Credit Contagion from Counterparty Risk

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Risk

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Credit model meltdown

Dealers still to achieve consensus on correlation models

Contracts for difference
Will the FSA impose disclosure rules

CMS spread options
Few choices for steepener investors

Municipal bonds
Muni structures find favour in Asia

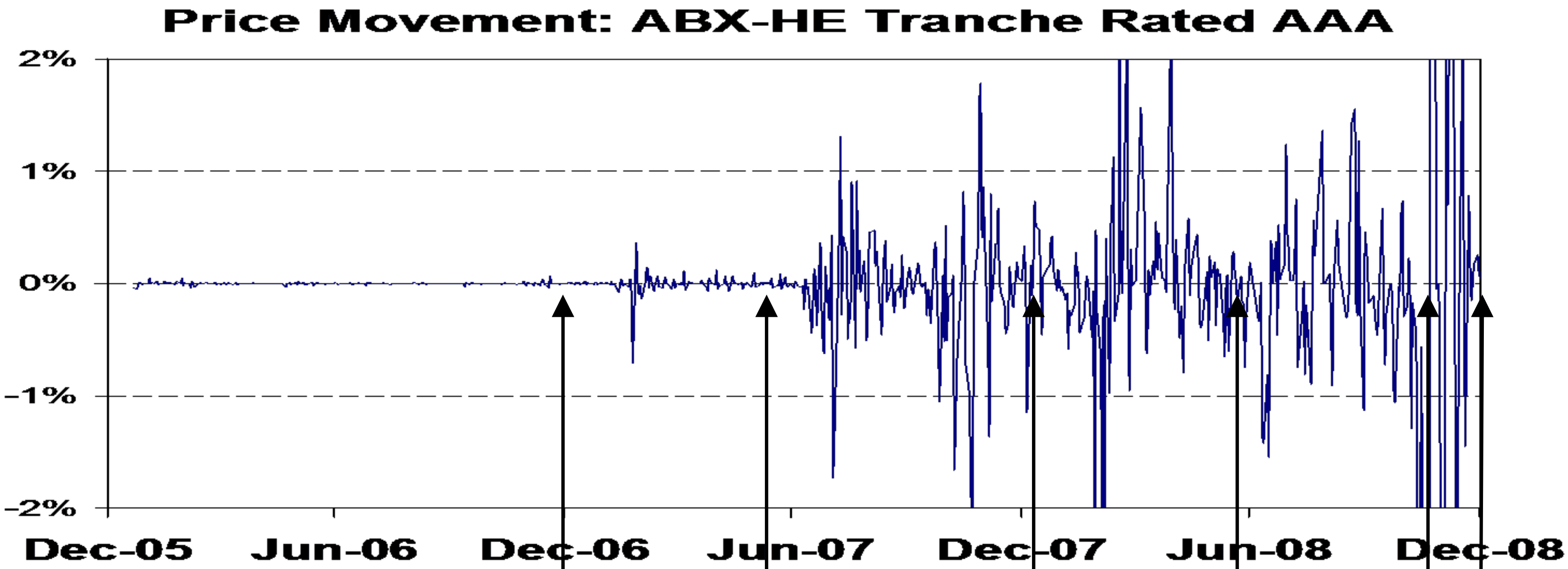
Cutting edge
Retail banking

2006 IACPM/ISDA Study: CONVERGENCE OF CREDIT CAPITAL MODELS

Exhibit 3 (Default Only)

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

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



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?

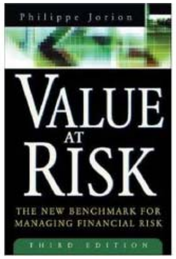
- Default correlations are the most important drivers of the tails of portfolio credit risk distributions
- Empirically, default correlations are positive, which increases portfolio risk
  - » example: wave of defaults in airlines, telecoms (56% of all bankruptcies in 2002)
  - » losses on CDOs "safe" tranches
- Default correlations cannot be measured directly, and must be inferred from a model

Tails of Portfolio Credit Risk Distributions

99.9% VAR

	CreditMetrics		
Rating:	$\rho V=0.05$	$\rho V=0.2$	$\rho V=0.5$
Aa	0.32%	0.68%	1.81%
Baa	0.98%	2.99%	9.24%
B	7.18%	18.19%	34.41%

⇨ Correlation of asset values ρV 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	**1.0%**
Step		Number
=	1	**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 <u>common risk factors</u>

» common negative shocks to cash flows

» e.g., Basel II is calibrated to a 1-factor model

(2) <u>Conditional</u> 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)

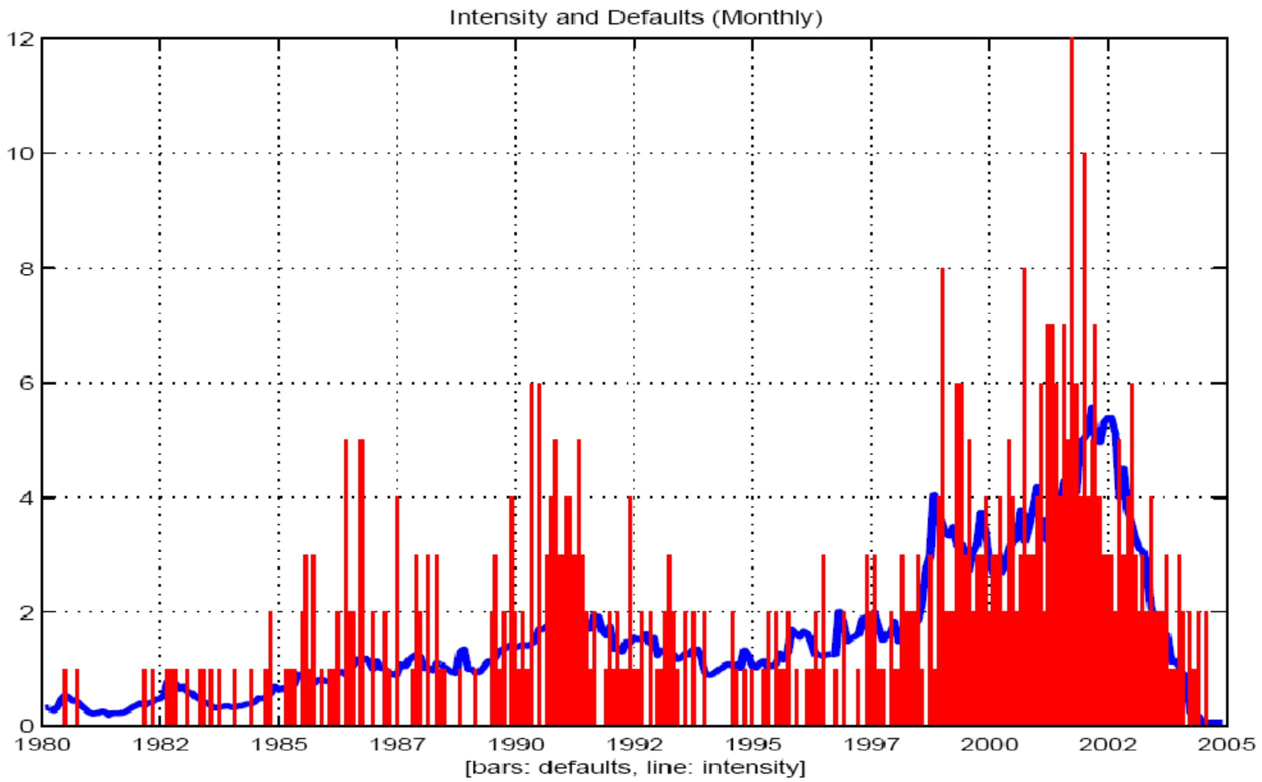


Illustration for Structured Credit

(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

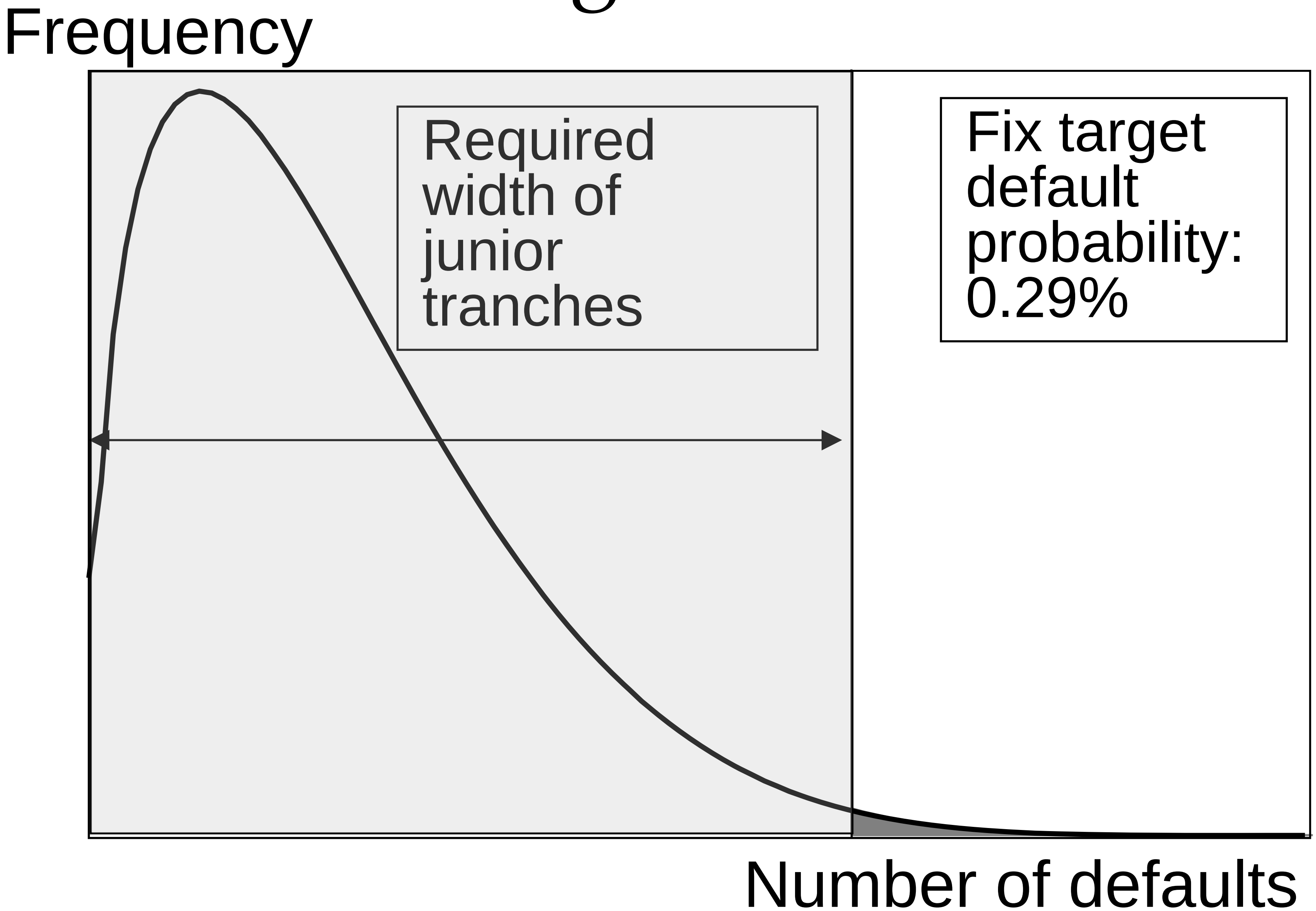
Default Probabilities

Standard & Poor's Cumulative Default Rates (%)

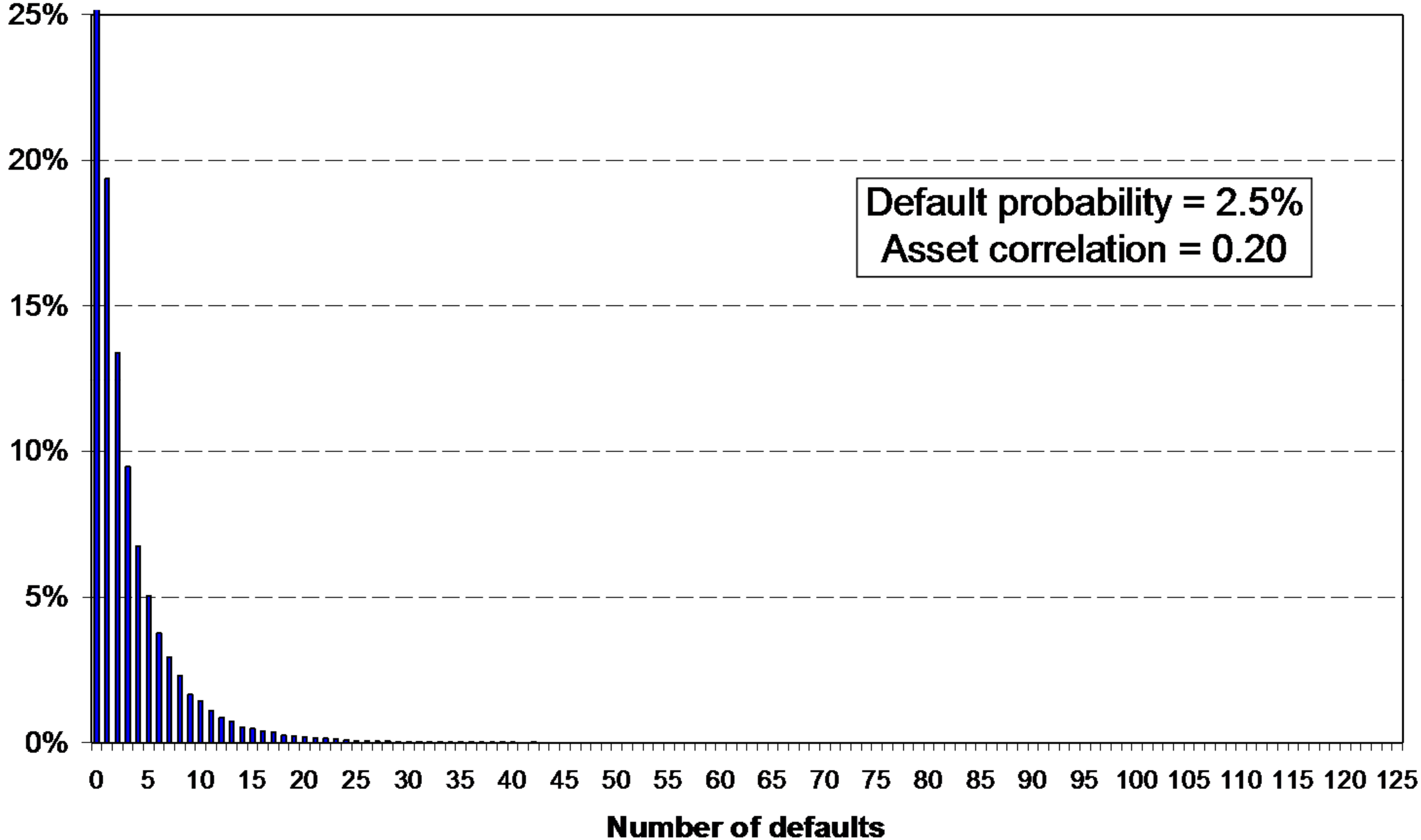
Global Corporates, 1981 to 2006

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

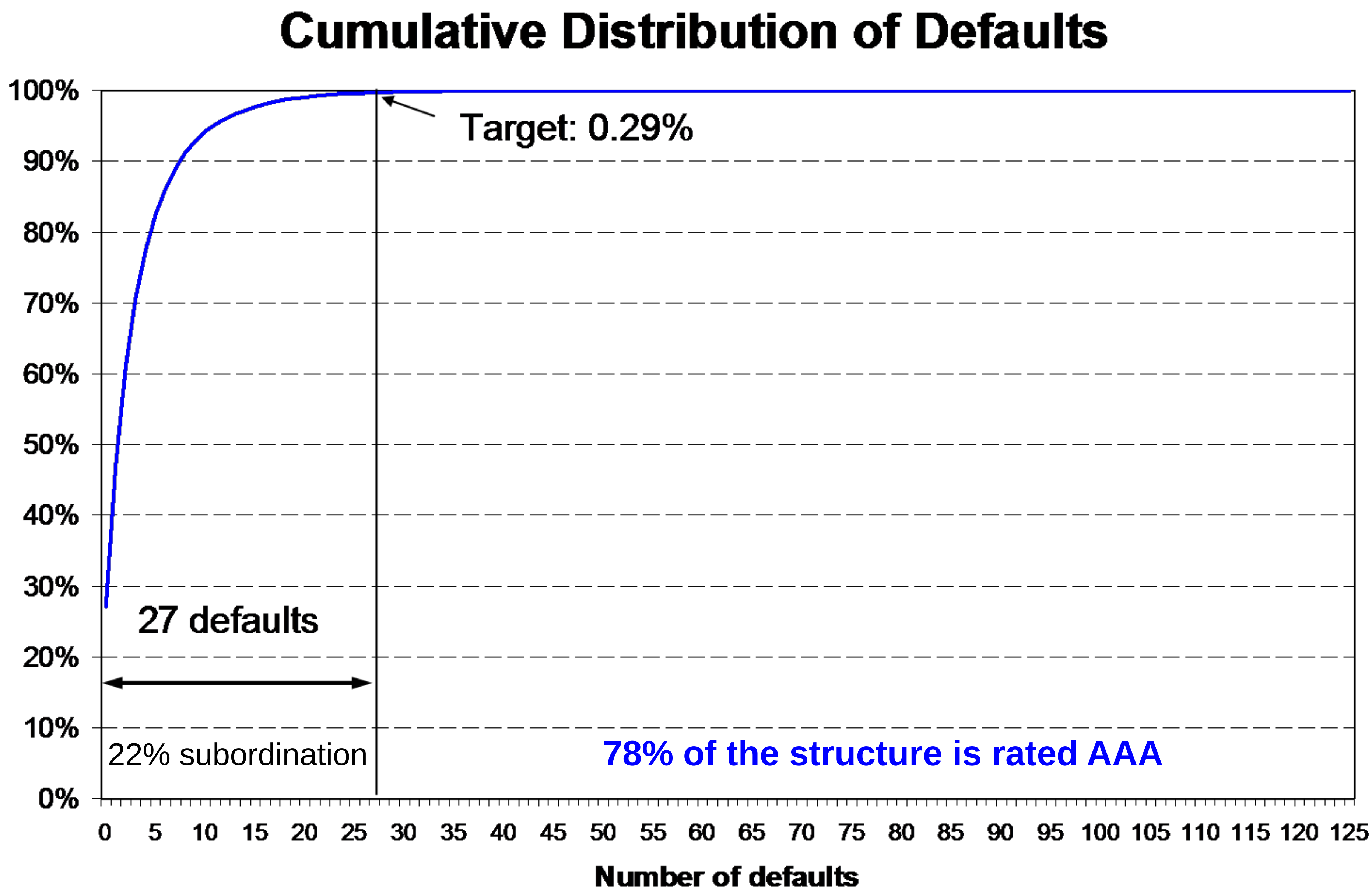
Building the Tranche



Distribution of Defaults: 125 BBB Credits

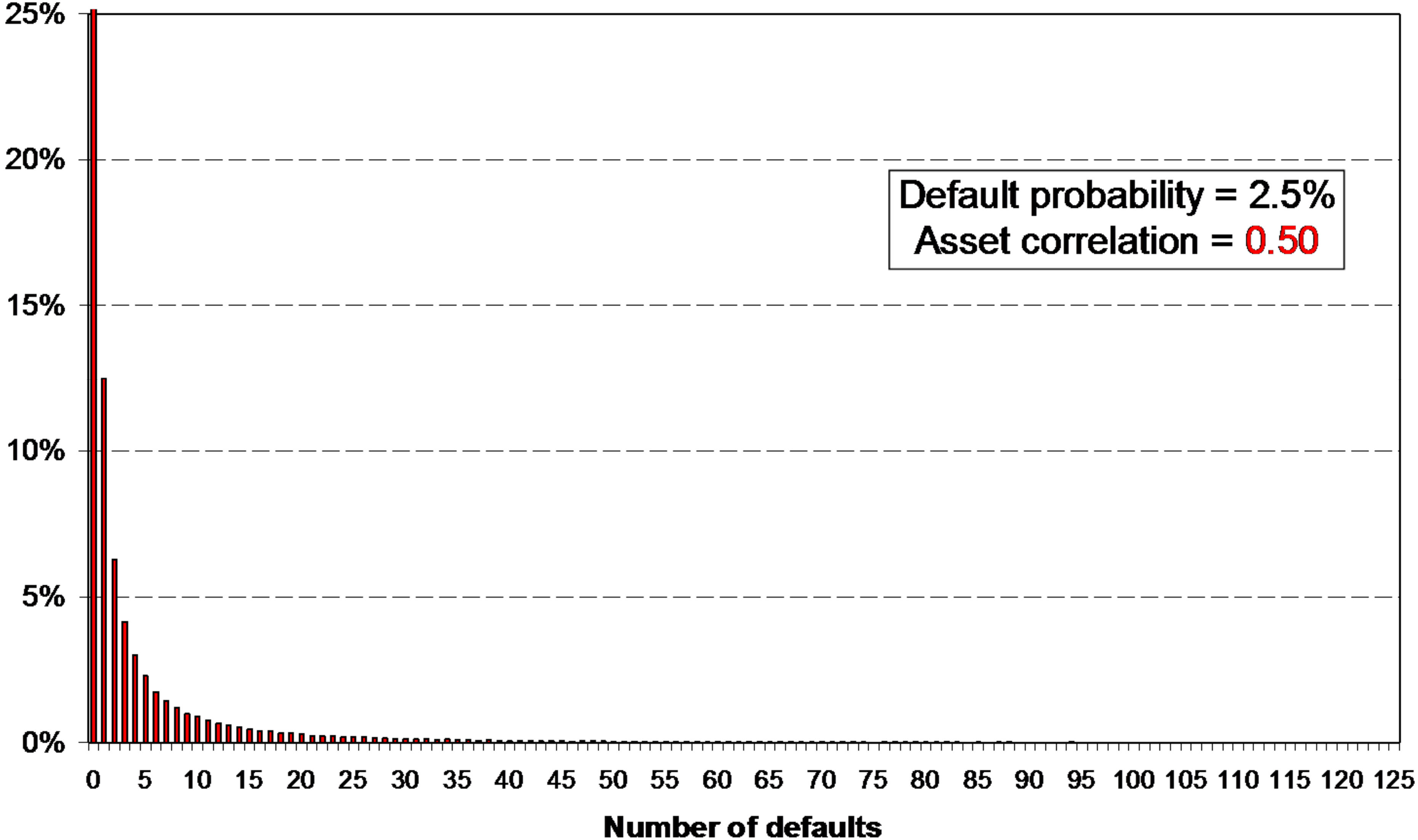


Default correlation =0.04



Cumulative Distribution of Defaults
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Target: 0.29%
27 defaults
22% subordination
78% of the structure is rated AAA
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100 105 110 115 120 125
Number of defaults

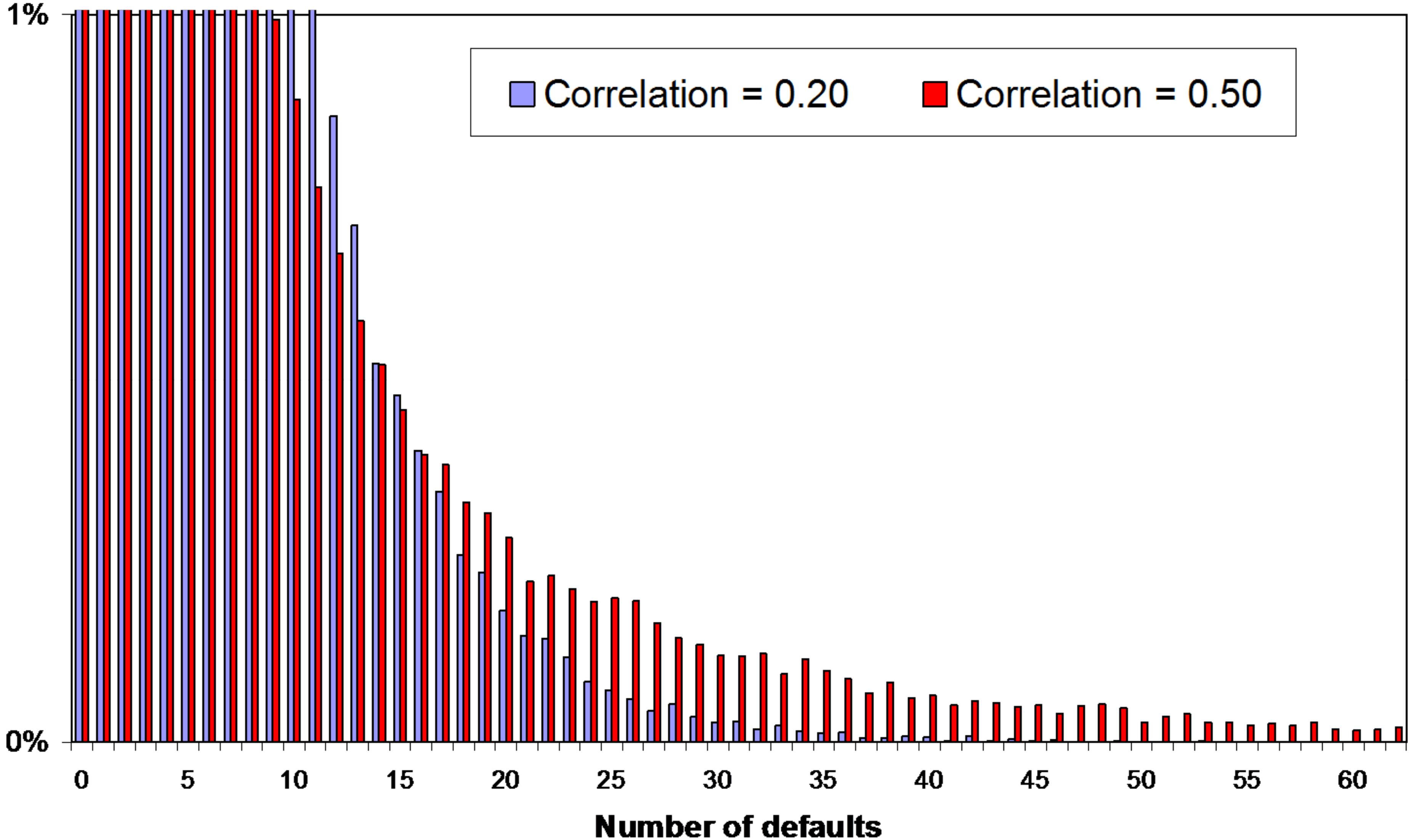
Distribution of Defaults: 125 BBB Credits



With default correlation of 1, 97.5% at 0, 2.5% at 1

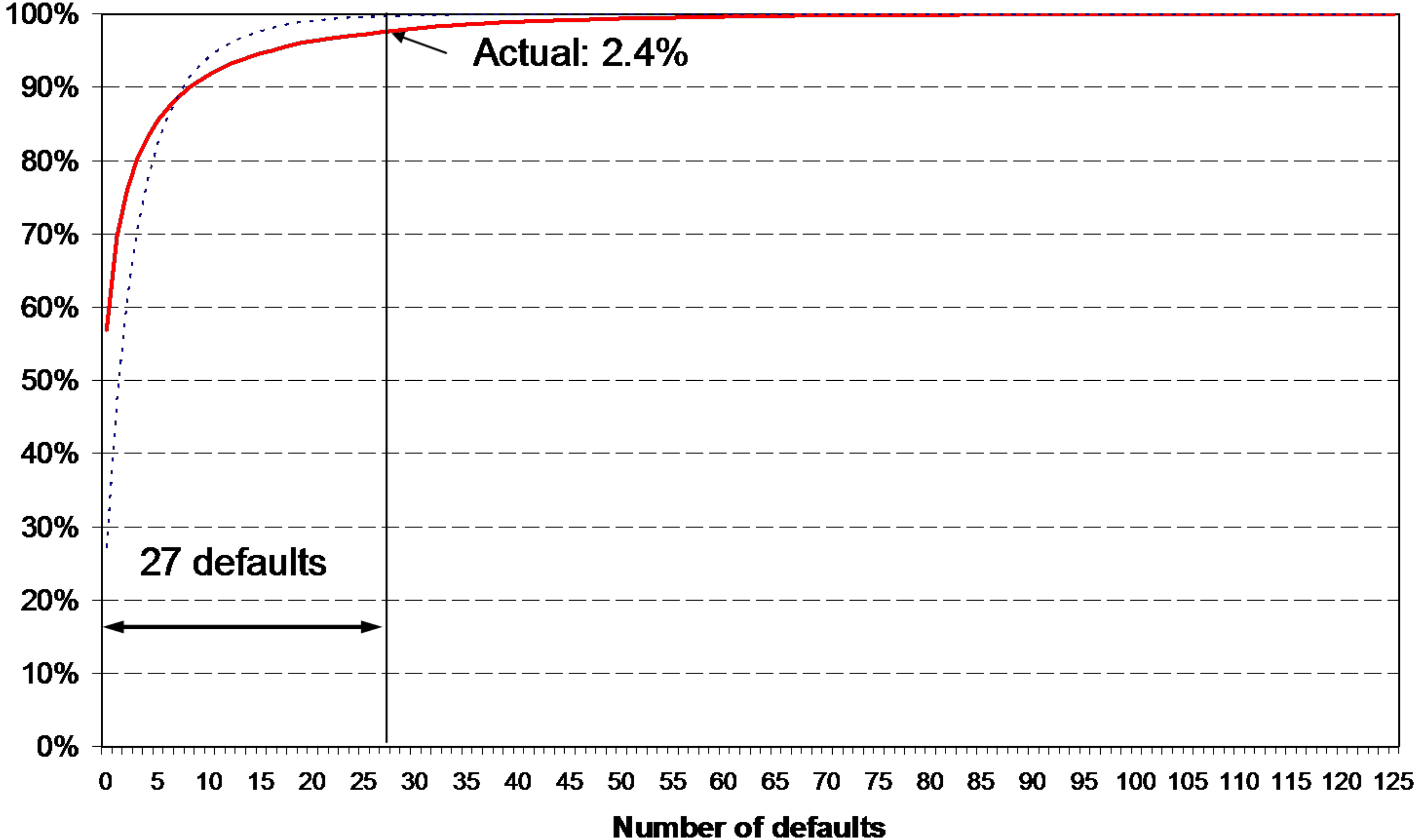
Default correlation =0.16

Distribution of Defaults: Effect of Correlation



Fixed PD

Cumulative Distribution of Defaults



Actual rating should be BBB, not AAA

Credit Contagion

(2)
Counterparty Risk as Another Channel of Credit Correlation

Second-Generation Correlation Model

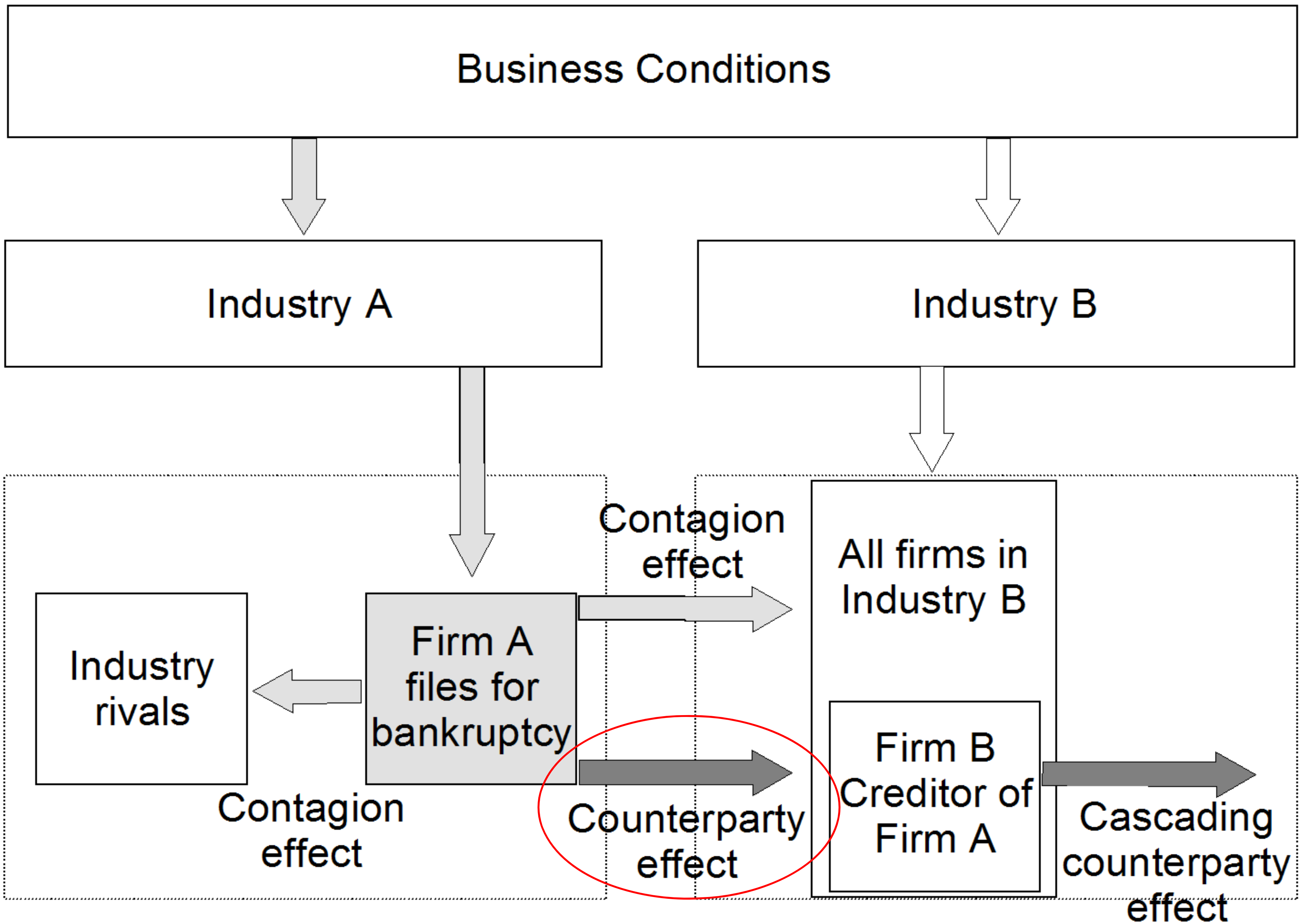
- Excess clustering could be explained by counterparty risk, which occurs when default of one firm causes financial distress on other firms with which it has close business ties
- Theoretical work by Davis and Lo (2001), Jarrow and Yu (2001)
- No empirical application yet: focus of this paper

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


Business Conditions
Industry A
Industry B
Contagion effect
All firms in Industry B
Industry rivals
Firm A files for bankruptcy
Firm B Creditor of Firm A
Contagion effect
Counterparty effect
Cascading counterparty effect

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)

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

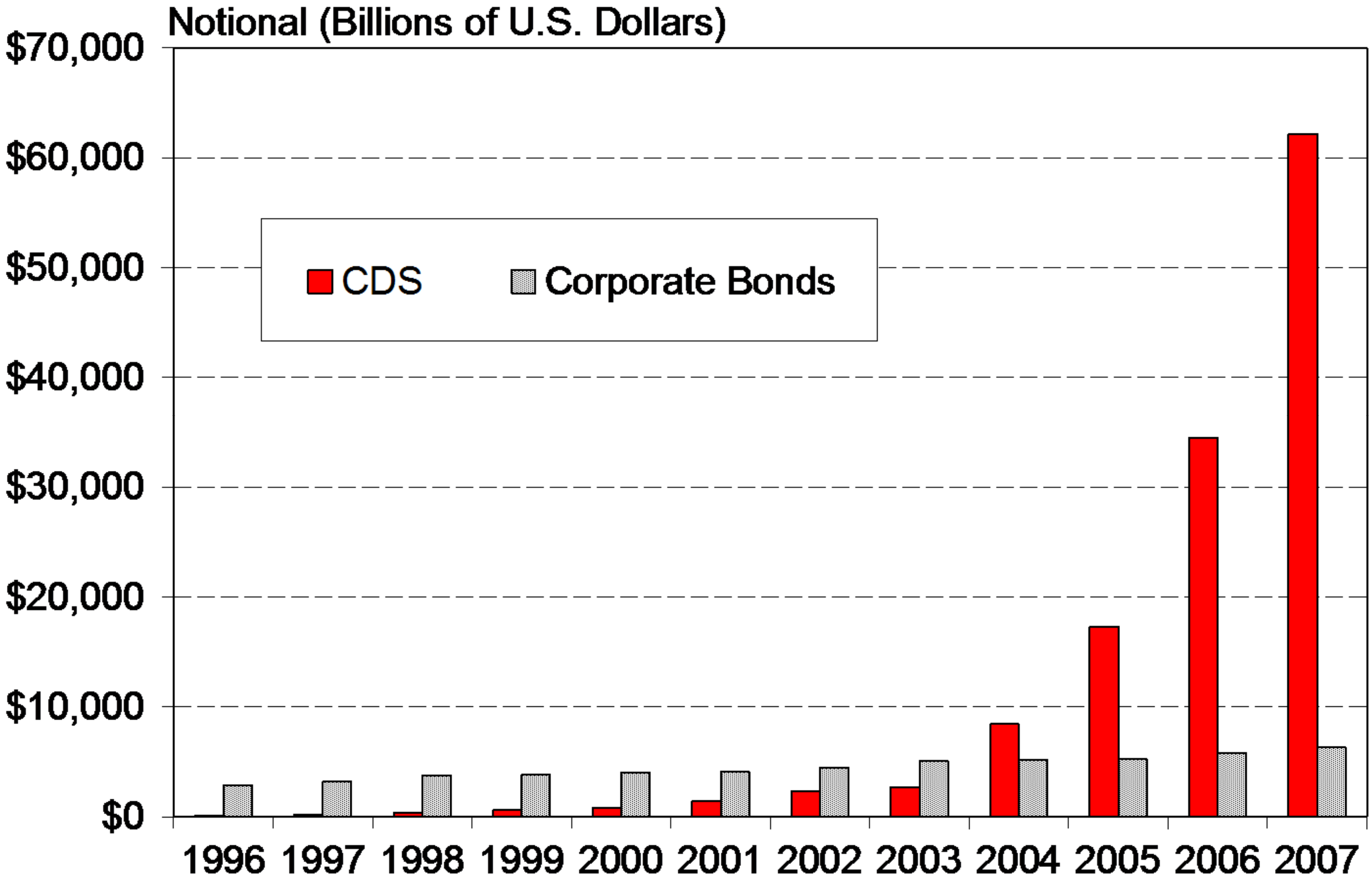
  » Example: XO Comm was unsecured creditor to Teligent, which went bankrupt in May 2001; stock price lost 50%; went bankrupt in June 2002

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

Credit Contagion

Credit Default Swaps

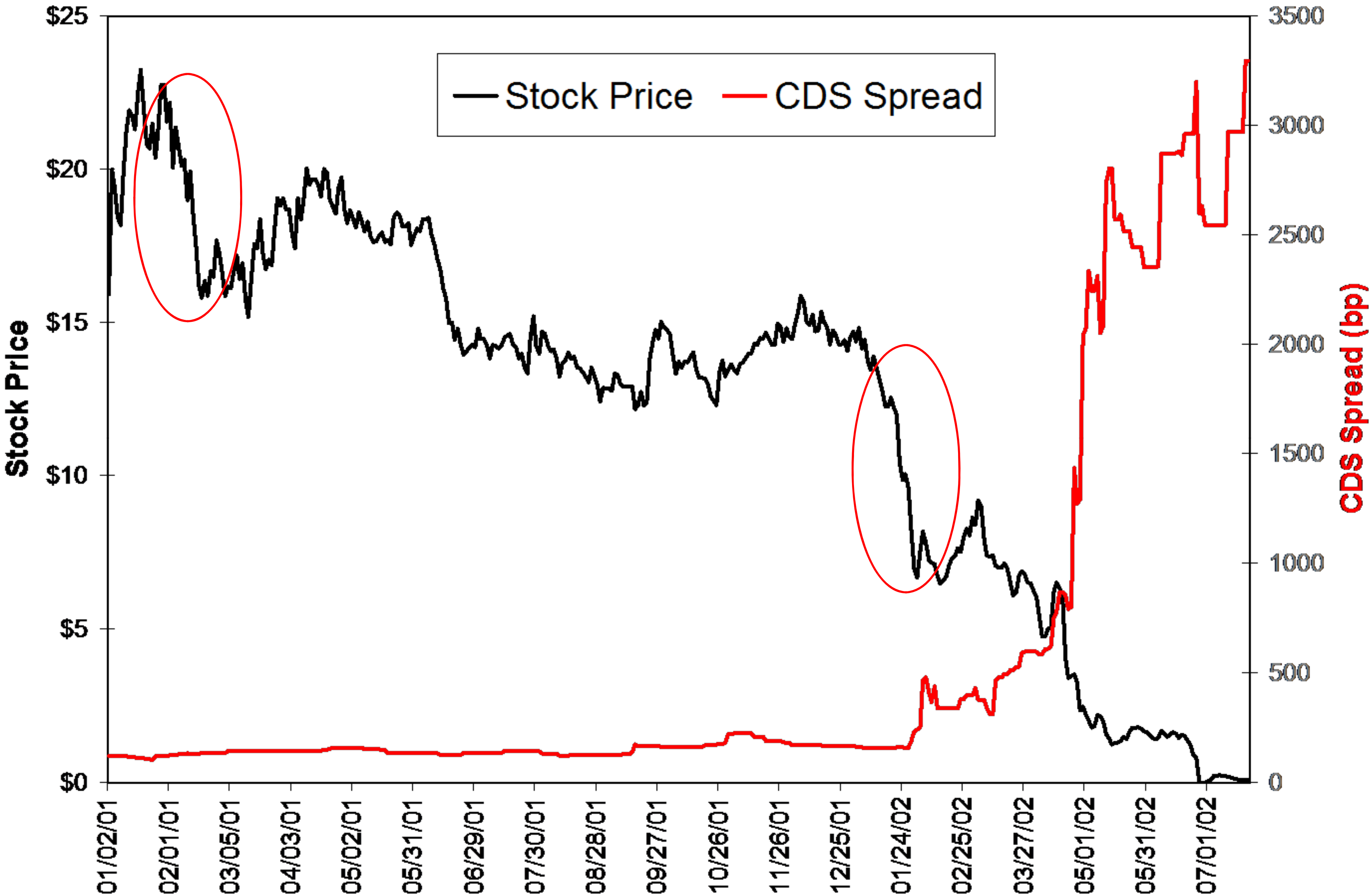
CDS and Corporate Bond Markets



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

WorldCom Bankruptcy



July 21, 02

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					
Year	Nb. of Bankruptcy Events	Nb. of Industry	Nb. of Event-Creditors	Nb. 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

Credit Amounts

Panel B: Credit Amount by Creditor								
		Nb. of Event–	Distribution of Amount ($ million)					
Creditor	Credit Type	Creditors	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

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

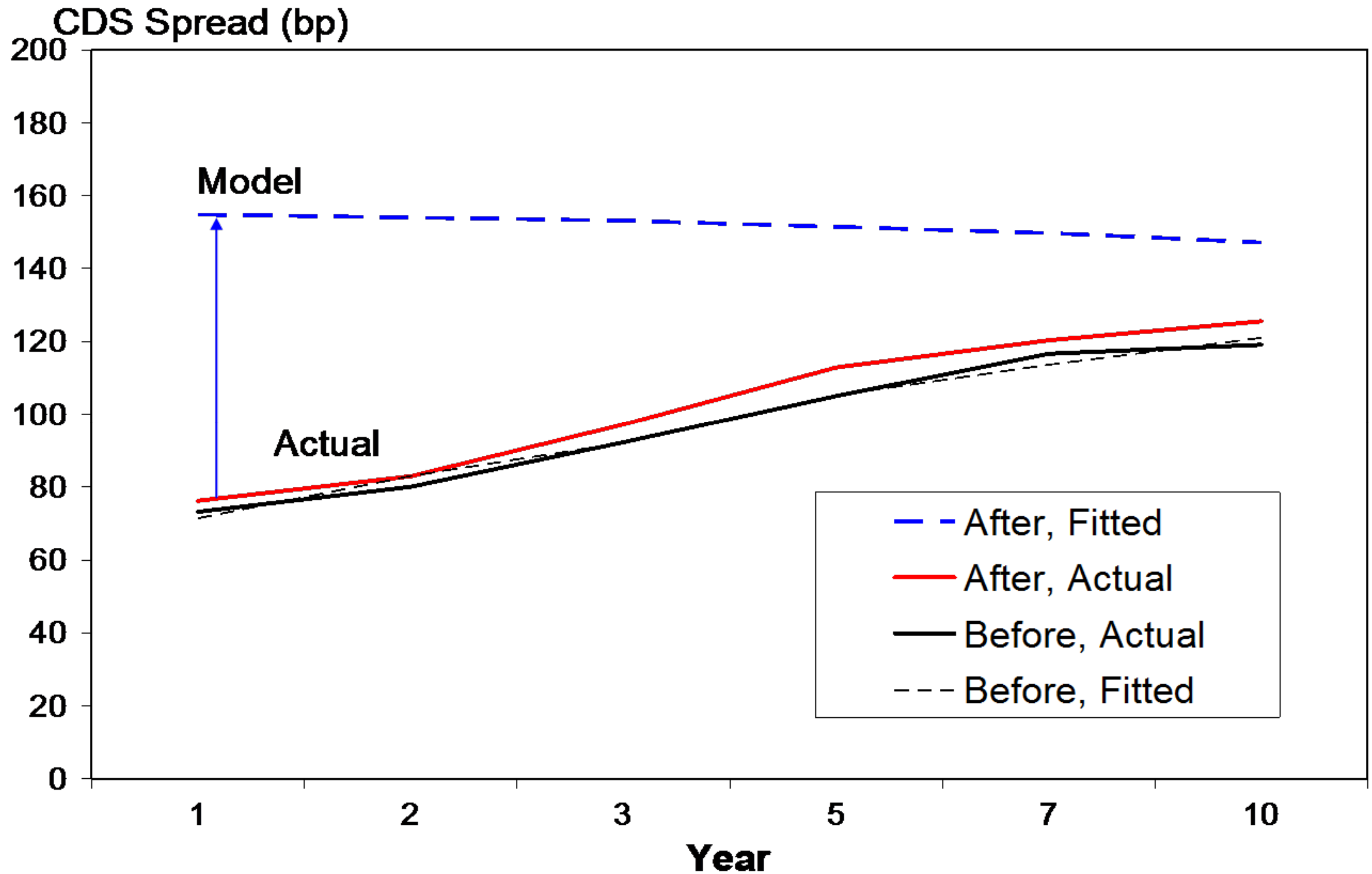
Effect on Creditors

	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

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

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

- 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

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

	Equity			CDS		
	EXP	REC	ECL	EXP	REC	ECL
All (N=694)	-0.83***	2.69*	**-1.01*** **	8.84***	-5.44	**14.71*** **
Industrials (N=583)	-0.82***	2.66	-1.00***	9.84***	-5.44	17.08***
Financials (N=111)	-1.39***	2.67*	-2.09***	5.17***	-2.74	7.65***
Liquidation (N=79)	-1.71**	27.17***	**-2.26** **			

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 ρ=0.20

(1) With no counterparty effect, default ρ=0.024, 23 defaults at the 99.9% confidence level

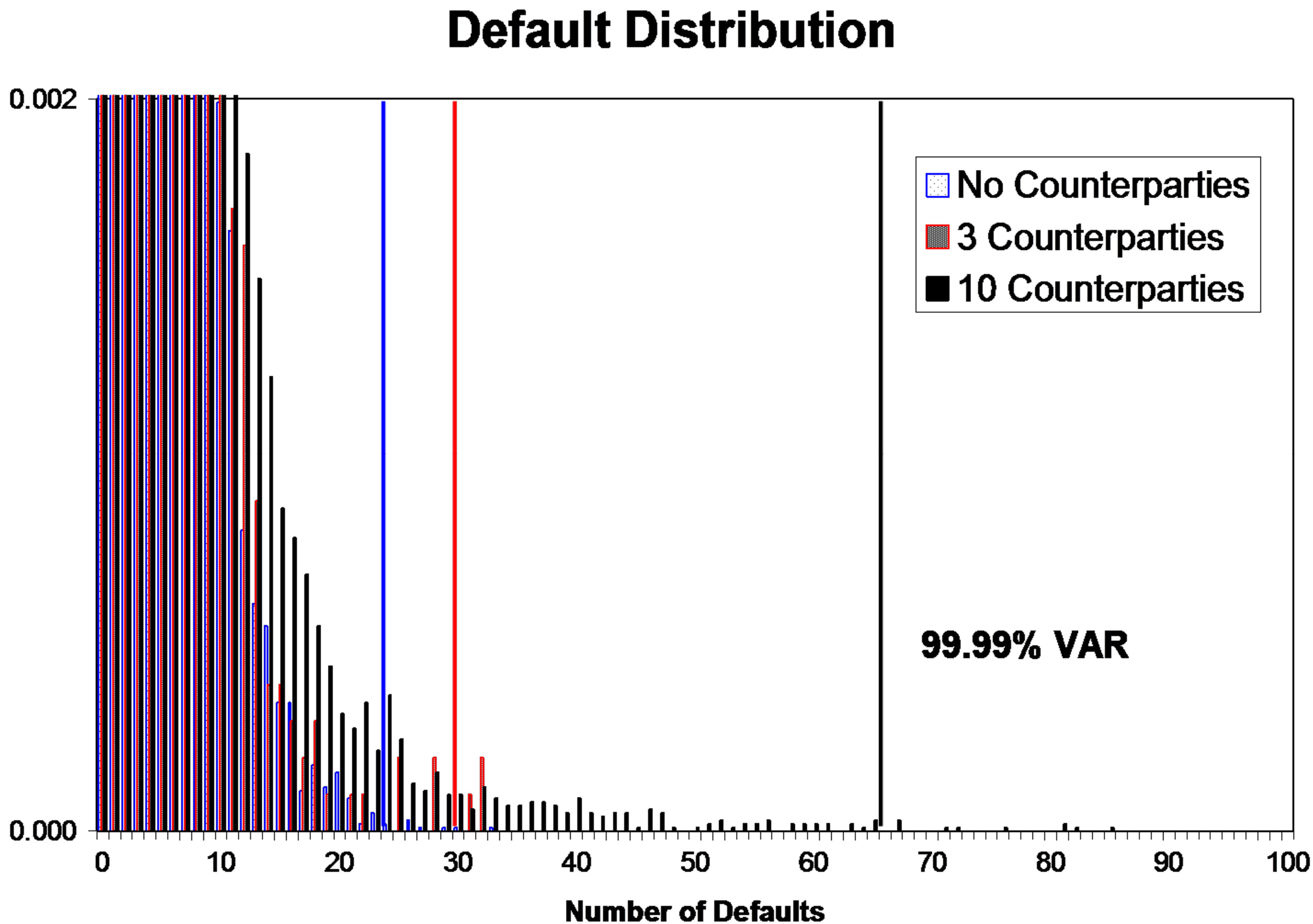
(2) With counterparty effects, K=3 creditors, PD changes by 0.5%, iterate on multiple defaults, cutoff moves from 23 to 29 defaults

With K=10 creditors, cutoff is 65 defaults

- Ignoring credit contagion understates capital

Simulations of Portfolio Distributions

	No Counterparty Risk		Counterparty Risk						
Number of counterparties	0	0	3	3	3	1	2	5	10
Probability of default (PD)	1.00%	1.05%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%
Conditional PD	1.00%	1.05%	1.50%	1.25%	2.00%	1.50%	1.50%	1.50%	1.50%
Default correlation:									
No counterparty effect	0.0237	0.0244	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237	0.0237
With first count.def.			0.0278	0.0258	0.0316	0.0251	0.0264	0.0307	0.0390
With multiple count.def.			0.0291	0.0262	0.0344	0.0252	0.0267	0.0331	0.0622
Average default rate	1.000%	1.050%	1.051%	1.024%	1.099%	1.016%	1.031%	1.083%	1.226%
Number of defaults:									
99% percentile	9	9	9	9	10	9	9	10	13
99.9% percentile	16	16	19	18	21	16	18	21	36
99.99% percentile	23	23	29	25	35	25	26	33	65



Default Distribution
0.002
0.000
0
10
20
30
40
50
60
70
80
90
100
Number of Defaults
No Counterparties
3 Counterparties
10 Counterparties
99.99% VAR

N=500, Conditional PD=1.25%

	No Counterparty Risk		Counterparty Risk						
Number of counterpart	0	0	3	3	3	3	1	10	10
Probability of default	1.00%	1.02%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%	1.00%
Conditional PD	1.00%	1.02%	1.25%	1.10%	1.50%	2.00%	1.25%	1.25%	1.50%
Default correlation:									
No counterparty	0.0243	0.0246	0.0243	0.0243	0.0243	0.0243	0.0243	0.0243	0.0243
First ct. default			0.0261	0.0250	0.0279	0.0312	0.0249	0.0309	0.0380
Multiple ct default			0.0262	0.0250	0.0285	0.0378	0.0249	0.0332	0.0595
Average default rate	1.000%	1.020%	1.022%	1.009%	1.046%	1.098%	1.007%	1.086%	1.229%
Number of defaults:									
99% percentile	39	39	40	39	42	46	39	46	58
99.9% percentile	75	77	81	78	88	103	77	100	166
99.99% percentile	115	117	127	121	136	159	121	168	306

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"

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