Credit Contagion from Counterparty Risk

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Credit model meltdown

Dealers still to achieve consensus on correlation models

Contracts for difference
Will the FSA impose disclosure rule?

CMS spread options
Few choices for steepener investors

Municipal bonds
Muni structures find favour in Asia

Cutting edge
Retail banking
2006 IACPM/ISDA Study: CONVERGENCE OF CREDIT CAPITAL MODELS

Setup: $100 billion notional, 3000 names
Bottom line: models are within 3% of the average, when using same (normal) copula and correlations

<table>
<thead>
<tr>
<th>Default Only ($MM)</th>
<th>Expected Loss</th>
<th>Capital at 99.90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>WG Run of PM with spreads and risk free rate set to zero</td>
<td>563.4</td>
<td>3,791.2</td>
</tr>
<tr>
<td>WG Run of CM</td>
<td>561.6</td>
<td>3,533.2</td>
</tr>
<tr>
<td>WG Run of CR+</td>
<td>563.8</td>
<td>3,662.0</td>
</tr>
</tbody>
</table>

Dec 06 – ICBI Geneva Risk Management Conference
Dec-06: Inception of paper
May-07: First submission
Jan-08: Second submission
Jun-08: Third submission
Nov-08: Fourth submission
Dec-08: Paper accepted
Paper published?
Credit Contagion

(1)
Correlations in Credit Risk Models
Correlation Models: Why?

- Default correlations are the most important drivers of the tails of portfolio credit risk distributions.
- Empirically, default correlations are positive, which increases portfolio risk.
  - Example: wave of defaults in airlines, telecoms (56% of all bankruptcies in 2002)
  - Losses on CDOs “safe” tranches.
- Default correlations cannot be measured directly, and must be inferred from a model.
Tails of Portfolio Credit Risk Distributions

99.9% VAR

<table>
<thead>
<tr>
<th>Rating</th>
<th>CreditMetrics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\rho V=0.05$</td>
</tr>
<tr>
<td>Aa</td>
<td>0.32%</td>
</tr>
<tr>
<td>Baa</td>
<td>0.98%</td>
</tr>
<tr>
<td>B</td>
<td>7.18%</td>
</tr>
</tbody>
</table>

Correlation of asset values $\rho V$ is the most important driver of Value at Risk (VAR), or economic capital as a buffer against losses.

Source: Grundke (2004)--500, 3-year zero-coupon bonds, normal copula
Parameters:
- Portfolio value: $100
- Default probability = 1.0%
- Step Number = 1
- Loss per bond $100.00

Distribution:
- Mean = $1.00
- SD = $9.95
- 99% VAR = $99.00
Factor Models: Principles

- We need to simplify the correlation matrix
- Factor models generate joint movements in defaults:

  (1) Defaults are driven by **common risk factors**
      » common negative shocks to cash flows
      » e.g., Basel II is calibrated to a 1-factor model

  (2) **Conditional** on these common factors, defaults are independent
Factor Models: Applications

- **Structural models**: (1) generate correlations in asset values from equity data, (2) infer default correlations from movements in asset value below threshold
  - CreditMetrics: joint multivariate normal
  - in general, other copulas can be used
  - default correlations lower than asset correlations

- **Reduced-form models**: generate correlations between defaults by allowing hazard rates to be stochastic and correlated with macroeconomic variables
Correlation Models:

Issues

- **Factor models** cannot explain fully clustering of defaults: Das, Duffie, and Kapadia (2005)

*Credit Contagion* - Philippe Jorion
Illustration for Structured Credit

(1) Fix default probability to desired credit rating
(2) Build portfolio distribution using a model
(3) Select the width of the subordinated tranches that will achieve the credit rating
### Default Probabilities

**Standard & Poor's Cumulative Default Rates (%)**

**Global Corporates, 1981 to 2006**

<table>
<thead>
<tr>
<th>Rating</th>
<th>Y1</th>
<th>Y2</th>
<th>Y3</th>
<th>Y4</th>
<th>Y5</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>0.00</td>
<td>0.00</td>
<td>0.09</td>
<td>0.19</td>
<td>0.29</td>
</tr>
<tr>
<td>AA</td>
<td>0.01</td>
<td>0.05</td>
<td>0.10</td>
<td>0.20</td>
<td>0.32</td>
</tr>
<tr>
<td>A</td>
<td>0.06</td>
<td>0.17</td>
<td>0.31</td>
<td>0.47</td>
<td>0.68</td>
</tr>
<tr>
<td>BBB</td>
<td>0.24</td>
<td>0.71</td>
<td>1.23</td>
<td>1.92</td>
<td>2.61</td>
</tr>
<tr>
<td>BB</td>
<td>1.07</td>
<td>3.14</td>
<td>5.61</td>
<td>7.97</td>
<td>10.10</td>
</tr>
<tr>
<td>B</td>
<td>4.99</td>
<td>10.92</td>
<td>15.90</td>
<td>19.76</td>
<td>22.55</td>
</tr>
<tr>
<td>CCC/C</td>
<td>26.29</td>
<td>34.73</td>
<td>39.96</td>
<td>43.19</td>
<td>46.22</td>
</tr>
</tbody>
</table>
Building the Tranche

Number of defaults

Frequency

Required width of junior tranches

Fix target default probability: 0.29%

Risk Management - Philippe Jorion
Distribution of Defaults: 125 BBB Credits

Default probability = 2.5%
Asset correlation = 0.20

Risk Management - Philippe Jorion

Default correlation = 0.04
Cumulative Distribution of Defaults

Target: 0.29%

27 defaults

22% subordination

78% of the structure is rated AAA

Number of defaults

Risk Management - Philippe Jorion
Distribution of Defaults: 125 BBB Credits

Default probability = 2.5%
Asset correlation = 0.50

With default correlation of 1, 97.5% at 0, 2.5% at 1
Default correlation = 0.16
Distribution of Defaults: Effect of Correlation

- Correlation = 0.20
- Correlation = 0.50

Number of defaults

Risk Management - Philippe Jorion
Cumulative Distribution of Defaults

Actual: 2.4%

27 defaults

Number of defaults

Risk Management - Philippe Jorion

Actual rating should be BBB, not AAA
Credit Contagion

(2)
Counterparty Risk as Another Channel of Credit Correlation
Second-Generation Correlation Model

- Excess clustering could be explained by **counterparty risk**, which occurs when default of one firm causes financial distress on other firms with which it has close business ties.
- No empirical application yet: focus of this paper.

Credit Contagion - Philippe Jorion
Measuring Exposures

- We collect a large sample of 251 bankruptcy filings over 1999-2005
- Filings include the list of top 20 unsecured creditors
  - exposures are trade credit, bonds, loans, services
  - 570 creditors, industrials and financials
- This is the first paper to study such data and provides a direct test of counterparty risk
  - Dahiya et al (2003) examine wealth effects of defaults on lead lending banks
Credit Contagion Effects

- We analyze the announcement effect on the creditor’s stock price and CDS spread
  » useful if the announcement is not totally anticipated; this is indeed the case because the debtor’s stock price falls by -30% over 3-day period
  » identity of creditors may not be known
- We track the creditor for signs of financial distress, i.e. credit downgrade or delisting: physical world
- To identify pure counterparty risk, we control for creditor industry effects

Credit Contagion - Philippe Jorion
Credit Contagion Effects

- The stock price effect can be decomposed into (1) the “expected credit loss”, from the exposure and recovery rate (balance sheet), (2) the NPV of lost future profits, especially for customer-lender relationships (income)

\[
\text{Rate of Return} = -\exp(1 - \text{REC}) - \text{NPV}
\]

> Example: XO Comm was unsecured creditor to Teligent, which went bankrupt in May 2001; stock price lost 50%; went bankrupt in June 2002

- So, the coefficient on ECL could be greater than one, or less if effect anticipated
Credit Contagion

Credit Default Swaps
CDS and Corporate Bond Markets

Notional (Billions of U.S. Dollars)

CDS
Corporate Bonds

Year:

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CDS vs. Stock and Bond Prices

- Comprehensive data source of CDS over 2001-2005 from MarkIt
- CDS superior to corporate-Treasury spreads
  - more transactions, better prices
  - corporate spreads may reflect liquidity, tax effects
  - CDS lead corporate spreads
- CDS complementary to stock market, as some events such as increase in leverage create wealth transfers from bonds to stockholders

Credit Contagion - P.Jorion
WorldCom Bankruptcy

Credit Contagion - P. Jorion
CDS Sample

- Use only five-year spreads
  » most liquid and constitute over 85% of market
- Use only quotes for senior unsecured debt with a modified restructuring (MR) clause and denominated in U.S. dollars
Credit Contagion

(3)

Empirical Analysis
## Bankruptcy Events

### Panel A: Number of Creditors within a Creditor Portfolio

<table>
<thead>
<tr>
<th>Year</th>
<th>Nb. of Bankruptcy Events</th>
<th>Nb. of Industry</th>
<th>Nb. of Event-Creditors</th>
<th>Nb. of Creditors</th>
<th>Total Credit Amount ($ million)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>34</td>
<td>29</td>
<td>99</td>
<td>91</td>
<td>292</td>
</tr>
<tr>
<td>2000</td>
<td>35</td>
<td>30</td>
<td>76</td>
<td>73</td>
<td>585</td>
</tr>
<tr>
<td>2001</td>
<td>44</td>
<td>37</td>
<td>145</td>
<td>140</td>
<td>4,405</td>
</tr>
<tr>
<td>2002</td>
<td>23</td>
<td>20</td>
<td>65</td>
<td>60</td>
<td>852</td>
</tr>
<tr>
<td>2003</td>
<td>41</td>
<td>32</td>
<td>128</td>
<td>122</td>
<td>536</td>
</tr>
<tr>
<td>2004</td>
<td>35</td>
<td>34</td>
<td>84</td>
<td>77</td>
<td>198</td>
</tr>
<tr>
<td>2005</td>
<td>39</td>
<td>35</td>
<td>97</td>
<td>89</td>
<td>1,136</td>
</tr>
<tr>
<td>Total</td>
<td>251</td>
<td>146</td>
<td>694</td>
<td>570</td>
<td>8,004</td>
</tr>
</tbody>
</table>
## Credit Amounts

### Panel B: Credit Amount by Creditor

<table>
<thead>
<tr>
<th>Creditor</th>
<th>Credit Type</th>
<th>Nb. of Event-Creditors</th>
<th>Total</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Median</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industrials</td>
<td>Trade credit</td>
<td>570</td>
<td>1,838</td>
<td>3.2</td>
<td>8.8</td>
<td>0.6</td>
<td>79</td>
<td>0</td>
</tr>
<tr>
<td>Bond</td>
<td></td>
<td>13</td>
<td>76</td>
<td>5.9</td>
<td>7.3</td>
<td>1.5</td>
<td>23</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>583</td>
<td>1,914</td>
<td>3.3</td>
<td>8.7</td>
<td>0.6</td>
<td>79</td>
<td>0</td>
</tr>
<tr>
<td>Financials</td>
<td>Trade credit</td>
<td>65</td>
<td>176</td>
<td>2.7</td>
<td>9.2</td>
<td>0.3</td>
<td>66</td>
<td>0</td>
</tr>
<tr>
<td>Bond</td>
<td></td>
<td>12</td>
<td>352</td>
<td>29.4</td>
<td>32.3</td>
<td>16.1</td>
<td>91</td>
<td>0</td>
</tr>
<tr>
<td>Loan</td>
<td></td>
<td>34</td>
<td>5,561</td>
<td>163.6</td>
<td>338.2</td>
<td>66.4</td>
<td>1,750</td>
<td>2.4</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>111</td>
<td>6,090</td>
<td>54.9</td>
<td>199.5</td>
<td>1.7</td>
<td>1,750</td>
<td>0</td>
</tr>
</tbody>
</table>
Empirical Results: Counterparty

• CASC rating-adjusted spread change
  \[ AS_{jt} = S_{jt} - I_{rt} \]
  » Investment Grade CDX, High Yield CDX

• CAR industry-adjusted stock return
  » using market model relative to industry

• Results for creditors:
  » contagion effect: 5bp spread change over 11 days,
    (vs. 46bp BBB+; 59bp BBB; 87bp BBB-)
  » industrials are more affected than financials
  » consistent effect for equities, but weaker
## Effect on Creditors

<table>
<thead>
<tr>
<th>Day</th>
<th>Abnormal Equity Returns</th>
<th>Adjusted CDS Spread Change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (%)</td>
<td>T-statistic</td>
</tr>
<tr>
<td></td>
<td>All Creditors (N=251)</td>
<td></td>
</tr>
<tr>
<td>-1,1</td>
<td>-0.90</td>
<td>-4.09***</td>
</tr>
<tr>
<td>-5,5</td>
<td>-1.90</td>
<td>-4.51***</td>
</tr>
<tr>
<td></td>
<td>Industrial Firms (N=230)</td>
<td></td>
</tr>
<tr>
<td>-1,1</td>
<td>-0.93</td>
<td>-3.68***</td>
</tr>
<tr>
<td>-5,5</td>
<td>-2.29</td>
<td>-4.73***</td>
</tr>
<tr>
<td></td>
<td>Financial Institutions (N=76)</td>
<td></td>
</tr>
<tr>
<td>-1,1</td>
<td>-0.74</td>
<td>-2.09**</td>
</tr>
<tr>
<td>-5,5</td>
<td>-0.34</td>
<td>-0.50</td>
</tr>
</tbody>
</table>
Counterparty Risk Model: Jarrow-Yu

- Closed-form solutions for a model with two firms only: a primary firm A and a secondary firm B that provides credit to A; model assumes constant unconditional default intensities.

- Model predicts a jump in the credit spread, from 105bp to **151bp** with flattening; in fact, from 105bp to **113bp** keeping upward slope.

- Thus, this particular model is unable to reproduce the actual change in CDS spreads.
  - But, more than one counterparty, and other reasons for upward slope in credit spreads.
Fitting the Creditor CDS Term Structure to the Jarrow-Yu Model
Cross-Sectional Analysis

\[ \text{CAR} = \alpha + \beta_1 \text{EXP} + \beta_2 \text{REC} + \beta_1^* \text{EXP}(1-\text{REC}) + \beta_3 \text{CORR} + \beta_4 \text{VOL} + \beta_5 \text{LEV} + \varepsilon \]

- **EXP**, exposure/MVE
  - average credit exposure is 0.32% of total market value for industrial creditors, and 0.16% for financial institutions
- **REC**, recovery rate
- **EXP(1-REC) = ECL**, expected credit loss
- **CORR**, correlation of equity returns (c,b) 252D
- **VOL**, volatility of creditor equity
- **LEV**, leverage of creditor

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Empirical Results: Explaining Creditor Effects

- Cross-sectional regressions of equity CAR on
  - exposure scaled by MVE gives negative coefficients, as greater exposure increases loss
  - recovery rate for borrower industry gives positive coefficients, as greater recovery lowers loss
  - ECL = EXP(1-REC) has coefficient close to –1
  - previous equity correlation gives positive coefficients, reflecting similarities in cash flows
  - creditor volatility and leverage give negative coefficients, reflecting greater distress

- All signs are inverted using CDS spreads
## Cross-Sectional Results

- For stocks, coefficients on EXP is negative, on REC is positive, and ECL close to -1
  - For financials, -2 (perhaps learning about all loans)
- For CDS, coefficients have reverse sign

<table>
<thead>
<tr>
<th></th>
<th>Equity</th>
<th>CDS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EXP</td>
<td>REC</td>
</tr>
<tr>
<td>All (N=694)</td>
<td>-0.83***</td>
<td>2.69*</td>
</tr>
<tr>
<td>Industrials (N=583)</td>
<td>-0.82***</td>
<td>2.66</td>
</tr>
<tr>
<td>Financials (N=111)</td>
<td>-1.39***</td>
<td>2.67*</td>
</tr>
<tr>
<td>Liquidation (N=79)</td>
<td>-1.71**</td>
<td>27.17***</td>
</tr>
</tbody>
</table>

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Financial Distress of Creditors

- Follow creditors for 1 year, comparing to a control sample of firms with the same rating and in the same industry and size group
  - Frequency of financial distress significantly higher for creditors, suggesting strong contagion effects
  - Industrials are much more affected than financials

<table>
<thead>
<tr>
<th>Fraction of firms</th>
<th>Industrials</th>
<th>Financials</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Creditor</td>
<td>Control</td>
</tr>
<tr>
<td>Delisted</td>
<td>1.9%</td>
<td>0.3%***</td>
</tr>
<tr>
<td>Downgraded</td>
<td>23.6%</td>
<td>8.3%***</td>
</tr>
</tbody>
</table>
Implications for Portfolio Risk

- Simulations calibrated to empirical results
- Homogeneous sample, $N=100$, PD=1% (BB)
- One-factor model with asset $\rho=0.20$
  1. With no counterparty effect, default $\rho=0.024$, 23 defaults at the 99.9% confidence level
  2. With counterparty effects, $K=3$ creditors, PD changes by 0.5%, iterate on multiple defaults, cutoff moves from 23 to 29 defaults
     With $K=10$ creditors, cutoff is 65 defaults
- Ignoring credit contagion understates capital

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<table>
<thead>
<tr>
<th>Simulations of Portfolio Distributions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Number of counterparties</td>
</tr>
<tr>
<td>No Counterparty Risk</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Probability of default (PD)</td>
</tr>
<tr>
<td>1.00% 1.05%</td>
</tr>
<tr>
<td>Conditional PD</td>
</tr>
<tr>
<td>1.00% 1.05%</td>
</tr>
<tr>
<td>Default correlation:</td>
</tr>
<tr>
<td>No counterparty effect</td>
</tr>
<tr>
<td>0.0237 0.0244</td>
</tr>
<tr>
<td>With first count.def.</td>
</tr>
<tr>
<td>0.0278 0.0258</td>
</tr>
<tr>
<td>With multiple count.def.</td>
</tr>
<tr>
<td>0.0291 0.0262</td>
</tr>
<tr>
<td>Average default rate</td>
</tr>
<tr>
<td>1.000% 1.050%</td>
</tr>
<tr>
<td>Number of defaults:</td>
</tr>
<tr>
<td>99% percentile</td>
</tr>
<tr>
<td>9 9</td>
</tr>
<tr>
<td>99.9% percentile</td>
</tr>
<tr>
<td>16 16</td>
</tr>
<tr>
<td>99.99% percentile</td>
</tr>
<tr>
<td>23 23</td>
</tr>
</tbody>
</table>

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N=500, Conditional PD=1.25%

<table>
<thead>
<tr>
<th>Number of default risk</th>
<th>No Counterparty</th>
<th>3</th>
<th>3</th>
<th>3</th>
<th>3</th>
<th>Counterparty Risk</th>
<th>1</th>
<th>10</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability of default</td>
<td>1.00% 1.02%</td>
<td>1.00% 1.00% 1.00% 1.00%</td>
<td>1.00% 1.00% 1.00% 1.00%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Conditional PD</td>
<td>1.00% 1.02%</td>
<td>1.25% 1.10% 1.50% 2.00%</td>
<td>1.25% 1.25% 1.50% 1.50%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Default correlation:</td>
<td></td>
<td>1.0243 0.0246</td>
<td>0.0243 0.0243 0.0243 0.0243</td>
<td>0.0243 0.0243 0.0243 0.0243</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No counterparty</td>
<td></td>
<td>0.0261 0.0250</td>
<td>0.0279 0.0312</td>
<td>0.0249 0.0309 0.0380</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First cr. default</td>
<td></td>
<td>0.0262 0.0250</td>
<td>0.0285 0.0378</td>
<td>0.0249 0.0332 0.0595</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multiple cr. default</td>
<td></td>
<td>1.000% 1.020%</td>
<td>1.022% 1.009% 1.046% 1.098%</td>
<td>1.007% 1.086% 1.229%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average default rate</td>
<td></td>
<td>39 39</td>
<td>40 39 42 46</td>
<td>39 46 58</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of defaults:</td>
<td></td>
<td>75 77</td>
<td>81 78 88 103</td>
<td>77 100 166</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>99% percentile</td>
<td></td>
<td>115 117</td>
<td>127 121 136 159</td>
<td>121 168 306</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>99.9% percentile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>99.99% percentile</td>
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Credit Contagion

(5)

Conclusions
“Irresistible Reasons for Better Models of Credit Risk”
Darrell Duffie – Financial Times, April 2004

• “Financial institutions are working hard to improve their modelling of credit risk”
• “Yet much remains to be done. In particular, it should be a priority to develop more realistic methods for quantifying correlations among the credit risks of corporate borrowers”
• “…this is one area of finance where our ability to structure financial products may be running ahead of our understanding of the implications”

Credit Contagion - Philippe Jorion
Conclusions (1)

- We need more research at the company level, modeling intra-industry, counterparty effects.
- Usual credit models extrapolate correlations from stock price histories (e.g. with a normal copula), which has limitations.
- It is more useful to focus directly on cross-sectional correlations across credit events, i.e. within the tails.
- Factor models have limitations.
Conclusions (2)

- Counterparty risk can lead to contagion effects, especially for industrial creditors
  - Abnormal equity return is -1.9%, or $174m
  - CDS spreads increase by 5bp
  - Effects are related to the size of ECL
- Firms suffering a large credit loss more likely to experience downgrade or default later
- Simulations calibrated to these results indicate that economic capital measures are understated by conventional credit models