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Effective Computation & Allocation of Enterprise Credit Capital for Large Retail and SME portfolios

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Summary & Concluding Remarks

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- **Enterprise credit risk management** of retail portfolios - still in its infancy
- Benefits: Potential reg. *capital relief & "beyond Basel II"*
    - Up to 50% for mortgages; 20% for unsecured lending*
- Vital to develop robust framework to satisfy key requirements:
    - Integrated enterprise view of credit risk: retail-wholesale-trading
    - Integrated economic & regulatory capital – effective allocation & reconciliation
    - Data modeling, consolidation and risk analytics
        - Vital to decompose: portfolio capital computation, allocation & reporting
- Effectively account for diversification: multi-factor modelling is important
    - Specially on enterprise portfolios across asset class and geographies
    - Correlations have great impact on capital calculation and allocation

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Retail vs Commercial Credits

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	Commercial	Retail
Borrowers/Portfolio	large and medium size businesses	individuals, medium and small businesses
# Loans	small/medium	large
Size	large/medium	small
Management	managed individually	managed as part of a large pool

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Retail vs Commercial Credits

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	Commercial	Retail
Default	borrower	borrower and transaction
Information	private and public	private (very private)
Availability: borrower characteristics	ongoing	at origination
Info. Update	periodically	not periodically
Product/collateral characteristics	available	available
Deliquency status	available	available
Credit model (PD, LGD, EADs, Correlations)	at loan level	at pool level

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Retail vs Commercial Credits

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	Commercial	Retail
Hedging, Trading & Risk mitigation	Diversification, structuring & collateral, 2nd markets & syndications, CDs, CDOs, bond & equity markets	Diversification, collateral, asset securitization
Expected Losses & Future margin Income	- EL can be substantial - Generally priced and provisioned for - Future income may depend on a small number of large accounts (low granualrity)	- EL is substantial - Generally priced and provisioned for - Future income can be counted on with high certainty (high granularity

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Summary: Regulatory Capital for Retail

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- For retail exposures: only advanced IRB approach (no foundation IRB)
- The key inputs to the IRB retail formulas are PD, LGD and EAD
  - Estimated for pools of similar exposures (each pool has its own PD, LGD & EAD)
- CP3 divides retail exposures into three primary categories:
  - Exposures secured by residential mortgages
  - Qualifying revolving retail exposures (QRRE)*
  - Other non-mortgage exposures (also known as ‘other retail.’)**
- CP3 provides a separate risk-weight formula for each of the three categories

* QRRE: unsecured revolving credits that exhibit appropriate loss characteristics, which would include many credit card relationships

** All other non-mortgage consumer lending including exposures to small businesses falls into the ‘other retail’ category

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Retail
Minimum Capital Requirements

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Residential mortgages

$$K = LGD \cdot N\left[\frac{1}{\sqrt{1-R}} G(PD) + \left(\frac{R}{\sqrt{1-R}} G(0.999) \right) \right]$$

$$R = 0.15$$

Revolving credit exposures

$$K = LGD \cdot N\left[\frac{1}{\sqrt{1-R}} G(PD) + \left(\frac{R}{\sqrt{1-R}} G(0.999) \right) \right] - (0.75 PD \cdot LGD)$$

$$R = 0.02\left(1-e^{-50PD}\right)/\left(1-e^{-50}\right) + 0.11\left[1-\left(1-e^{-50PD}\right)/\left(1-e^{-50}\right)\right]$$

Other retail credit exposures

$$K = LGD \cdot N\left[\frac{1}{\sqrt{1-R}} G(PD) + \left(\frac{R}{\sqrt{1-R}} G(0.999) \right) \right]$$

$$R = 0.02\left(1-e^{-35PD}\right)/\left(1-e^{-35}\right) + 0.17\left[1-\left(1-e^{-35PD}\right)/\left(1-e^{-35}\right)\right]$$

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Best Practices Economic Capital
Product Segmentation

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- Typically, banks may perform product segmentations into more than the three regulatory segments.
- For example, in RMA (2003) – “Retail Credit Economic Capital Estimation - Best Practices”, banks identified 9 product lines:
  - Single-family first mortgages
  - Term Home Equity Loans
  - Home Equity Lines of Credit (HELOCs)
  - Credit Cards
  - Retail Leases
  - Unguaranteed Student Loans
  - Small Business Loans (managed as retail credits)
  - Other, Secured Retail
  - Other, Unsecured Retail

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Credit Risk Models – General Remarks

- Loss probability distributions through segmentation, or bucketing
  - Product level or more finely grained (PD band, multi-dimensional matrix of risk characteristics, e.g. FICO score, delinquency status, account age, etc.)
- Most banks use 1-year horizon, but some use "life of loan" horizon
- Best practice banks generally use an explicit correlation model (either obligor asset value correlations – AVC or loan default correlations LDC)
  - Consistent with their application in the corporate portfolios
  - Most banks have less than 6 years of data (a couple had >12 years)
- Models in practice are 1-factor (provides general closed form solutions)

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Credit Risk Models – General Remarks

- Banks generally use as a capital measure only unexpected losses (say the 99.9% losses minus the EL)
  - Loan loss provisions are generally based on EL
- Banks generally still compute total economic capital as the sum of the capital of each bucket – no benefit of cross diversification
  - This is also a direct consequence of 1-factor models
  - This is sometimes corrected in ad-hoc ways (e.g. reduced confidence level)
- Industry benchmarking works are underway to establish reasonable ranges for correlation parameters

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Example: Asset Correlations for First Mortgages

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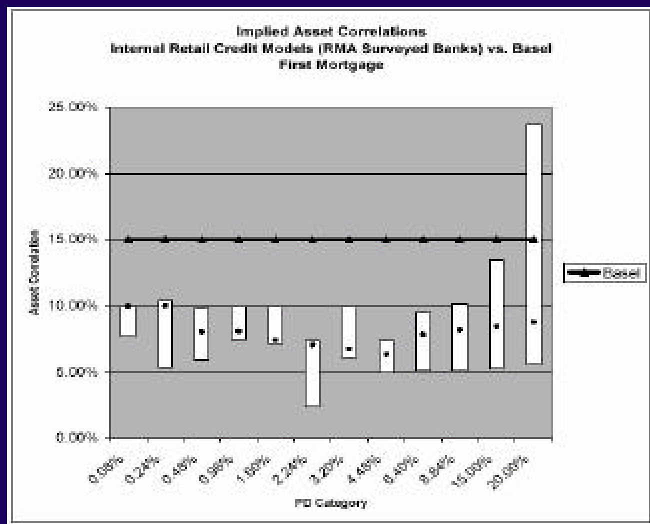

Source: Retail Credit Economic Capital Estimation -Best Practices, RMA, February 2003

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Example: Asset Correlations for Credit Cards

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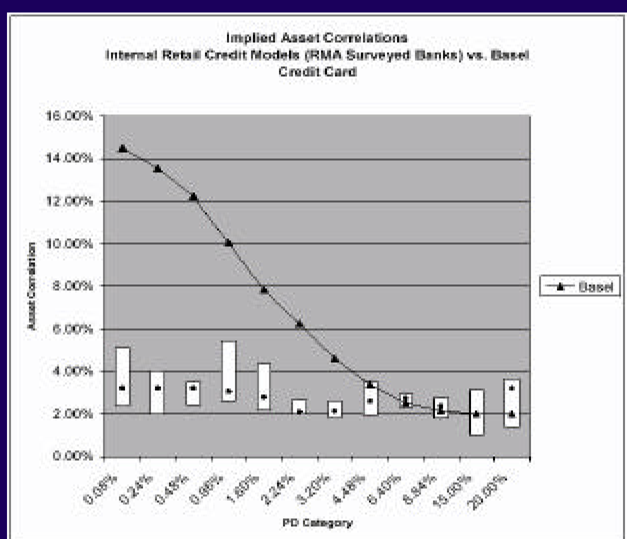

Source: Retail Credit Economic Capital Estimation -Best Practices, RMA, February 2003

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Retail Credit Portfolio Modelling & Enterprise Credit Risk

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Enterprise credit risk management of retail portfolios - still in its infancy

- Vital to develop robust framework to satisfy key requirements:
  - Integrated enterprise view of credit risk: retail-wholesale-trading
  - Integrated economic & regulatory capital
    - Effective allocation & reconciliation
  - Data modeling, consolidation and risk analytics
- Must simultaneously address characteristics of commercial and retail
- Effectively account for diversification

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Mark-to-Future Framework for Portfolio Credit Risk

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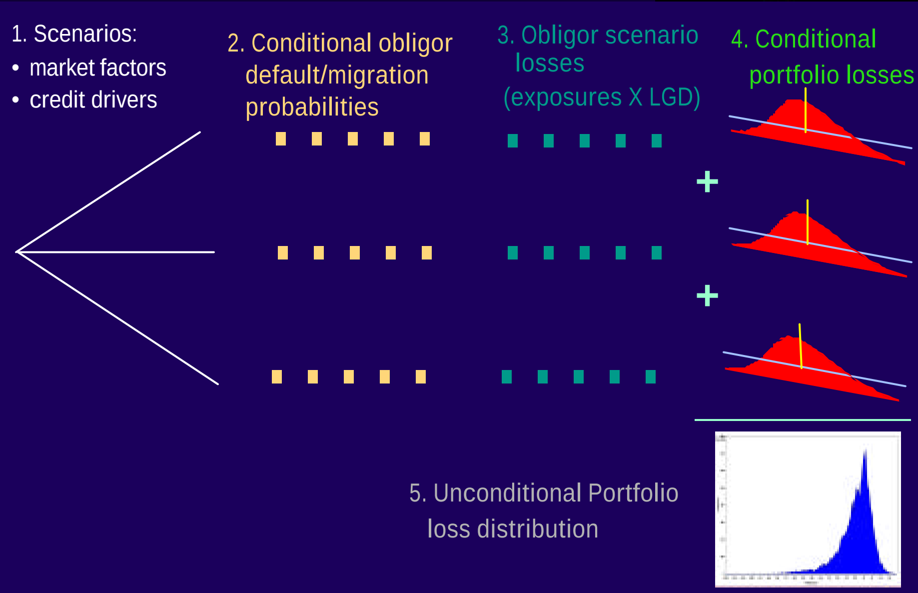

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Components of Credit Portfolio Management – Retail Portfolios

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Commonly, we focus on 1-year default losses only (systemic & idiosyncratic)

- Framework is clearly extendable

- Set of homogeneous buckets/segments/pools
  - N obligors
  - PD, EAD (or discrete EAD distribution) , LGDs
  - Obligor credit codependence structure
  - Set of extra dimensions for allocation/reporting
- For MtM losses
  - Represent each bucket by a single instrument (or a small set); e.g. a loan, revolver, etc… which can be valued under each credit state
  - Require, transition matrix, and spread curves (prices)

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Capital Computation & Reporting Segmentation/Bucketing

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- Given the size of the portfolios and the reporting requirements, it is key to understand the "bucketing requirements" for capital calculation and reporting
  - Effective strategy: <u>break computation vs. reporting/allocation</u>

Example:

- 10 countries 8 products 12 PD Grades 10 LGD Grades
- 10 LTV values 15 Residual Maturity Bands 5 application/dist. channels

- Total of 7,200,000 possible reporting buckets !!!
- Not uncommon to have over 10 reporting dimensions

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Minimum Capital Requirements & Segmentation/Bucketing

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At a minimum, for reg. capital calculations (in CP3), retail transactions (in a given geographic location/country) must be assigned to buckets based on 3 dimensions:

- Product category (RMEs, QRRE, ORE)
- PD rating
- LGD rating

- Each of these buckets can be represented by a single RW/unit-exposure
  - Each transaction in each of these buckets shares the same risk weight K

- We refer to these set of buckets as the regulatory, or Iso-K, buckets

Note: we use interchangeably bucket-segment-pool

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Minimum Capital Requirements & Segmentation/Bucketing

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- Number of Iso-*K* buckets is (for multiple rating systems on *C* countries, and *P* products) :

$$N_{IK} = \sum_{C} \sum_{P} N_{PD}(C,P) \cdot N_{LGD}(C,P)$$

- For a portfolio with *C* countries, and *P* products and single system

$$N_{IK} = C \cdot P \cdot N_{PD} \cdot N_{LGD}$$

  - e.g. for 5 countries with 3 products, 12 PD and 10 LGD classes = 1,800 Iso-*K* buckets

- Iso-*K* bucket: pool of products that share four basic dimensions, and has a unique *K* and *EAD*; we can write it (in general) as

B (Country, Product, PD, LGD) → [*K* (P, PD, LGD); EAD]

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Minimum Capital Requirements & Segmentation/Bucketing

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Simple representation: store risk weight/unit-EAD for all Iso-K buckets as a set of matrices (per product and country):

K = Min Reg. Capital /unit EAD (pre-computed)

Product
RME QRRE ORE

	LGD	Grade 1	Grade 2	Grade 3
PD		25%	50%	75%
A	0.04%			
BBB	0.29%			
BB	1.00%			
B	3.32%			
C	20.00%			

UK

	LGD	Grade 1	Grade 2	Grade 3
PD		25%	50%	75%
A	0.04%			
BBB	0.29%			
BB	1.00%			
B	3.32%			
C	20.00%			

France

	LGD	Grade 1	Grade 2	Grade 3
PD		25%	50%	75%
A	0.04%			
BBB	0.29%			
BB	1.00%			
B	3.32%			
C	20.00%			

USA

- Note that *K* is simply a function of (C, P, PD, LGD) and ***not*** of the actual portfolio
- It is only to be recomputed when
  - Ratings are re-calibrated
  - Stress testing

$$K = LGD \cdot N\left[\frac{1}{\sqrt{1-R}}G(PD)+\left(\frac{R}{\sqrt{1-R}}G(0.999)\right)\right]$$

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Basic Mapping/Bucketing from Transaction Source System into Iso-K buckets

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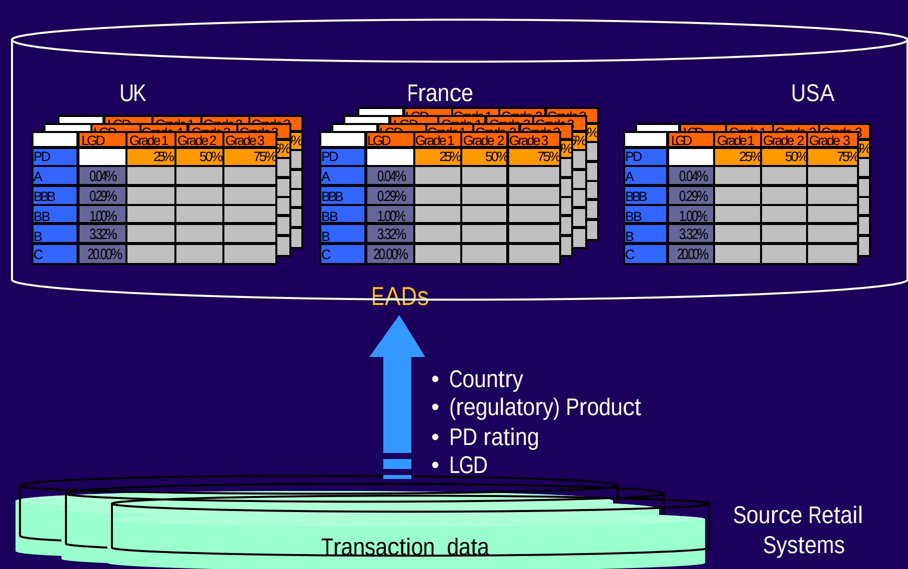

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Minimum Capital Requirements & Segmentation/Bucketing

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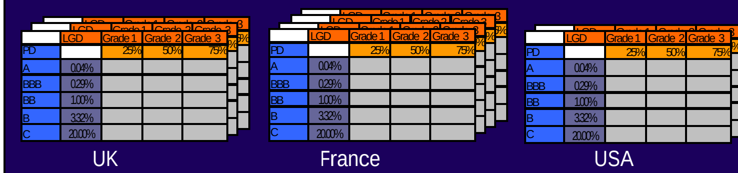
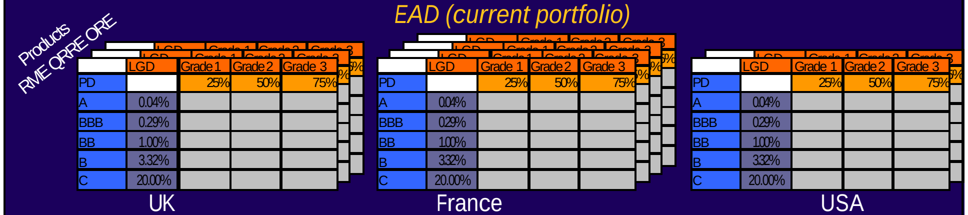
K (Min Reg. Capital /unit EAD)



- A bucket's EAD is a portfolio property: a product of the "bucketing/mapping"

EAD (current portfolio)



- The regulatory capital calculation proceeds by simple multiplication

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Min Capital + Reporting & Segmentation/Bucketing

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- The previous scheme, while sufficient to compute the overall capital of the retail portfolio, only allows the breakdown of capital along the underlying four dimensions: country, product, PD and LGD ratings
- For regulatory reporting (Pillar 3) and best practice risk management management, we need capital contributions across a larger number of dimensions, e.g.
  - LTV   Residual maturity   Vintage   Application distribution channel   etc…
- Not uncommon to quote up to 10-20 dimensions for allocation

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Min Capital + Reporting & Segmentation/Bucketing

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- Brute force approach: create buckets which contain each cell in this multi-dimensional breakdown (the ***reporting segments or buckets***),

  B(C, P, PD, LGD; dim 1, …, dim *m*) → [*K* (C,P,PD, LGD); EAD]

- This results in an exponential growth of the number of buckets, e.g.
  - 10 countries 8 products 12 PD Grades 10 LGD Grades
  - 10 LTV values 15 Residual Maturity Bands 5 application/Distribution Channels
  - Results in 7,200,000 segments (this is only 3 extra dimensions!)

- Large number of pools share *K - EAD* is the result of the appropriate mapping
- Might end up with more pools than retail products we started with!

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Min Capital + Reporting & Segmentation/Bucketing

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Solution: define retail bucket as an Iso-*K* bucket (not necessarily identical), with an extra set of attributes - allow to break capital in bucket into various dimensions

- Represent bucket as:

  B(C, P, PD, LGD) → [K; EAD, D1 (% breakdown), …, DC(% breakdown)]

  where each Di (% breakdown) is a vector, which sums to one, representing the % bucket exposure in that consolidation dimension (or combination of dimensions)

- More generally, define set of bucketing dimensions d1, d2,…, dk; and set of consolidation dimensions (or combinations) D1, D2, …, Dc, a retail bucket is then

  B(d1,…,dk) → [K; EAD, D1 (% breakdown), …, Dc(% breakdown)]

- Consolidation engine must understand then how to perform such aggregations

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Basic Mapping/Bucketing from transaction source system into Iso-K buckets

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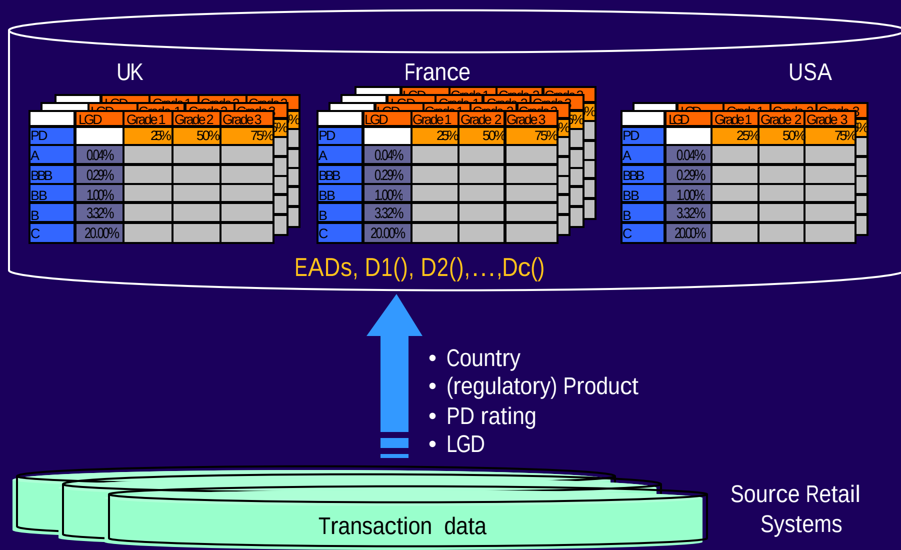

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Min Capital + Reporting & Segmentation/Bucketing

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Using the previous example:

- 10 countries 8 products 12 PD Grades 10 LGD Grades
- 10 LTV values 15 Residual Maturity Bands 5 application/Distribution Channels

- We have minimum of 3, 600 Iso-K buckets (mapping each of the 8 products into the 3 regulatory product groups RMEs, QRREs, OREs)
- We have a total of 7,200,000 possible reporting buckets
- A natural modelling assumption would be to break this portfolio into
  - 9,600 retail buckets,
  - Each bucket has 3 consolidation dimensions (LTV, RM, app/dist) - 3 vectors of dimensions 10, 15, 5
  - We could also allow for joint breakdown across 2 dimensions: e.g. LTV&RM (matrix of 10X15), etc..

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Retail Buckets for Regulatory Capital Calculation

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- Large international bank → >50 million retail exposures
- Effective 'bucketing' into segments becomes essential

ORE | QRRE

RME	LGD	Grade 1	Grade 2	Grade 3
PD		25%	50%	75%
A	.004%			
BBB	.029%			
BB	1.00%			
B	3.32%			
C	20.00%			

Loan to value
< 50%
50% - 75%
75% - 90%
90% - 100%
100% - 120%
> 120%

Maturity band
< 3m
3m – 1y
1y – 3y
3y – 5y
> 5y

Channel
branch
e-delivery
telephone
other

Example

- *3 x 15 x 6 x 5 x 4* = 5,400 retail segments
- More dimensions → exponential increase
- However…. K = *f (PD, LGD, Product type)*

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Retail Buckets for Regulatory Capital Calculation

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5,400 retail segments → only 45 unique instruments (15 per retail product type)

ORE | QRRE

RME	PD	LGD	K	EAD
1	0.004%	25%	0.0024	$94,212
2	0.004%	50%	0.0048	$95,631
3	0.004%	75%	0.0073	$94,568
4	0.29%	25%	0.0113	$93,789
5	0.29%	50%	0.0226	$94,269
6	0.29%	75%	0.0338	$92,060
7	1.00%	25%	0.0276	$83,755
8	1.00%	50%	0.0551	$90,470
9	1.00%	75%	0.0826	$88,485
10	3.32%	25%	0.0610	$100,243
11	3.32%	50%	0.1221	$85,085
12	3.32%	75%	0.1831	$91,978
13	20.00%	25%	0.1625	$91,968
14	20.00%	50%	0.3250	$87,876
15	20.00%	75%	0.4875	$99,479

Loan to value	%
< 50%	17.92
50% - 75%	15.23
75% - 90%	17.10
90% - 100%	19.30
100% - 120%	15.12
> 120%	15.33

Maturity band	%
< 3m	20.35
3m – 1y	17.93
1y – 3y	20.94
3y – 5y	22.75
> 5y	18.04

Channel	%
branch	21.94
e-delivery	22.19
telephone	25.44
other	30.43

Split the complexity of the computation & the complexity of the aggregation!

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Retail Bucketing & Economic Capital

- The regulatory capital formulae, require only the PD, LGD, EAD of each bucket to compute its contribution to overall regulatory capital
- For economic capital calculation, we further require (at least):
  - The number N of exposures in each bucket
  - The credit correlation model of each bucket
- Simple extension: each bucket, represents a homogeneous portfolio, with same PD, LGD, EAD and credit correlation model
  - Reasonable, given that the bucket already defines a product, country… and perhaps a sector where applicable)

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Example: Economic Capital of Credit Card Portfolio

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Credit Card Portfolio

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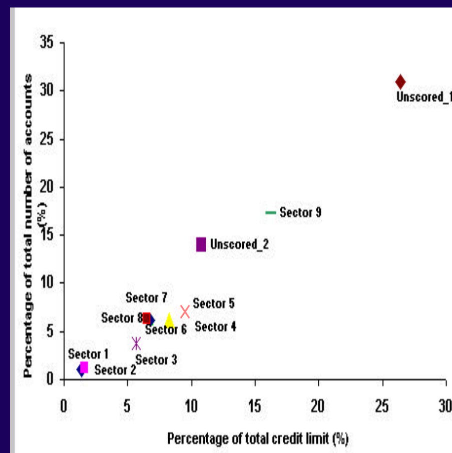
- ≈ 500,000 cards
- 28 cohorts
- Risk class: accounts with similar score at acquisition

11 sectors

- sector 1 — high risk-low score
- sector 9 — low risk-high score
- unscored_1 — cards issued to existing customers
- unscored_2 — cards without reliable score



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Credit Card Portfolio

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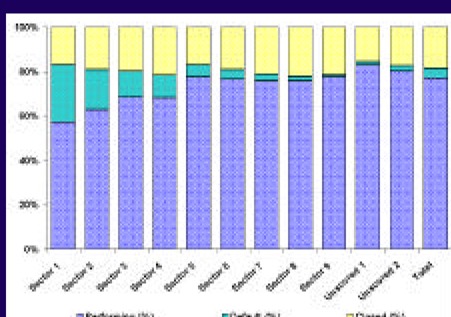

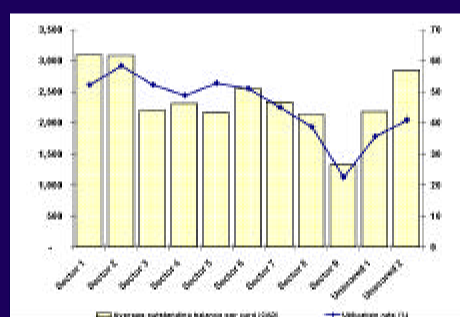

- Portfolio as of 1Q'99
  - Performing balance ≈ 700 million USD
  - Average performing balance per card ≈ $1,500 USD
  - Average utilization rate 39%

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Modeling Assumptions

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Sectors

- Homogeneous (accounts ≈ same size)
- Accounts are assumed to be statistically identical

PDs

- Ratings
  - At time of default accounts keep acquisition score
- Default events
  - Bankruptcy or charge-offs
- Probabilities of default
  - Estimated by one-year default rates for each cohort (28)

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Modeling Assumptions

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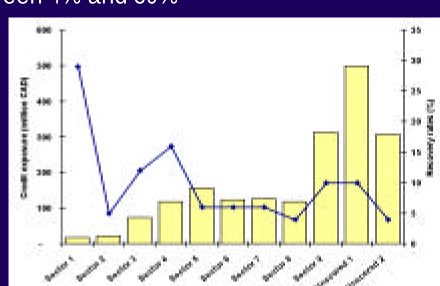
EAD

- Average utilization rate at time of default
- Average exposure ≈ $2,700 USD

Recovery rates

- Deterministic, and estimated directly from historical experience
- Range between 4% and 30%



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Modeling assumptions

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Correlation Model

- Tested various functional forms of (single-step) default models:
- Merton and Logit - with both economic and sector-specific (implicit) factors
  - Calibration using historical time series of default rates in each sector (see appendix)

Economic Credit drivers

- industrial production
- stock index
- consumer price index
- retail sales
- unemployment level
- interest rates

Model	Conditional default probabilities
Sector-based logit model	$p_j(Z^S) = \dfrac{1}{1 + a_j \exp\left\{b_j\left(\sum_k \beta_{jk}^{S*} Z_k^S\right)\right\}}$
Factor-based logit model	$p_j(Z) = \dfrac{1}{1 + a_j \exp\left\{b_j\left(\sum_k \beta_{jk}^{M*} Z_k^M + \beta_{jj}^{S*} Z_j^S\right)\right\}}$
Factor-based Merton model	$p_j(Z) = \Phi\left(\dfrac{\alpha_j - \left(\sum_k \beta_{jk}^M Z_k^M + \beta_{jj}^S Z_j^S\right)}{\sigma_j}\right)$

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Portfolio Loss Distribution

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Capital definition

- Default losses over 1 year (single-step)

Computational methodology

- Explicit simulation of systemic factors (both economic and sector-specific)
- Systemic risk – LLN (expected portfolio losses under each scenario)

- Assumption that portfolio is large enough so that systemic losses well represent the total portfolio losses
  - Easy to extend analysis and explicitly measure concentration risk (or the actual granularity adjustment)

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Loss Distributions and Statistics

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	Sector-based logit model	Factor-based logit model	Factor-based Merton model
Expected losses	1.0	1.0	1.0
Standard deviation	0.4	0.3	0.3
Maximum losses (99%)	2.1	2.1	1.9
Credit VaR (99%)	1.1 (3.2)	1.1 (3.2)	0.9 (2.8)
Expected shortfall (99%)	2.4	2.3	2.2
Maximum losses (99.9%)	2.7	2.6	2.5
Credit VaR (99.9%)	1.8 (5.0)	1.6 (4.6)	1.6 (4.8)
Expected shortfall (99.9%)	3.1	3.0	2.8

Table 7: Statistics for one-year loss distribution

Results are similar with all models, in this case

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Sources of Risk

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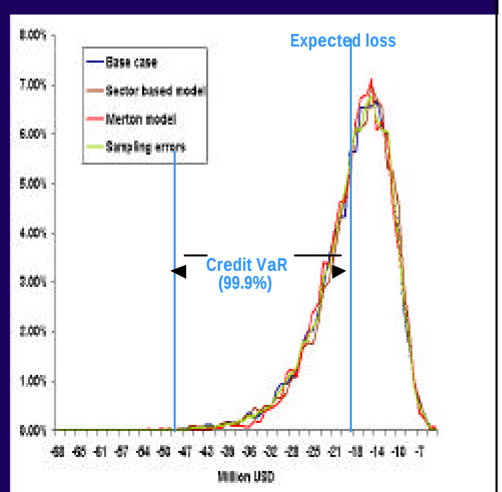
Systematic stress testing

- Sampling errors
- Independent defaults
- Correlated credit risk drivers
- False-performing accounts



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Sources of Risk

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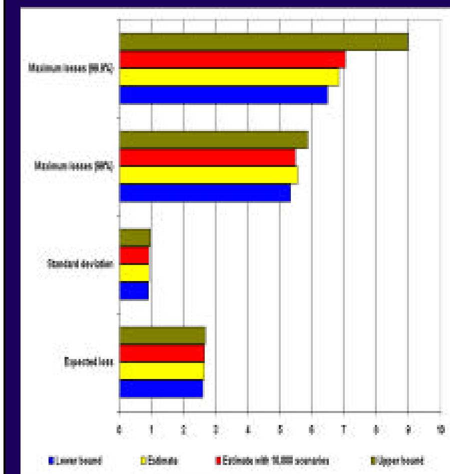

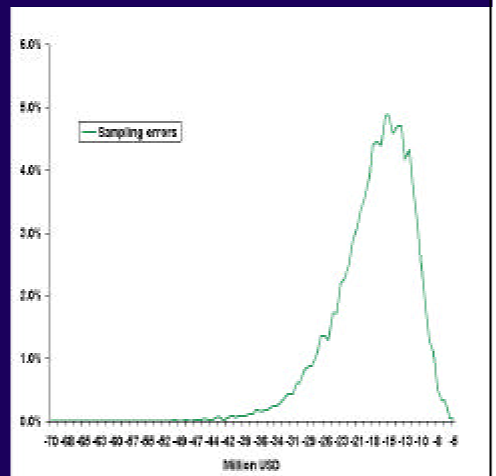

Sampling errors: confidence bounds

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Sources of Risk

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Independent defaults

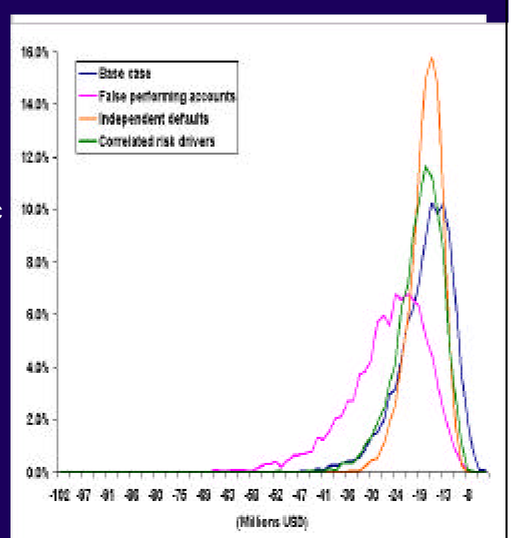
- Higher mass in center than base case
- Thinner tails
- Credit VaR 60% lower than base case

Correlated credit risk drivers

- New scenarios capture effect of economic cycle on consumer finance
- Higher mean loss and lower volatility (σ)
- Credit VaR (99.9%) is 25% larger than base case

False performing accounts

- Default accounts that at the end of each month are classified as performing
- Higher mean loss and economic capital ≈ 50%



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Credit Risk Management

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"Hot Spots" report

- Sectors with largest contribution to portfolio credit risk
- Ranked by expected shortfall
- Expected loss non-diversifiable
- Three sectors concentrate more than 50% of portfolio credit risk
- High-risk sectors (1 and 2) have a relatively low contribution to portfolio risk

	Mean loss	Standard deviation	Maximum loss (99%)	Maximum loss (99.9%)	Expected shortfall (99%)	Expected shortfall (99.9%)
Unscored_1	27.6%	24.0%	23.3%	37.8%	28.0%	27.8%
Unscored_2	15.7%	9.7%	9.6%	7.2%	16.2%	14.8%
Sector 4	10.3%	13.1%	20.6%	11.6%	11.1%	11.4%
Sector 5	11.5%	10.9%	12.5%	8.9%	10.7%	9.7%
Sector 3	7.6%	10.4%	6.3%	9.1%	6.8%	8.6%
Sector 6	7.3%	6.4%	4.5%	5.3%	6.8%	7.6%
Sector 7	5.3%	3.0%	6.7%	3.4%	5.3%	4.2%
Sector 1	3.5%	2.5%	5.4%	6.2%	4.0%	4.5%
Sector 2	4.0%	3.1%	3.9%	6.5%	3.8%	5.8%
Sector 8	3.7%	1.6%	3.2%	2.3%	3.7%	2.7%
Sector 9	3.6%	1.9%	3.9%	1.8%	3.5%	2.8%

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Credit Risk Management

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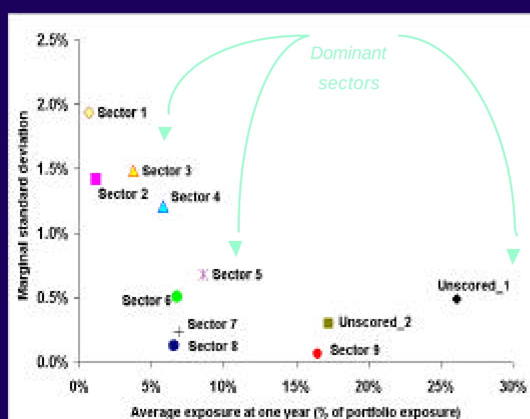
Marginal Risk

- Dominant sectors have higher marginal risk and exposure than other sectors
  - Candidates for restructuring
- Marginal risk decreases with original score
- Correlations matter
  - Sector 3 has higher marginal risk than sector 2
- Sectors with high marginal risk
  - ⇒ increase scoring thresholds
  - Securitization



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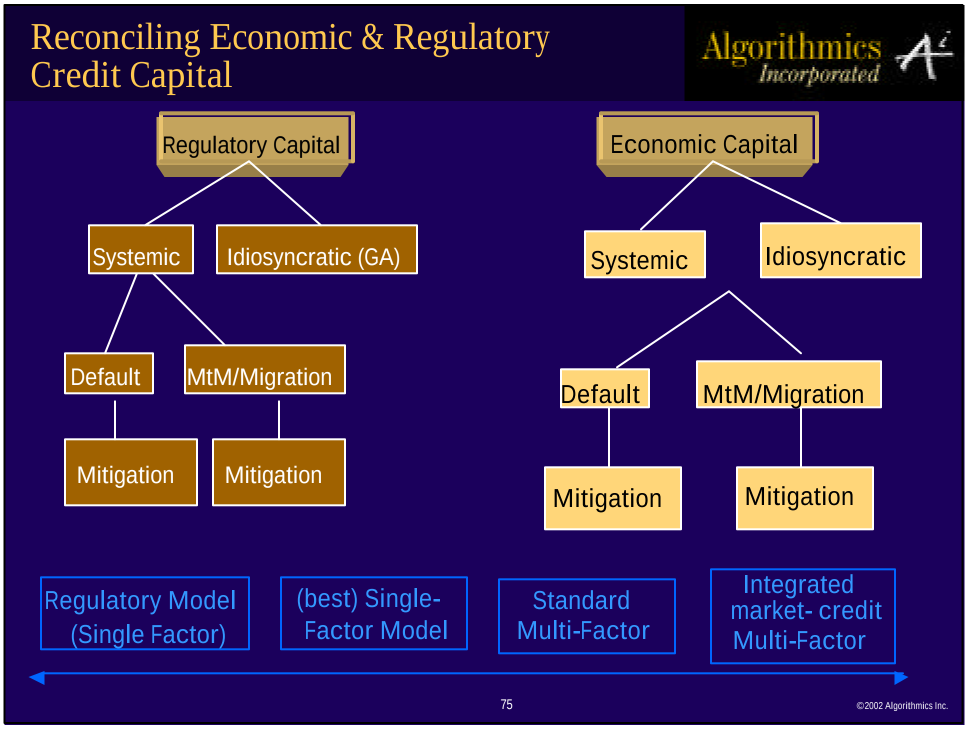
Reconciling Economic & Regulatory Credit Capital
Algorithmics Incorporated
Regulatory Capital
Systemic
Idiosyncratic (GA)
Default
MtM/Migration
Mitigation
Mitigation
Economic Capital
Systemic
Idiosyncratic
Default
MtM/Migration
Mitigation
Mitigation
Regulatory Model (Single Factor)
(best) Single-Factor Model
Standard Multi-Factor
Integrated market- credit Multi-Factor
75
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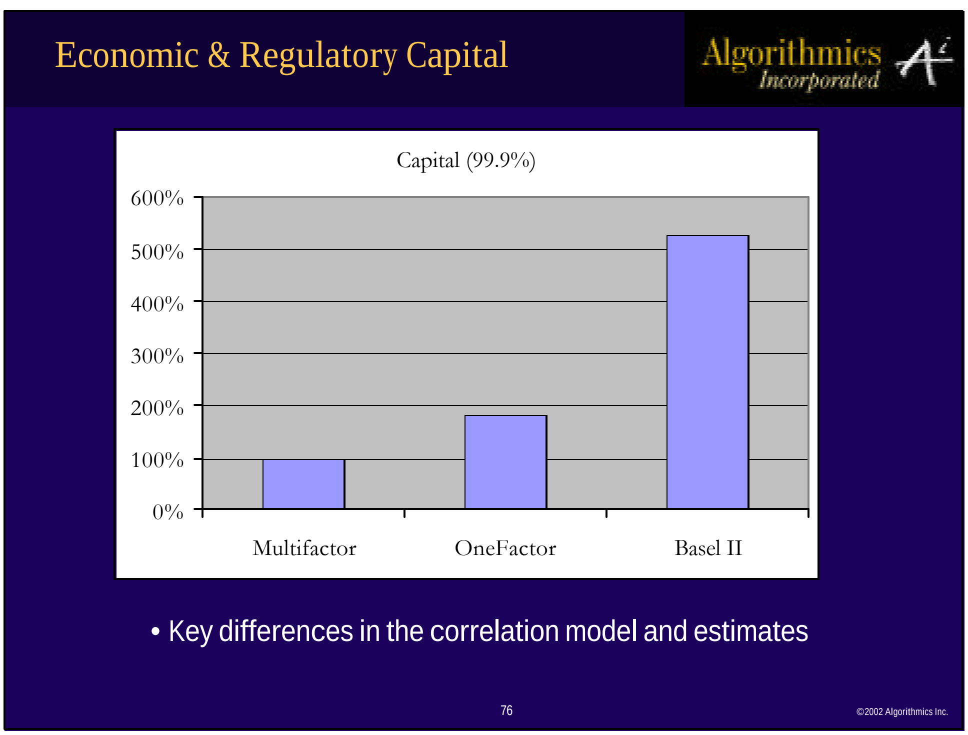
Economic & Regulatory Capital
Algorithmics Incorporated
Capital (99.9%)
600%
500%
400%
300%
200%
100%
0%
Multifactor
OneFactor
Basel II
• Key differences in the correlation model and estimates
76
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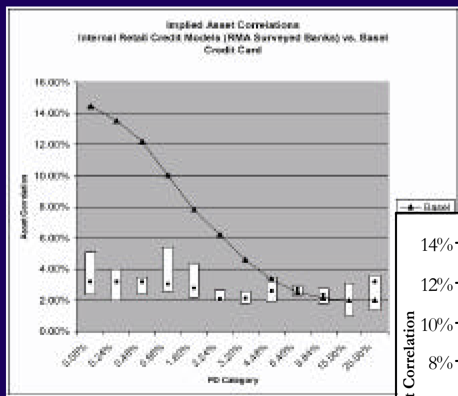
Impact of Asset Correlations on Capital

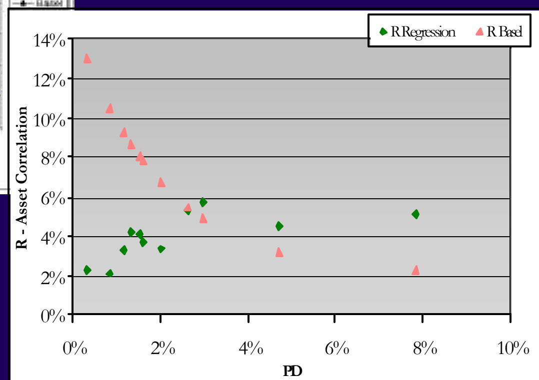
Algorithmics *Incorporated*



Average (EL weighted) asset correlations:

-Basel: 7.4%

-Internal 1-factor model: 4.1%



Implied asset correlations:

-Basel: 7.9 %

-Internal 1-factor model: 4%

-Internal n-factor model: 1.6%

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Summary & Concluding Remarks

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- Enterprise credit risk management of retail portfolios - still in its infancy
- Vital to develop robust framework to satisfy key requirements:
  - Integrated enterprise view of credit risk: retail-wholesale-trading
  - Integrated economic & regulatory capital – effective allocation & reconciliation
  - Data modeling, consolidation and risk analytics
- Effectively account for diversification: multi-factor modelling is important
  - Specially on enterprise portfolios across asset class and geographies
  - Correlations have great impact on capital calculation and allocation
- Vital to decompose portfolio capital computation, allocation & reporting

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