Credit Contagion from Counterparty Risk

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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

Correlation Models

- Doubly stochastic models:

  (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
  - CreditMetrics: joint multivariate normal

  (2) Conditional on these common factors, defaults are independent
- Issues: cannot fully explain default correlations
  - Das et al.(2007) find evidence of excess clustering of defaults conditional on their set of common factors
  - major problem for portfolio credit risk models
    - Insufficient risk capital provisions for banks and a higher systemtic risk
    - Risk of senior tranches of CDOs understated

Correlation Models

- Second-generation models try to explain remaining correlations through additional channel of default correlation
  - Bayesian updating of the conditional distribution of the unobservable frailty factors:
    - Collion-Dufresne et al. (2003), Giesecke (2004), etc.
    - Duffie et al. (2008) find evidence for the presence of unobservable risk factors
  - Azizpour and Giesecke (2008) find evidence of *additional* impact of contagion beyond that due to firms' exposure to observable or unobservable risk factors.
  - Evidence of intra-industry contagion effects: Lang and Stulz (1992), Jorion and Zhang (2007)

Counterparty Risk

- Default of one firm causes financial distress on other firms with which it has close business ties
- Anecdotal evidence
  - "The Kmart effect: Many companies feel the pain" (CBS Marketwatch, 1/23/02)
  - "EDS joins US Airways casualties" (Financial Times, 9/17/04)
  - Teligent Inc. and XO Communications
    - May 21, 2001: Teligent Inc. Inc filed for Chapter 11 bankruptcy
    - July 26, 2001: XO Communications reported a wider earnings loss due to loss of business of Teligent Inc.
    - Nov.28, 2001: XO Communications was delisted
    - Feb. 23, 2002: XO Communications announced plans to file for Chapter 11 bankruptcy
    - June 18, 2002: XO Communications filed for Chapter 11 bankruptcy.

Counterparty Risk

- Theoretical studies
  - Davis and Lo (2001), Jarrow and Yu (2001), and Boissay (2006)
- No empirical application yet: focus of this paper
  - Magnitude? Drivers? No empirical evidence
  - Information on counterparty relationship is hard to obtain
  - We identify creditor-borrower relationship by examining firms filing for Chapter 11 bankruptcy that publicized top creditors

Research Questions

- What are the short-term and long-term effects of bankruptcy of a firm on its creditors?
- Is counterparty effect different for industrial creditors compared to financial lenders?
  - Industrial creditors
    - Trade credit is not well diversified / involuntary lending in nature
    - Business relationship is impaired (NPV effect)
  - Financial creditors
    - Loans or bonds are well diversified / higher recovery rate / hedging
    - Reputation loss?
- What are other determinants of counterparty effect?
  - Credit exposure, recovery rate, correlation, volatility, leverage, hedging, etc.
- Is counterparty effect stronger if the debtor is also a major customer of the creditor? Is counterparty effect stronger when a firm liquidates?

Essential Results

- Creditors experience negative abnormal equity returns and increases in CDS spreads
  - Negative industry-adjusted abnormal return of -1.9% around the [-5,5] event window, or a loss of $174mn for a median creditor.
  - 5/13bp index-adjusted CDS spread change over 11/70 days, 13bp same as from BBB+ to BBB
- Creditors are more likely to suffer from financial distress later.
  - Within one or two years, the probability of a downgrade of a company suffering a credit loss is about 3 times the unconditional probability.
  - The control samples have a much lower fraction of firms experiencing a delisting within one year or two.
- The effect is stronger for industrial creditors than financials. The counterparty effects are also associated with the relative size of the exposure, the recovery rate, and previous stock return correlations.
- The effect is stronger for creditors for whom the bankrupt firm represents a large fraction of sales, and when a firm liquidates rather than reorganizes.

Measuring Exposures

- We hand-collected credit relationship information on 721 Chapter 11 bankruptcies during 1999-2005.
- Filings include the list of top 20 unsecured creditors
  - Exposures are trade credit, bonds, loans
  - Excluding creditors that have other informative corporate news on their own.
  - Require creditors having CRSP & COMPUSTAT information
  - The final equity sample consists of 251 bankruptcies, 694 event-creditor observations, 570 creditors, and 146 industries.
- The Credit default swap (CDS) final sample consists of 128 bankruptcies, 209 event-creditor observations, 178 creditors, and 91 industries.
  - Require creditors having CDS daily quotes on five-year CDS spreads for senior unsecured debt with a modified restructuring (MR) clause and denominated in U.S.
- 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

Distribution of Bankruptcy Events

Panel A: Number of Creditors within a Creditor Portfolio					
Year	N of Bankruptcy Events	N of Industry	N of Event–Creditors	N of Creditors	Total Credit Amount ($ million)
1999	34	29	99	91	292
2000	35	30	76	73	585
2001	44	37	145	140	4,405
2002	23	20	65	60	852
2003	41	32	128	122	536
2004	35	34	84	77	198
2005	39	35	97	89	1,136
Total	251	146	694	570	8,004

Panel B: Number of Creditors within a Creditor Portfolio					
N of Events	Mean	Std Dev	Median	Max	Min
251	2.8	1.8	2.0	10	1

Panel C: Number of Credit Claims per Creditor					
N of Creditors	Mean	Std Dev	Median	Max	Min
570	1.2	1.0	1.0	19	1

Description of Credit Claims

Panel A: Credit Amount by Credit Type

Credit Type	Nb.of Event–Creditors	Distribution of Amount ($ million) Total	Mean	Std Dev	Median	Max	Min
Trade credit	635	2,014	3.2	8.8	0.5	79	0
Bond	25	429	17.1	25.4	5.5	91	0
Loan	34	5,561	163.6	338.2	66.4	1,750	2.4
Total	694	8,004	11.5	82.1	0.6	1,750	0

Panel B: Credit Amount by Creditor

Creditor	Credit Type	Nb.of Event–Creditors	Distribution of Amount ($ million) Total	Mean	Std Dev	Median	Max	Min
Industrials	Trade credit	570	1,838	3.2	8.8	0.6	79	0
	Bond	13	76	5.9	7.3	1.5	23	0
	Total	583	1,914	3.3	8.7	0.6	79	0
Financials	Trade credit	65	176	2.7	9.2	0.3	66	0
	Bond	12	352	29.4	32.3	16.1	91	0
	Loan	34	5,561	163.6	338.2	66.4	1,750	2.4
	Total	111	6,090	54.9	199.5	1.7	1,750	0

Method

- For each event, we construct a creditor portfolio as an equally-weighted portfolio of firms.
- Apply the standard event study method to creditor portfolios to obtain CAR [MacKinlay (1997)]
  - Market index as the benchmark
  - Industry portfolio as the benchmark (net of industry effect)
- For each creditor portfolio, calculate cumulative abnormal CDS spread changes (CASCs) adjusting for CDS rating indices.

$$AS_{jt} = S_{jt} - I_{rt} \qquad CASC_j(t_1, t_2) = AS_{jt_2} - AS_{jt_1}$$

  - Investment-Grade CDX, High-Yield CDX

Effect on Creditors

	Abnormal Equity Returns			Adjusted CDS Spread Change		
Day	**Mean (%)**	**T-statistic**	**% (<0)**	**CASC**	**T-statistic**	**% (>0)**
	All Creditors (N=251)			**All Creditors (N=128)**		
-1,1	-0.90	-4.09***	57.6	2.11	3.24***	68.0
-5,5	-1.90	-4.51***	55.6	5.17	4.15***	67.2
	Industrial Firms (N=230)			**Industrial Firms (N=111)**		
-1,1	-0.93	-3.68***	56.6	2.47	3.17***	70.3
-5,5	-2.29	-4.73***	57.0	5.58	3.74***	66.7
	Financial Institutions (N=76)			**Financial Institutions (N=30)**		
-1,1	-0.74	-2.09**	61.2	0.13	0.13	56.7
-5,5	-0.34	-0.50	53.7	2.66	1.40	70.0

Cross-Sectional Analysis

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

- 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 252D
- VOL, volatility of creditor equity
- LEV, leverage of creditor

Counterparty Risk

- 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 supplier/lender relationships (income)

$$\boxed{\text{RATE OF RETURN} = -\text{EXP}(1 - \text{REC}) - \text{NPV}}$$

  – Example: Handleman had exposure of $65m to Kmart; market value loss was $100m
- So, the coefficient on EXP(1-REC) could be greater than one, or less if effect anticipated

Cross-Sectional Results

- 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

	Equity			CDS		
	EXP	REC	ECL	EXP	REC	ECL
All	-0.83***	2.69*	-1.01***	8.84***	-5.44	14.71***
Industrials	-0.82***	2.66	-1.00***	9.84***	-5.44	17.08***
Financials	-1.39***	2.67***	-2.09***	5.17***	-2.74	7.65***

Discussion: Effects When the Debtor Liquidates

- Effects should be stronger because the creditor will not only lose its exposure, but also lose its future business.
- We identify a sub-sample of firms that are likely to liquidate from their bankruptcy filings (32 events, 79 creditors)
- The coefficient on EXP(1-REC) is **-2.32**.**

Discussion: Effects on Creditors/Suppliers

- Firms have to disclose in their 10-Ks the identity of any customer representing more than 10% of total sales.
- We find six cases where the creditor lists the firm subsequently filing for bankruptcy as a major customer in the two fiscal years ending prior to the bankruptcy announcement date.
- The average 3-day, 11-day, and 70-day industry-adjusted CARs around *the bankruptcy announcement* dates are

  -9.23%, -23.34%***, and -53.17%***,** respectively.
- The average 3-day, 11-day, and 70-day industry-adjusted CARs around *the default dates* are

  -12.19%*, -18.71%***, and -51.21%***,** respectively.

Subsequent 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

Fraction of firms	Industrials		Financials	
	Creditor	Control	Creditor	Control
Delisted	1.9%	0.3%***	1.0%	0.2%
Downgraded	23.6%	8.3%***	14.0%	6.8%***

Implications for Portfolio Risk

- Simulations calibrated to empirical results
- Homogeneous sample, N=100, PD=1% (BB)
- One-factor model with asset corr.=0.20

(1) With no counterparty effect, default corr.=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

- Simulations suggest that the tails of the distribution, or economic capital measures, are severely understated by conventional credit models

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

- Financial institutions are working hard to improve their modeling 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

Conclusions

- This study focuses on contagion via counterparty risk at the *micro*-level as opposed to contagion at the *aggregate* economy level or the *industry* level.
- It is useful to focus directly on cross-sectional correlations around distress periods, i.e. within the tails.
- Counterparty risk can lead to severe contagion effects, especially when the creditor is also a major supplier, when the debtor liquidates, and when the exposure is greater.
- Firms suffering a credit loss are more likely to experience subsequent financial distresses