The NYU Stern Systemic Risk Rankings

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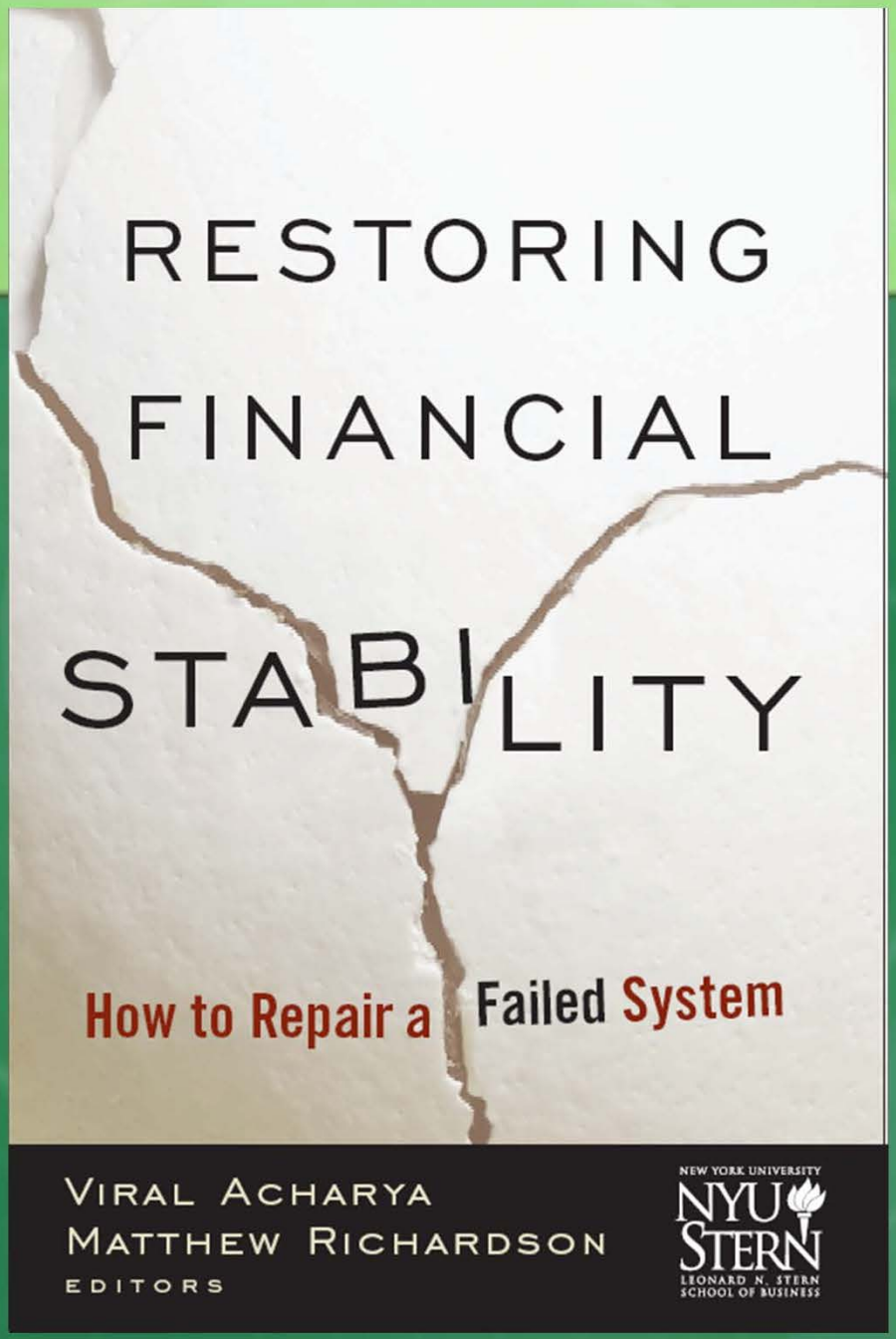
LESSONS FROM THE CRISIS

- The failure of large complex financial institutions can impose costs on the whole economy
- When they are failing, governments are in a compromised position. Unless there are liquidation or resolution mechanisms, governments need to rescue these firms.
- The potential of such a rescue reduces market discipline leading to excessive leverage and risk taking.
- Regulation of systemically risky firms is needed.
- But how can they be identified?


RESTORING
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How to Repair a Failed System
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WHAT CAN WE EXPECT?

OR

IDENTIFYING SYSTEMIC RISK

TWO KINDS OF RISK

- INDIVIDUAL RISK
- SYSTEMIC RISK

SYSTEMIC RISK

- "*Financial institutions are systemically important if the failure of the firm to meet its obligations to creditors and customers would have significant adverse consequences for the financial system and the broader economy*."

  - Daniel Tarullo
  - Federal Reserve Governor

LEVERAGE

- Highly levered firms have a greater risk of default.
- The default of a firm is far more dangerous if the economy is weak and highly levered as there are no buyers to assume the liabilities.
- Thus firms that are considered systemically risky are firms that face capital shortages just when the financial sector as a whole is capital constrained.

“LEVERAGE EXTERNALITY”

- High leverage is only dangerous for the economy when everyone is doing it – this is an externality!
- This is why regulation is required.

MEASURING SYSTEMIC RISK

- Acharya, Pedersen, Philippon, and Richardson(2010) propose the use of market data to estimate systemic risk contributions of firms.
- Their central measure is Marginal Expected Shortfall or MES. This is like a down side beta.
- MES is used to predict equity losses in a future crisis and when combined with leverage and size data it reveals capital shortages and systemic risk.
- Brownlees and Engle use new time series methods to estimate and forecast MES.

THE APPROACH

- We want to estimate for firm i, the expected loss in a future crisis: $E\left(Equity\ Loss_i \middle| Crisis\right)$
- As we have little data on crises, it is necessary to carefully structure the problem.
- Estimate the expected equity losses for a firm from a modest decline in overall returns.
- Extrapolate this to a full financial crisis.
- Calculate capital shortages.

INTRODUCING THE RISK PAGE

- Now we introduce a page providing estimates of risk for the 102 largest US Financial firms.
- Risk is estimated both for the firm itself and for its contribution to risk in the system.
- This is called the *NYU Stern Systemic Risk Ranking.*
- This is updated weekly/daily to allow regulators, practitioners and academics to see early warnings of system risks.

Volatility, Correlation and Tails for Systemic Risk Measurement

Christian Brownlees and Robert Engle
Stern School of Business

MARGINAL EXPECTED SHORTFALL

- The expected shortfall of a market index is defined by

$$ES_t = E_{t-1}\left(-R_{m,t} \middle| R_{m,t} < c\right)$$

- ES is a useful and coherent measure of risk.
- Recognizing that the market return is a weighted average of individual firm returns,

$$ES_t = \sum_{i=1}^{N} w_i E_{t-1}\left(-R_{i,t} \middle| R_{m,t} < c\right)$$

- MES can be interpreted as each firm's contribution to system losses.

$$MES_{i,t} = E_{t-1}\left(-R_{i,t} \middle| R_{m,t} < c\right)$$

INTERPRETING MES

- In words, MES is the expected loss incurred by equity investors in a firm, when the general market suffers a big decline.
- We will often use a 2% daily market decline to measure MES. Hence the market expected shortfall is a number greater than or equal to 2. It is higher when volatility is high.
- Firms with MES much bigger than 2, are the biggest losers in a market downturn.

HOW TO ESTIMATE MES DYNAMICALLY

- Use flexible time series approaches to modeling volatilities, correlations and tails.
- The Model:

$$R_{m,t} = \sigma_{m,t}\varepsilon_{m,t}$$

$$R_{i,t} = \sigma_{i,t}\left(\rho_t\varepsilon_{m,t} + \sqrt{1-\rho_t^2}\,\xi_{i,t}\right)$$

$$\left(\varepsilon_{m,t}, \xi_{i,t}\right) \sim F$$

- Disturbances are serially independent, mean zero, variance one, uncorrelated but not independent random variables. Copula.
- Volatilities are Asymmetric GARCH models
- Correlations are Asymmetric DCC.

THE CALCULATION

- At time t, MES is given by

$$MES_{i,t} = E_{t-1}\left(-R_{i,t} \middle| R_{m,t} < c\right)$$

$$= \sigma_{i,t}\rho_{i,t}E_{t-1}\left(\varepsilon_{m,t} \middle| \varepsilon_{m,t} < c/\sigma_{m,t}\right) + \sigma_{i,t}\sqrt{1-\rho_t^2}\,E_{t-1}\left(\xi_{i,t} \middle| \varepsilon_{m,t} < c/\sigma_{m,t}\right)$$

- Firms are risky if they have high volatility
- Firms are systemically risky if they also have high correlations.
- Market ES is the same for all firms
- Estimate tail probabilities non-parametrically

ILLUSTRATION: BAC VOLATILITY

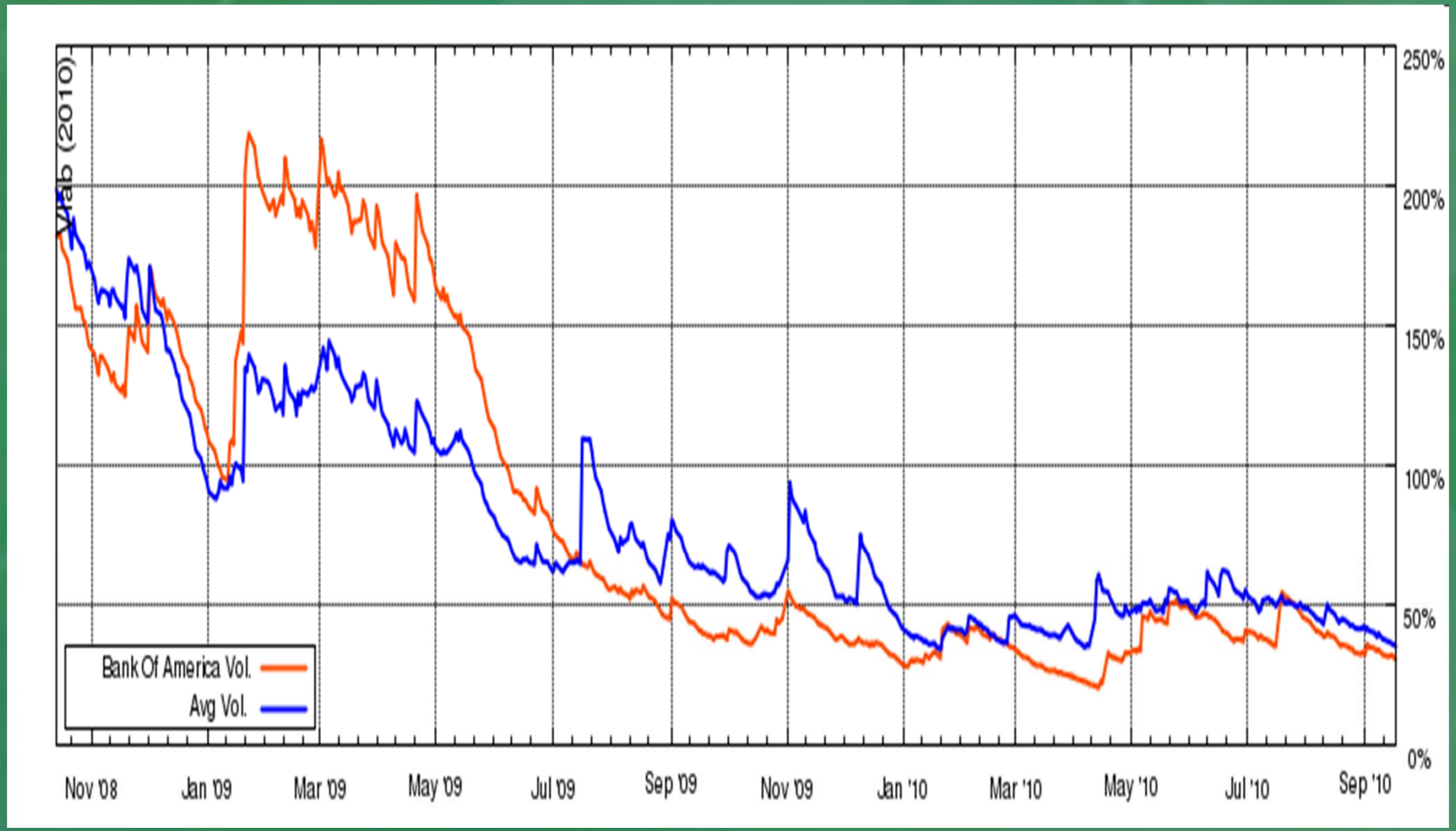


ILLUSTRATION: BAC CORRELATION WITH SP500

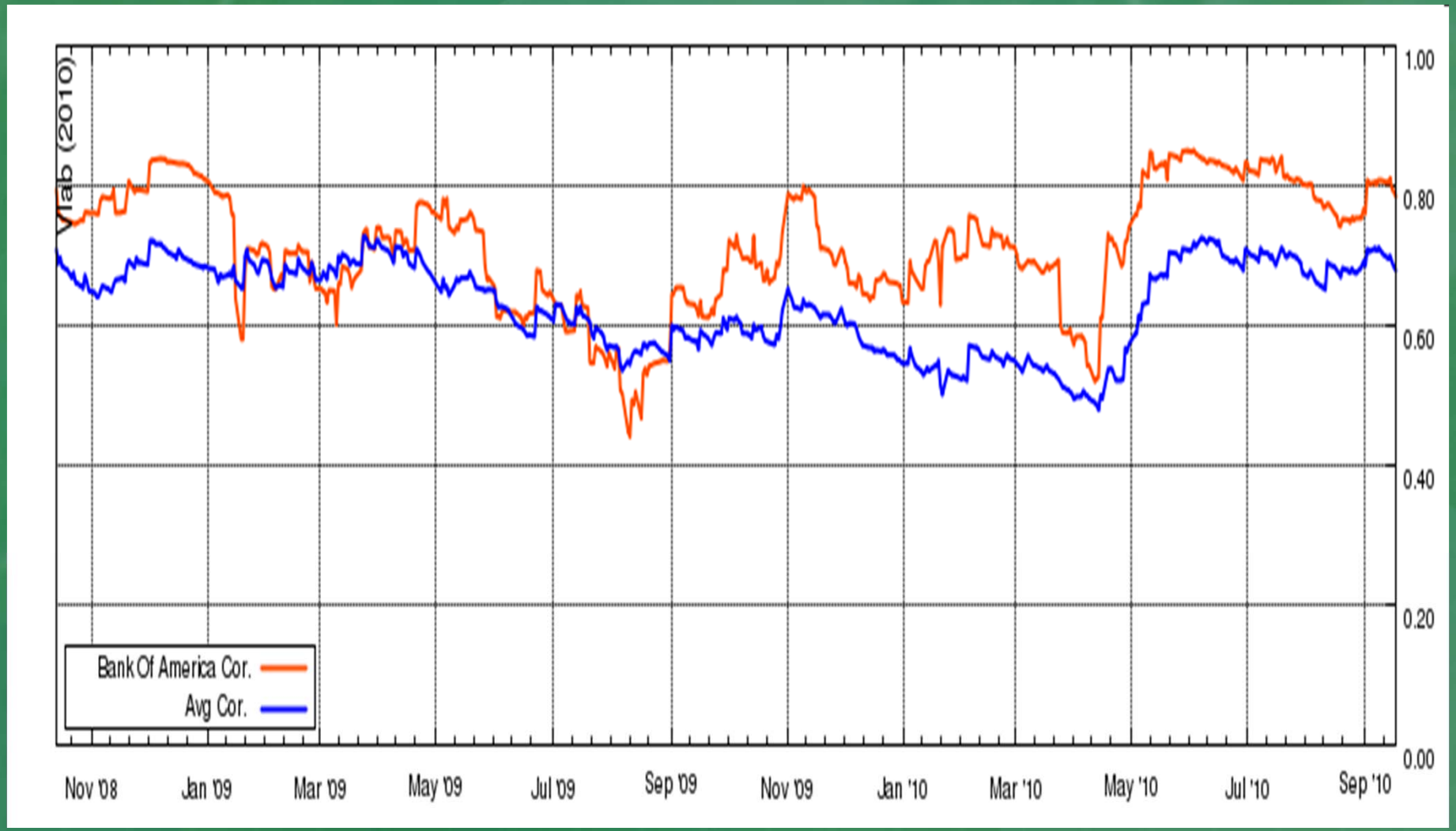
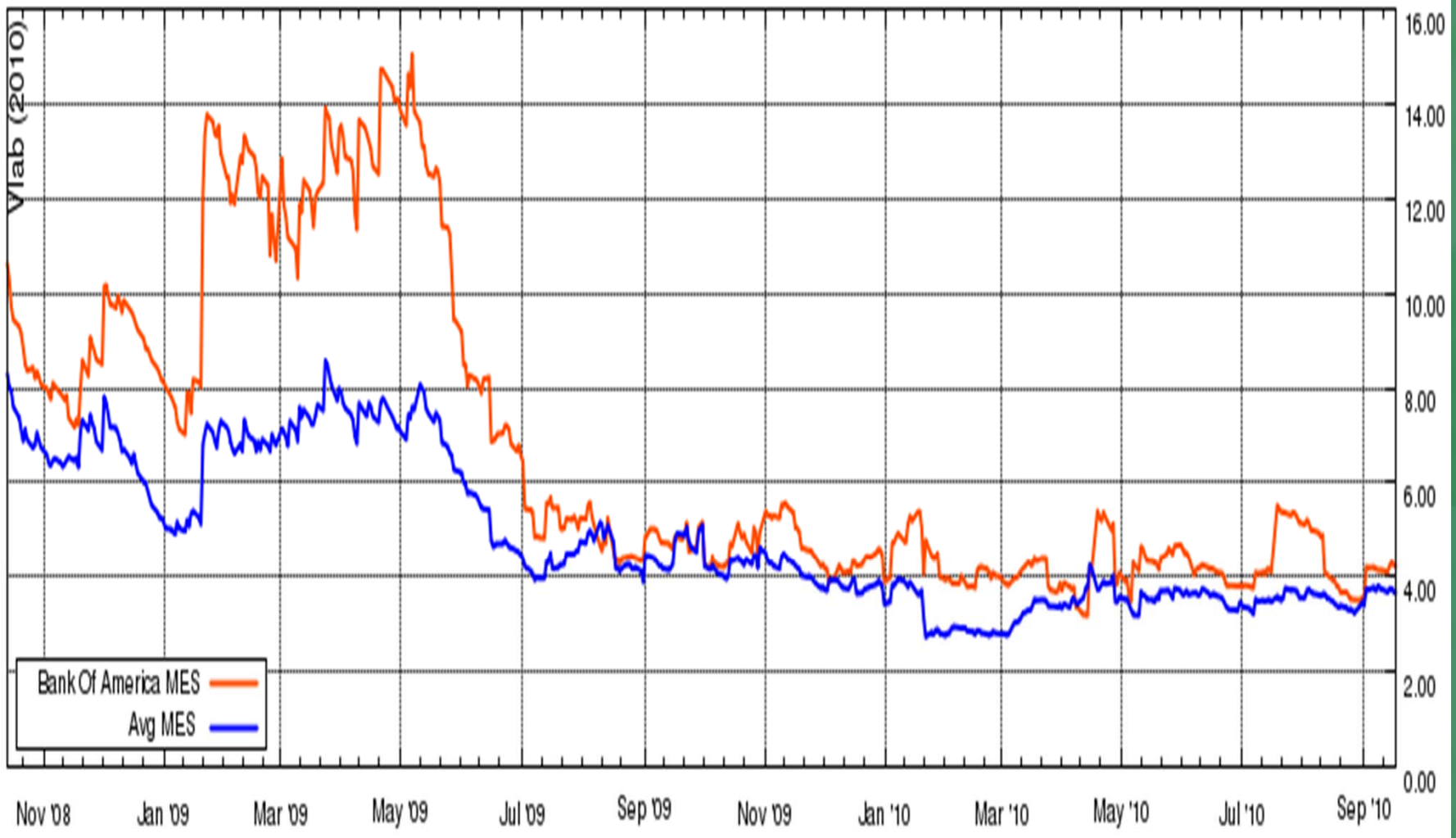


ILLUSTRATION: BAC MES



Volatility

We model volatility using the classic TGARCH specification

TGARCH

The TGARCH model is defined as

$$\sigma^2_{i\,t} = \omega^i_G + \alpha^i_G r^2_{i\,t-1} + \gamma^i_G r^2_{i\,t-1} I^-_{i\,t-1} + \beta^i_G \sigma^2_{i\,t-1}$$

$$\sigma^2_{m\,t} = \omega^m_G + \alpha^m_G r^2_{m\,t-1} + \gamma^m_G r^2_{m\,t-1} I^-_{m\,t-1} + \beta^m_G \sigma^2_{m\,t-1}$$

with $I^-_{i\,t-1} = r_{i\,t-1} < 0$ and $I^-_{m\,t-1} = r_{m\,t-1} < 0$

DCC Modeling

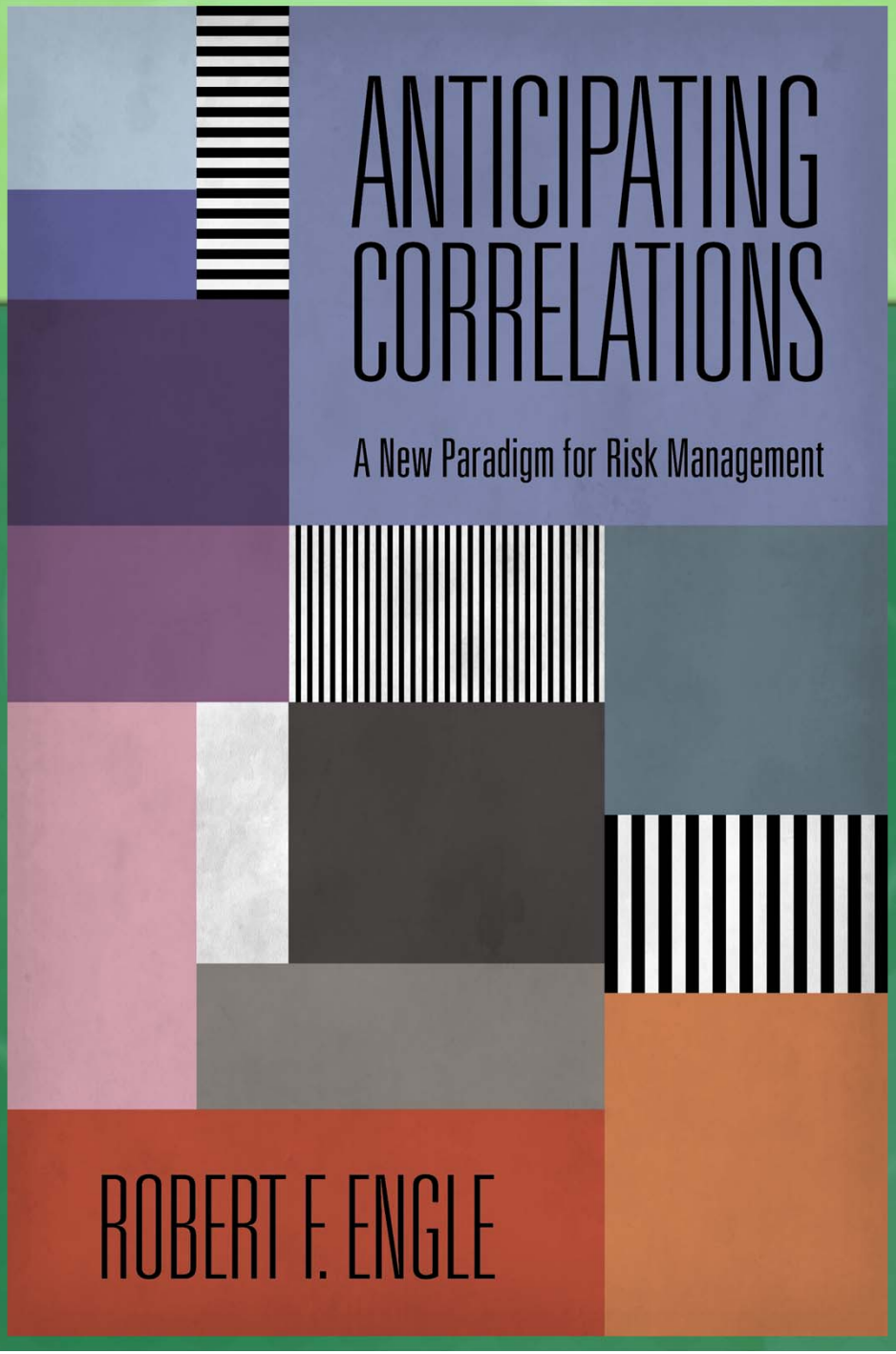
Asymmetric DCC

The Asymmetric DCC model is defined as

$$
\begin{aligned}
Q_t &= ((1-\alpha-\beta)\widehat{S} - \gamma\widehat{N}) + \alpha\, \epsilon^*_{t-1}\epsilon^{*\prime}_{t-1} + \gamma\, n^*_{i\,t-1}n^{*\prime}_{i\,t-1} + \beta\, Q_{t-1} \\
P_t &= diag(Q_t)^{-1/2}\, Q_t\, diag(Q_t)^{-1/2}
\end{aligned}
$$

where

- $\epsilon^*_t = Q^*_t \epsilon_t$, with $Q^*_{t-1} = diag(\sqrt{q_{11\,t}}, \sqrt{q_{22\,t}})$ and
- $n^*_{i\,t} = \epsilon^*_t \odot I[\epsilon^*_t < 0]$
- $\widehat{S} = n^{-1}\sum_t \epsilon^*_t \epsilon^{*\prime}_t$ and $\widehat{N} = n^{-1}\sum_t n^*_t n^{*\prime}_t$



The Erasmus Lectures 2003

TAILS

- Estimate tail probabilities non-parametrically

$$\hat{E}_{t-1}\left(\varepsilon_{m,t}\left|\varepsilon_{m,t}<\kappa\right.\right)=\frac{\sum_t \varepsilon_{m,t} I\left(\varepsilon_{m,t}<\kappa\right)}{\sum_t I\left(\varepsilon_{m,t}<\kappa\right)}$$

$$\hat{E}_{t-1}\left(\xi_{i,t}\left|\varepsilon_{m,t}<\kappa\right.\right)=\frac{\sum_t \xi_{i,t} I\left(\varepsilon_{m,t}<\kappa\right)}{\sum_t I\left(\varepsilon_{m,t}<\kappa\right)}$$

USING A KERNEL

- Because there are relatively few observations in the tail, it is reasonable to smooth the tail estimators with a kernel.
- With kernel

$$G_h(t) = \int_{-h}^{h} k(u)\,du$$

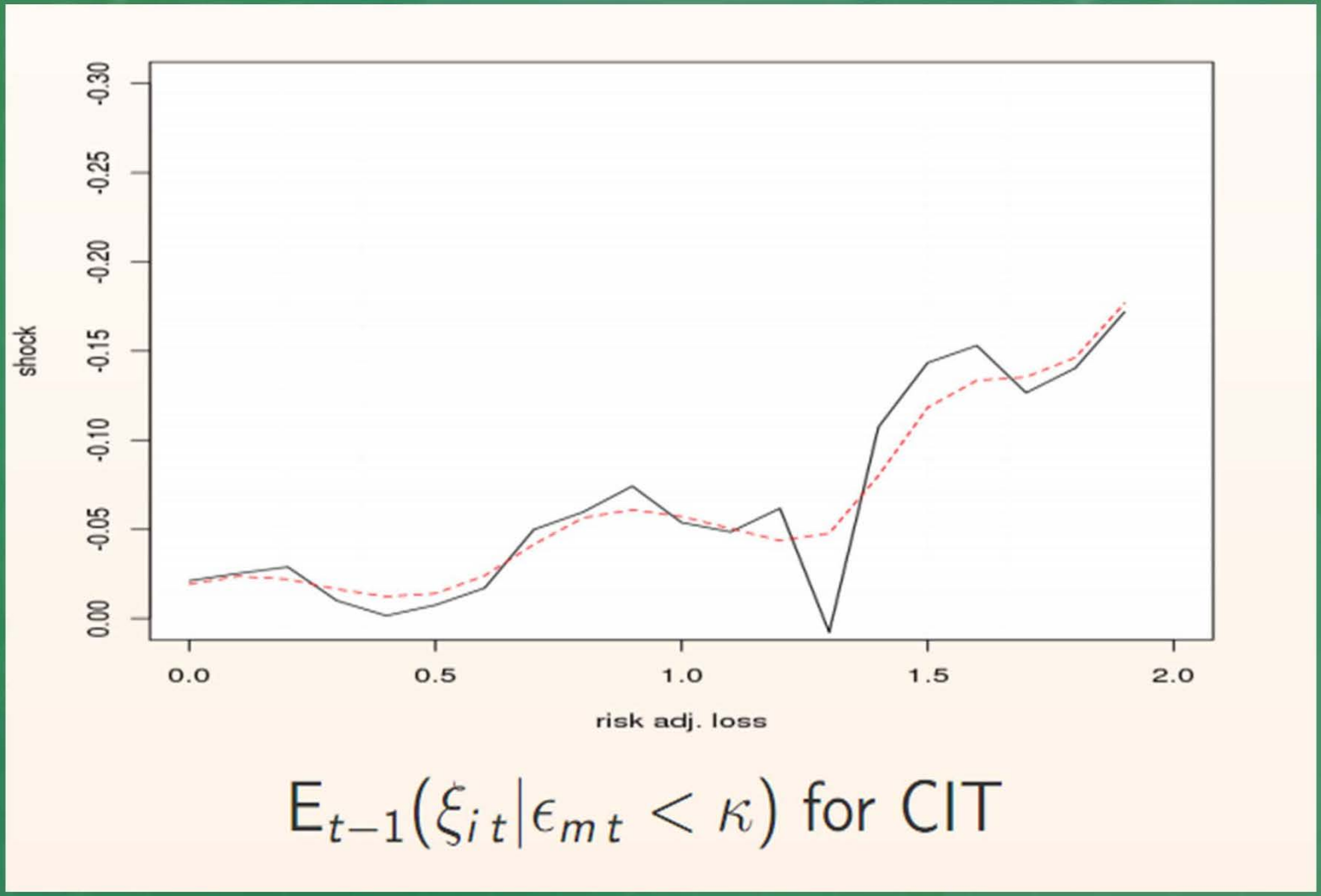
- Then

$$\tilde{E}_{t-1}\left(\varepsilon_{m,t} \middle| \varepsilon_{m,t} < \kappa\right) = \frac{\sum_t \varepsilon_{m,t} G_h\left(\kappa - \varepsilon_m\right)}{\sum_t G_h\left(\kappa - \varepsilon_m\right)}$$

- and

$$\tilde{E}_{t-1}\left(\xi_{i,t} \middle| \varepsilon_{m,t} < \kappa\right) = \frac{\sum_t \xi_{i,t} G_h\left(\kappa - \varepsilon_m\right)}{\sum_t G_h\left(\kappa - \varepsilon_m\right)}$$

SMOOTHING THE TAILS



$\mathsf{E}_{t-1}\left(\xi_{i\,t} \middle| \epsilon_{m\,t} < \kappa\right)$ for CIT

DATA

- Unbalanced panel of 102 large U.S. financial firms 1990-2008
- Firms in 4 industry groups
  - Depository Institutions
  - Insurance
  - Security and Commodity Brokers
  - Others
- Market Index
- Quarterly Data from Compustat on Quasi-Leverage.

GARCH DCC Estimation Results

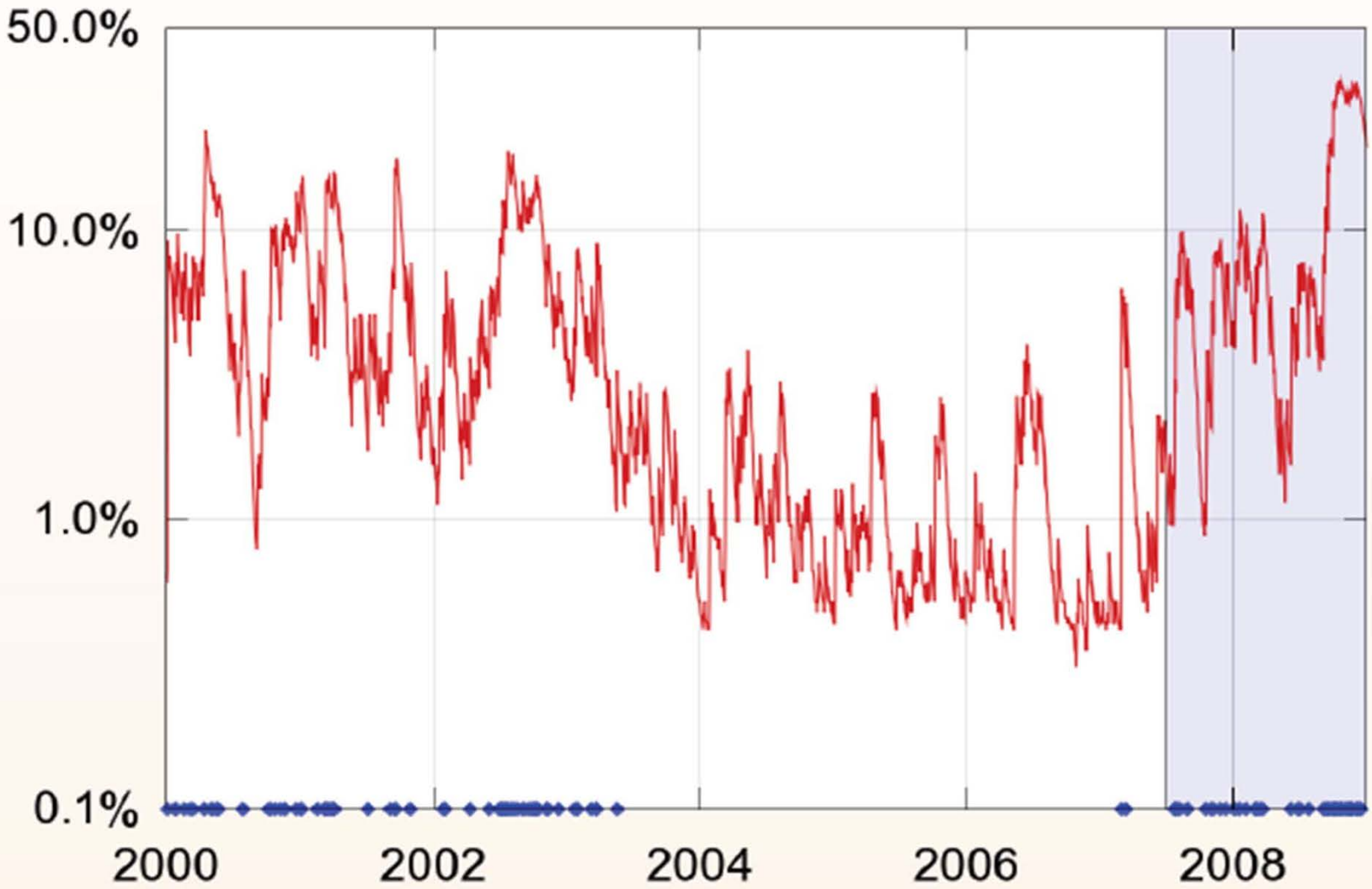
Industry	vol	α_G	γ_G	β_G	cor	α_C	γ_C	β_C
Dep. Ins.	36.53	0.0501	0.085	0.900	0.546	0.012	0.003	0.969
Insurance	40.30	0.0405	0.103	0.899	0.467	0.008	0.002	0.961
S&D B	48.73	0.0407	0.114	0.891	0.640	0.006	0.002	0.959
Other	47.30	0.0321	0.090	0.915	0.551	0.009	0.002	0.937

Remark – Volatility

Estimated persistance is ≈ 1, as usual

α_G greater than usual - higher unconditional kurtosis

Probability of Systemic Event (2% mkt decline)

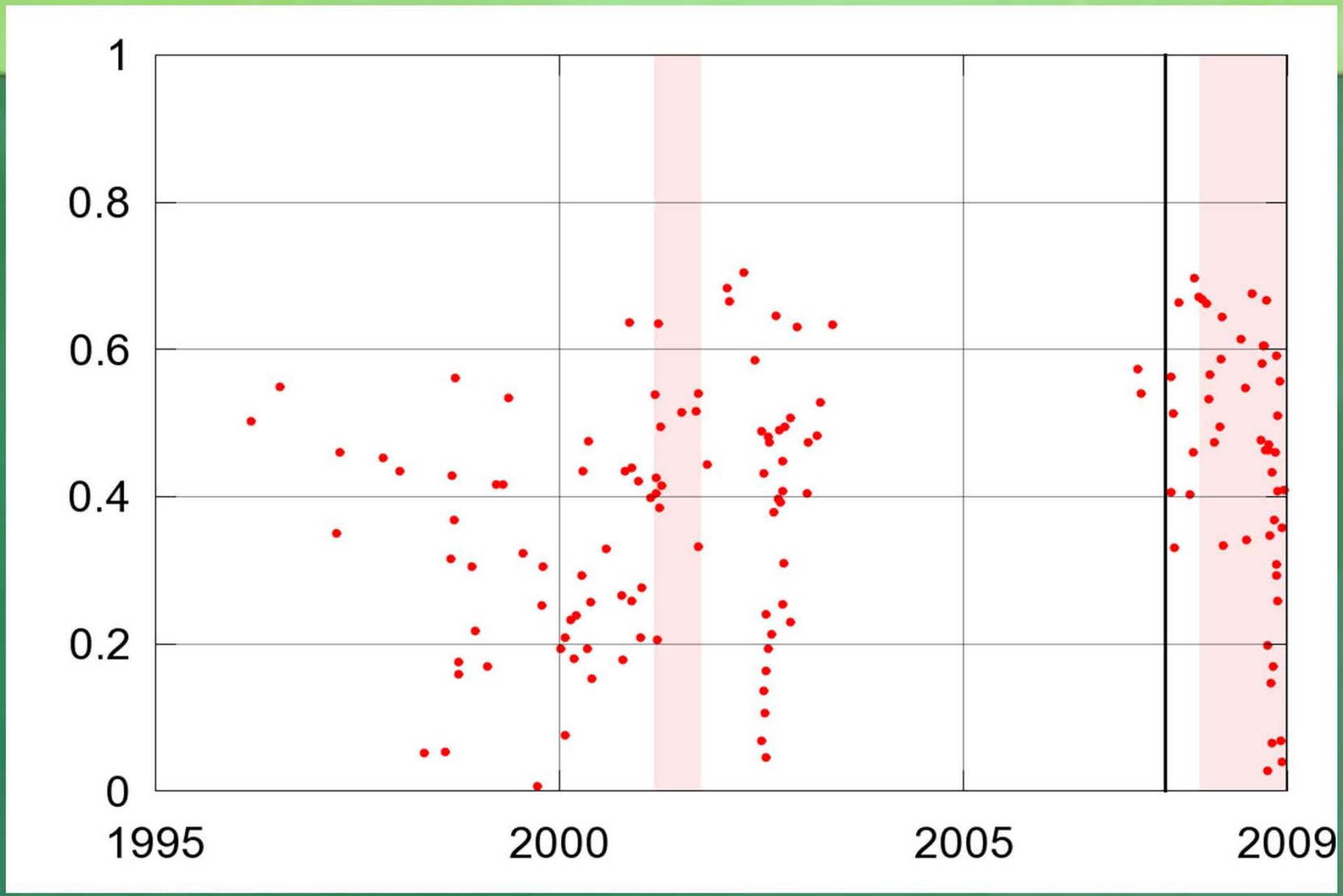


CROSS SECTIONAL FORECASTING

- On a day when R_m<C, what is the rank correlation between $loss_{i,t}$ and $MES_{i,t}$?

- How accurate is the cross sectional distribution of losses. Construct a Gini coefficient between MES and future losses.

RANK CORRELATIONS



THE RISK PAGE

Equity Loss in Crisis

- To estimate the fall in equity value in a crisis, an adjustment is made to MES
  - MES is adjusted to measure the expected fall in equity prices that would occur in six months if the market return is worse than a 40% decline.
  - Approximately this is 18 times daily MES.

MULTI-STEP FORECASTING

- Simulate the bivariate outcome of (r_i, r_m) for six months starting on date t using the estimated model for volatilities, correlations and copula.
- Examine all the scenarios where market return falls by at least 40%. Find average loss for firm i.
- Average loss in a six month crisis/average loss in a 2% down day is ~~18. More precision will come later.

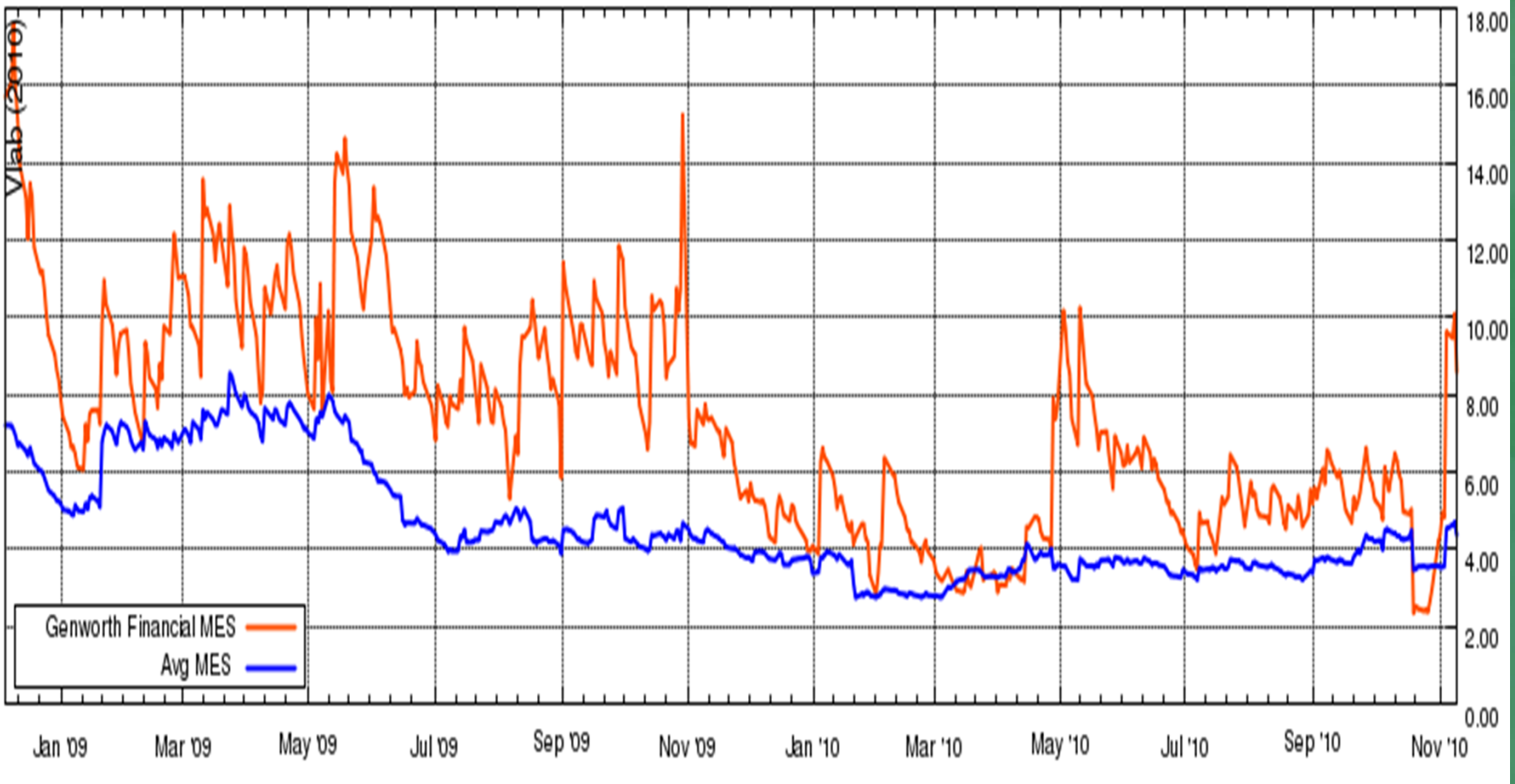
$$\theta = \frac{E_t\left(\sum_{j=1}^{126} R_{i,t+j} \,\middle|\, \sum_{j=1}^{126} R_{m,t+j} < -.40\right)}{E_t\left(R_{i,t+1} \,\middle|\, R_{m,t+1} < .02\right)} \approx 18$$

AVERAGE MES - Nov 17, 2010

TOP MES Nov 17,2010

Asset	SRISK%	MES	QLVG	MV
Genworth Financial	1.9%	8.59	16.03	5904.52
MBIA	0.49%	8.43	24.64	2300.36
Janus Capital	0.02%	7.83	1.66	2160.85
C.B. Richard Ellis Group	0.06%	7.61	1.64	6519.23
NYSE Euronext	0.22%	6.87	1.88	7769.96
Ameriprise Financial	1.48%	6.62	9.74	13412.24
Legg Mason	0%	6.28	1.55	5226.47
UNUM Group	0.06%	6.1	7.5	7012.05
Wells Fargo	9.66%	6.07	9.18	150009.2
E-Trade	0.69%	6	13.1	3374.09

GENWORTH FINANCIAL: MES



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Systemic Risk Top Ten

TOP 10	SRISK%	MES	MV
Bank Of America	18%	5.93	126770.3
Citigroup	17.79%	5.83	128401.6
JP Morgan Chase	12.08%	4.75	158790.8
Morgan Stanley	11.04%	5.05	40166.86
Wells Fargo	9.66%	6.07	150009.2
Goldman Sachs	6.85%	3.61	85490.06
Prudential Financial	5.49%	4.02	25937.7
MetLife	4.33%	4.86	40316.61
Hartford Financial Services Group	3.09%	5.16	11540.28
Genworth Financial	1.9%	8.59	5904.52

Nov 17,2010

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Systemic Risk Top Ten

TOP 10	SRISK%	MES	MV
Bank Of America	20.14%	4.23	134453.4
Citigroup	16.14%	3.24	114445.4
JP Morgan Chase	12.18%	3.94	158844.5
Wells Fargo	10.04%	4.83	136121.3
Morgan Stanley	5.64%	4.09	36977.75
Goldman Sachs	5.44%	3.04	77847.69
Prudential Financial	3.84%	4.09	25677.29
MetLife	3.55%	4.22	36410.93
Hartford Financial Services Group	3.18%	5.95	9997.29
PNC Financial Services	2.01%	4.29	28555.46

Oct 15, 2010

WHAT DOES THIS MEAN?

- If we have a future financial crisis, these are the firms that will need to raise the most capital to remain solvent.
- If they cannot, then these losses spread into the real economy or go to taxpayers.

PAST RANKINGS

- Table includes all firms ranked within top 10 for any of the dates.
- Firms that are not in business are -
- Dates are
  - July 1, 2007 before crisis begins.
  - March 1, 2008 before Bear Stearns purchase
  - September 12, 2008 before Lehman bankruptcy
  - March 31, 2009 before SCAP

TABLE 4.1 Systemic Risk Rankings during the Financial Crisis of 2007 to 2009

	July 1, 2007 Risk % (Rank)			March 1, 2008 Risk % (Rank)			September 12, 2008 Risk % (Rank)			March 31, 2009 Risk % (Rank)		
	SRISK%		MES	SRISK%		MES	SRISK%		MES	SRISK%		MES
Citigroup	14.3	#1	3.27	12.9	#1	4.00	11.6	#1	6.17	8.8	#4	12.55
Merrill Lynch	13.5	#2	4.28	7.8	#3	5.36	5.7	#5	6.86	—		—
Morgan Stanley	11.8	#3	3.25	6.7	#6	3.98	5.2	#7	4.87	2.8	#7	9.16
JPMorgan Chase	9.8	#4	3.44	8.5	#2	4.30	8.6	#4	5.2	12.1	#2	10.55
Goldman Sachs	8.8	#5	3.6	5.3	#9	3.14	4.2	#9	3.58	3.7	#5	6.61
Freddie Mac	8.6	#6	2.35	5.9	#7	4.60	—		—	—		—
Lehman Brothers	7.2	#7	3.91	5.0	#9	4.88	4.6	#8	15.07	—		—
Fannie Mae	6.7	#8	2.47	7.1	#4	5.88	—		—	—		—
Bear Stearns	5.9	#9	4.4	2.9	#12	4.16	—		—	—		—
MetLife	3.6	#10	2.57	2.2	#15	2.93	1.9	#12	3.20	3.2	#6	11.93
Bank of America	0	#44	2.06	6.7	#5	3.60	9.6	#2	6.33	12.7	#1	13.41
AIG	0	#45	1.51	5.5	#8	4.63	9.6	#3	10.86	—		—
Wells Fargo	0	#48	2.38	1.9	#16	4.14	3.0	#10	5.40	10.4	#3	12.15
Wachovia	0	#51	2.2	4.6	#11	4.64	5.7	#6	9.61	—		—
Prudential Fin.	3.3	#11	3.09	2.6	#13	3.94	2.1	#11	4.17	2.6	#8	15.89
U.S. Bancorp	0	#40	1.62	0	#54	2.41	1.1	#15	5.20	2.6	#9	10.4
PNC Financial	0	#49	2.46	0	#43	2.84	0.3	#32	3.78	1.6	#10	10.03

Table 4.1 ranks the 10 most systemically risky financial firms among the 100 largest financial institutions for four dates ranging from July 1, 2007, through March 31, 2009. The Marginal Expected Shortfall (MES) measures how much the stock of a particular financial company will decline in a day, if the whole market declines by at least 2 percent. When equity values fall below prudential levels of 8 percent of assets, the Systemic Risk Contribution, SRISK%, measures the percentage of all capital shortfall that would be experienced by this firm in the event of a crisis. Note that the SRISK% calculations here incorporate existing capital shortfalls from failed institutions.

Source: www.systemicriskranking.stern.nyu.edu.

FSB and G-20 from Korea

- Will identify globally systemicaly risky firms by mid 2011
- Will suggest menu of options for reducing risk of such firms by end of 2011.
- Implement Basel III for all banks.

NEW INITIATIVES

- WORKING WITH UNIVERSITE DE LAUSANNE AND THE AUSTRALIAN GRADUATE SCHOOL IN SYDNEY
- WE PLAN TO EXTEND THIS ANALYSIS TO EUROPEAN AND AUSTRALASIAN FIRMS OVER THE NEXT YEAR

CONCLUSIONS

- Methodology relies on public information and well informed investors
- Historical rankings are fairly reasonable
- Model can be improved and data can be improved
- Goal is a screening technique that can be used to select firms for greater scruitiny.