: adding lagged values of the macro variables in addition to the current variables provides no additional benefit in recovering the liquidity state.
- What can lagged macro values (excluding the current values) tell us about the liquidity state?
- Still relatively high Hit Rates at 5, 10, 15 day lags when fitting the model pre-Lehman and pre-Bear Stearns

*Naive Hit Rate = 33%*

### Table 5: Lagged Macro Variable Hit Rates for Equity Price Impacts

<table>
<thead>
<tr>
<th>Lag</th>
<th>Full Series</th>
<th>2004-05-01 to 2008-09-01 (Pre-Lehman)</th>
<th>2004-05-01 to 2008-02-21 (Pre-Bear Stearns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag0</td>
<td>0.66</td>
<td>0.58</td>
<td>0.56</td>
</tr>
<tr>
<td>Lag1</td>
<td>0.65</td>
<td>0.58</td>
<td>0.56</td>
</tr>
<tr>
<td>Lag2</td>
<td>0.66</td>
<td>0.59</td>
<td>0.56</td>
</tr>
<tr>
<td>Lag3</td>
<td>0.65</td>
<td>0.59</td>
<td>0.56</td>
</tr>
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<td>0.65</td>
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<td>0.57</td>
</tr>
<tr>
<td>Lag5</td>
<td>0.65</td>
<td>0.59</td>
<td>0.57</td>
</tr>
<tr>
<td>Lag10</td>
<td>0.65</td>
<td>0.59</td>
<td>0.56</td>
</tr>
<tr>
<td>Lag15</td>
<td>0.65</td>
<td>0.58</td>
<td>0.56</td>
</tr>
</tbody>
</table>

Source: CRSP, WRDS, OFR analysis
Macro variables exhibit high autocorrelation or “stickiness”
This suggests that the macro variables could provide predictive power
Consider pre-August 2007 (BNP Paribas)? Would we have seen symptoms of liquidity stress?
Predicting Liquidity Regimes (model fit Mar 2004 through June 2007)

Lag 15

State1 (High Liquidity)
State2 (Medium Liquidity)
State3 (Low Liquidity)

BNP Paribas halts redemptions Aug 2007
Lehman Brothers Sept 2008
Bear Stearns March 2008

Source: CRSP, WRDS, OFR analysis
Hierarchical Model (Before Crisis)

Coefficients for model fit to June 2007 (pre-crisis)

- Smaller MCMC Average Hit Rate, but significance in most slope coefficients

<table>
<thead>
<tr>
<th>Posterior Mean (15-Day Lag)</th>
<th>Jun 2007 Model Fit</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>State 2</td>
<td>State 3</td>
</tr>
<tr>
<td><strong>Intercept</strong></td>
<td>-0.81**</td>
<td>-1.16**</td>
</tr>
<tr>
<td>LIBOR - OIS Spread</td>
<td>0.12</td>
<td>1.98**</td>
</tr>
<tr>
<td>Moody's Baa Index</td>
<td>0.03</td>
<td>0.25**</td>
</tr>
<tr>
<td>S&amp;P 500 P/B Ratio</td>
<td>0.59**</td>
<td>-1.1**</td>
</tr>
<tr>
<td>3m Repo Rate</td>
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<td>VIX</td>
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</tr>
<tr>
<td>WTI</td>
<td>-0.26*</td>
<td>0.51**</td>
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<tr>
<td>TED Spread</td>
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<td>Dow Jones Real Estate Index</td>
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<td>U.S. 5y Breakeven Inflation</td>
<td>0.09</td>
<td>0.07</td>
</tr>
</tbody>
</table>

** Significant at a 99% confidence level
* Significant at a 95% confidence level

MCMC Average Hit Rate = 42%, Naive Hit Rate = 33%

Source: CRSP, Bloomberg, WRDS, OFR analysis
Hierarchical Model (Before Crisis)

Macro Variables (z-scores)

- 3-Month GCF Repo Rate
- TED Spread
- LIBOR - OIS Spread

Macro Variables (z-scores)

- VIX
- Dow Jones U.S. Real Estate Index
- S&P 500 P/B Ratio

Macro Variables (z-scores)

- Moody's Baa Corp Bond Yield
- Yield Curve: 10yr less 2yr Treas
- WTI Oil
- DXY Dollar Index

Source: CRSP, Bloomberg, WRDS, OFR analysis
Hierarchical Model (Before Crisis)

Macro Variables (z-scores)

- VIX
- Dow Jones U.S. Real Estate Index
- S&P 500 P/B Ratio

BNP Paribas halts redemptions Aug 2007

Source: CRSP, Bloomberg, WRDS, OFR analysis
Hierarchical Model (Before Crisis)

Macro Variables
(z-scores)

- 3-Month GCF Repo Rate
- TED Spread
- LIBOR - OIS Spread

BNP Paribas halts redemptions Aug 2007

Source: CRSP, Bloomberg, WRDS, OFR analysis
Hierarchical Model (Before Crisis)

No Lag

Lag 15

Source: CRSP, Bloomberg, WRDS, OFR analysis

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Next Steps: Under Construction

Accounting for Missing Data

- Incorporating a feature where we can have missing observations in our input data
- Create a Bayesian Factor model, where the missing price impacts are treated as unobserved values which can be estimated in a manner that is consistent with the factor structure
- The program will assume that a ‘reasonable guess’ of the missing value comes in with the dataset

Model estimation and different macro variables

- How would the model perform over multiple crises? We need to explore performance for a range of different periods of extreme liquidity, outside of just 2008.
- This may lead us to conclude that the impact of different macro variables on predicting liquidity changes over time, ultimately leading us to developing a dynamic component in the model.

Alternative asset markets

- Our initial analysis looked at the equity markets, corporate bond markets, and VIX and WTI futures markets; we plan to expand to other contracts/securities and eventually add an international aspect
Thanks!