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Normalized Exponential Tilting:  
Pricing and Measuring **Multivariate Risks**

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# Agenda

- The **Univariate** Case
  - **Exponential** Tilting
  - **Normalized** Exponential Tilting
  - Probability **Distortion**
- How to Extend to the **Multivariate** Case?
- Portfolio Risk Measures (**no time to get into detail**)

# Why is it an important problem?

- Multivariate risk modelling & Portfolio Risk Measure directly impact corporate decisions
  - Copulas & Correlation Models
  - Combining market risk, credit risk, insurance risk, and operational risk
  - Capital allocation
- Let us turn to a new page of risk theory:  
**multivariate risk adjustment**

# Exponential Tilting of $X$ w.r.t. $Y$

$$f_X^*(x) = f_X(x) \cdot \frac{E[\exp(\lambda Y) | X = x]}{E[\exp(\lambda Y)]}$$

$X$ : Bernoulli(1/5)

$Y$ : Normal(0, 1),

How to do exponential  
tilting?

**Case 1:  $X$  and  $Y$   
independent**

**Case 2:  $X$  and  $Y$   
are co-monotone**

# Exponential Tilting

Buhlmann  
Economic Model  
(AB 1980)

When  $X=Y$ ,  
we get Esscher  
transform

$\lambda$  controls the  
magnitude of risk-  
adjustment.

A big problem?  
No consistent  
interpretation of  
 $\lambda$

# Normalized Exponential Tilting

Let  $Z$  be normal(0,1) such that  $Y = \Phi^{-1}(Z)$ , where  $\Phi$  is the CDF of normal(0,1).

**Before:** Exponential tilting of  $X$  w.r.t  $Y$

**Now:** Transform  $Y$  into normal(0,1) variable  $Z$

**After:** exponential tilting of  $X$  w.r.t.  $Z$ .

$$f_X^*(x) = f_X(x) \cdot \frac{E[\exp(\lambda Y) | X = x]}{E[\exp(\lambda Y)]}$$

$Y \rightarrow Z$

$$f_X^*(x) = f_X(x) \cdot \frac{E[\exp(\lambda Z) | X = x]}{E[\exp(\lambda Z)]}$$

We got consistent interpretation of  $\lambda$ :

**Sharpe Ratio,**  
**Market price of risk**

# Normalized Exponential Tilting

## → Probability Distortion

**Theorem 1:** If the correlation between  $X$  and  $Y$  follows a normal copula, the *normalized* exponential tilting is equivalent to applying the Wang transform

$$F_X^*(x) = \Phi\left[\Phi^{-1}(F_X(x)) - \beta\right]$$

$$\beta = \rho_{X,Y} \cdot \lambda$$

# Univariate Distortion: Radon-Nikodym Derivative

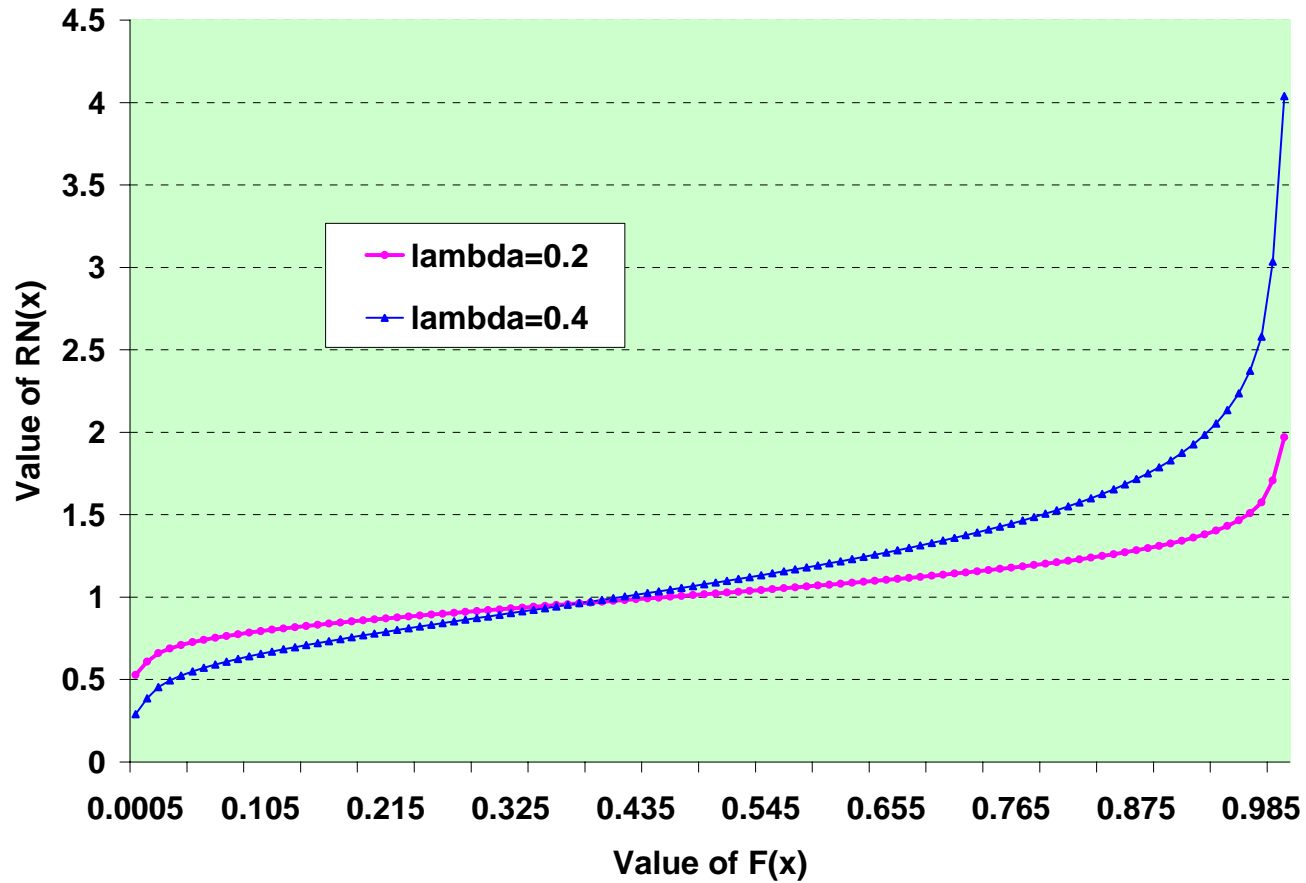
$$F_X^*(x) = g(F_X(x))$$

**The Radon-Nikodym Derivative:**

$$RN_g(x) = f^*(x) / f(x) = g'(F_X(x))$$



# Univariate Normalized Exponential Tilting → Wang transform Radon-Nikodym derivatives



# Multivariate Exponential Tilting

The exponential tilting of  $\{X_1, X_2, \dots, X_n\}$  with respect to references  $\{Y_1, Y_2, \dots, Y_k\}$  is defined by

$$f^*(x_1, \dots, x_n) = c \cdot f(x_1, \dots, x_n) \cdot \prod_{j=1}^k E[\exp(\lambda_j Y_j) \mid X_1 = x_1, \dots, X_n = x_n]$$

The references  $\{Y_1, \dots, Y_k\}$  can be

- ✓ business unit, company, and industry aggregates,
- ✓ the underlying risks for contingent claims  $\{X_1, \dots, X_n\}$ ,
- ✓ the risks  $\{X_1, \dots, X_n\}$  themselves

# Multivariate Normalized Exponential Tilting

To get consistent interpretation of  $\{\lambda_1, \lambda_2, \dots, \lambda_k\}$ , we **normalize**  $\{Y_1, Y_2, \dots, Y_k\}$  to  $\{Z_1, Z_2, \dots, Z_k\}$  .

$$Z_j = \Phi^{-1}\left(F_{Y_j}(Y_j)\right),$$

$$f^*(x_1, \dots, x_n) = c \cdot f(x_1, \dots, x_n) \cdot \prod_{j=1}^k E\left[\exp(\lambda_j Z_j) \mid X_1 = x_1, \dots, X_n = x_n\right]$$

### Example 1. The effect of Correlation!

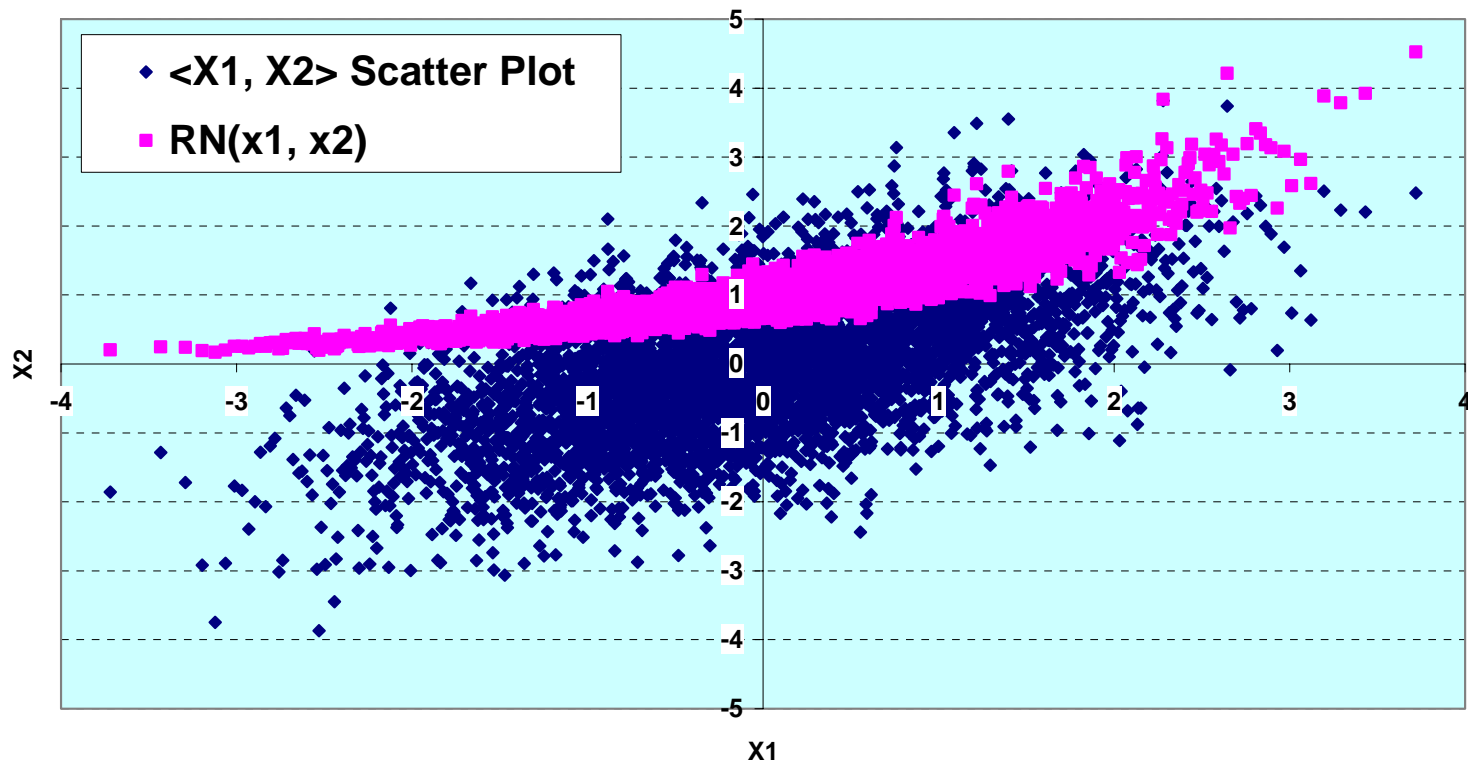
Assume that the risks  $\{X_1, X_2\}$  have a bivariate normal(0,1) with correlation coefficients:

$$\Sigma = \begin{pmatrix} 1 & \rho_{X_1, X_2} \\ \rho_{X_1, X_2} & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0.6 \\ 0.6 & 1 \end{pmatrix}.$$

The bivariate normalized exponential tilting with references  $Y_1 = X_1$  and  $Y_2 = X_2$ ,  $\lambda_1 = 0.3$  and  $\lambda_2 = 0.2$ , is equivalent to applying *separate* Wang transforms  $F_{X_j}^*(x) = \Phi[\Phi^{-1}(F_{X_j}(x)) - \beta_j]$  for  $j = 1, 2$ , with

$$\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} 1 & \rho_{X_1, X_2} \\ \rho_{X_1, X_2} & 1 \end{pmatrix} \begin{pmatrix} \lambda_1 \\ \lambda_2 \end{pmatrix} = \begin{pmatrix} \lambda_1 + \rho_{X_1, X_2} \lambda_2 \\ \rho_{X_1, X_2} \lambda_1 + \lambda_2 \end{pmatrix} = \begin{pmatrix} 0.42 \\ 0.38 \end{pmatrix}$$

# Bivariate Normalized Exponential Tilting: Radon-Nikodym derivatives



# Define Joint Distortion

The Radon-Nikodym Derivative:

$$f_{X_1, \dots, X_n}^*(x_1, \dots, x_n) = RN_{g_1, \dots, g_n}(x_1, \dots, x_n) \cdot f_{X_1, \dots, X_n}(x_1, \dots, x_n)$$

$$RN_{g_1, \dots, g_n}(x_1, \dots, x_n) = c \cdot \prod_{j=1}^n g_j'(F_{X_j}(x_j))$$

**Main Theorem:**

**Multivariate Normalized Exponential Tilting  
of  $\{X_1, \dots, X_n\}$  w.r.t. themselves**

**→ Joint Distortions by Wang transforms**

# Example 2: Bivariate Normalized Exponential Tilting

- Given the following bivariate p.f., how to perform normalized exponential tilting with  $\lambda_1=0.3$  and  $\lambda_2=0.2$ ?

	$X_2=1$	$X_2=2$	$X_2=3$	$X_2=4$	$X_2=5$
$X_1=1$	<i>0.20</i>	<i>0.07</i>	<i>0.06</i>	<i>0.05</i>	<i>0.04</i>
$X_1=2$	<i>0.06</i>	<i>0.05</i>	<i>0.04</i>	<i>0.03</i>	<i>0.03</i>
$X_1=3$	<i>0.05</i>	<i>0.04</i>	<i>0.03</i>	<i>0.03</i>	<i>0.02</i>
$X_1=4$	<i>0.03</i>	<i>0.03</i>	<i>0.02</i>	<i>0.02</i>	<i>0.01</i>
$X_1=5$	<i>0.03</i>	<i>0.02</i>	<i>0.01</i>	<i>0.02</i>	<i>0.01</i>

- First apply the Wang transform to  $X_1$  with  $\lambda_1=0.3$ .

- Then apply the Wang transform to  $X_2$  with  $\lambda_2=0.2$

$X_1 = x_1$	$f(x_1)$	$F(x_1)$	$F^*(x_1)$	$f^*(x_1)$
1	0.42	0.42	0.30787	0.30787
2	0.21	0.63	0.51271	0.20483
3	0.17	0.80	0.70596	0.19325
4	0.11	0.91	0.85101	0.14505
5	0.09	1.00	1.00000	0.14899

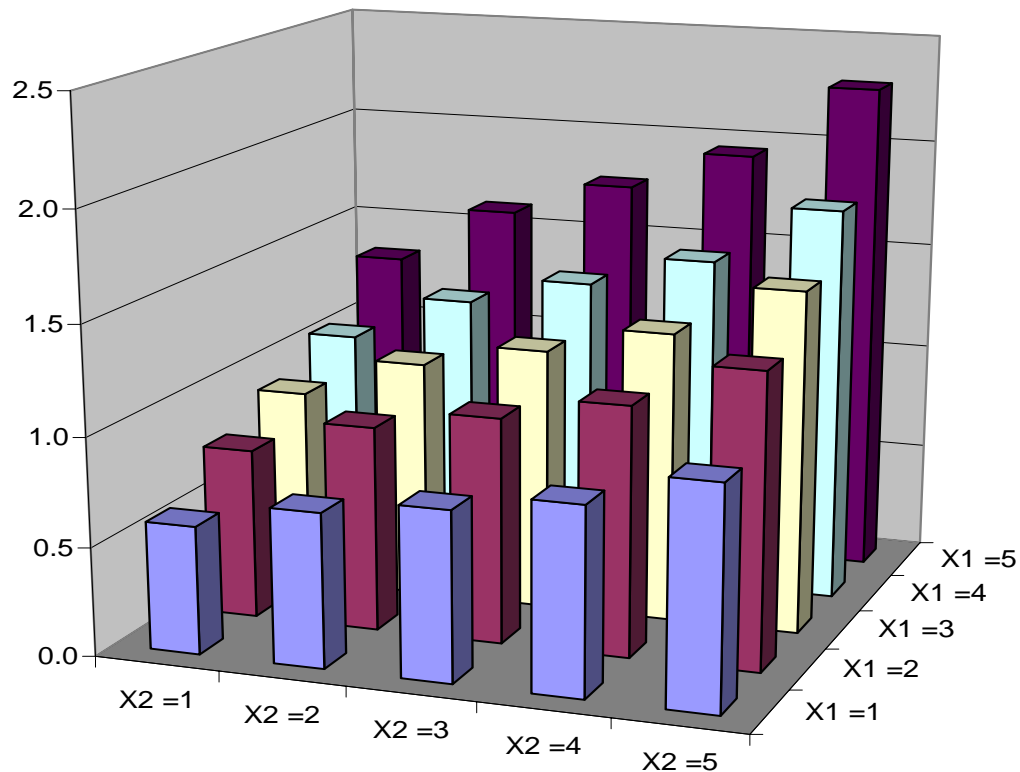
$X_2 = x_2$	$f(x_2)$	$F(x_2)$	$F^*(x_2)$	$f^*(x_2)$
1	0.37	0.37	0.29741	0.29741
2	0.21	0.58	0.50076	0.20334
3	0.16	0.74	0.67124	0.17049
4	0.15	0.89	0.84768	0.17644
5	0.11	1.00	1.00000	0.15232



# The bivariate Radon-Nikodym derivatives

$$RN_g(x_1, x_2) = \frac{f_{X_1, X_2}^*(x_1, x_2)}{f_{X_1, X_2}(x_1, x_2)} = c \cdot \frac{f_{X_1}^*(x_1)}{f_{X_1}(x_1)} \cdot \frac{f_{X_2}^*(x_2)}{f_{X_2}(x_2)}$$

Radon-Nikodym Derivatives



Scenario	Loss	LAE
1	-	1,954.08
2	-	2,239.22
3	-	2,974.21
4	-	3,275.38
5	-	3,351.93
6	-	6,526.96
7	-	9,542.63
8	-	13,999.95
9	-	14,279.63
10	-	14,519.32
11	-	16,179.92
12	-	19,134.14
13	-	35,071.98
14	-	57,591.43
15	-	62,967.38
16	-	82,638.17
17	-	248,909.05
18	638.80	3,331.31
19	1,533.11	2,047.14
20	5,110.36	1,159.07
21	6,387.95	2,152.74
22	6,387.95	8,940.58
23	8,943.13	4,949.35
24	11,498.32	-
25	15,331.09	-
26	27,279.12	-
27	35,772.54	5,634.79
28	93,264.12	24,115.73
29	102,207.25	6,287.06
30	191,638.60	34,096.74
31	246,010.43	232,641.59
32	511,036.26	39,161.24
33	511,036.26	150,301.30
34	662,650.50	73,140.35

## Example 3: Pricing of Bivariate Contingent Claims

Contract #1 has a  
payoff  $X_1 =$   
*loss* in excess of  
200,000

Contract #2 has a  
payoff  $X_2 = 50\% * \text{LAE}$

Contract #3:  
 $X_3 = X_1 + X_2$

# Additive Pricing is Achieved

	$X_1$	$X_2$	$X_1+X_2$
<b>No Risk Adjustment</b>	\$ 33,257	\$ 17,399	\$ 50,656
<b>With Risk Adjustment</b>	\$ 68,240	\$ 24,847	\$ 93,087
<b>Loading</b>	105%	43%	84%

# A Sequel Paper:

The Radon-Nikodym Derivative for a measure change from Bivariate Standard Normal to Bivariate Student-t with d.f.=9.

