

QFII-104-14 Correlation Pitfalls And Alternatives



Linear correlation is unproblematic when dealing with **elliptical distributions**

- **Examples:** Multivariate normal distribution, multivariate t-distribution





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 - Correlation does not tell us anything about the degree of dependence in the tails of the underlying distribution
- 2 Given marginal distributions F_1 and F_2 for X_1 and X_2 , all linear correlations between -1 and 1 can be attained through a suitable specification of the joint distribution F**
 - In general, the attainable correlations depend on F_1 and F_2 , and form a closed interval $[\rho_{min}, \rho_{max}]$ (containing zero) that is a subset of $[-1, 1]$





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 - **Example:** $\ln(X_1)$ and $\ln(X_2)$ do not have the same correlation as X_1 and X_2
- 6 Correlation is only defined when the variances of the risks are finite
 - Not appropriate for very heavy-tailed risks where variances appear infinite





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Disadvantages:

- Still has deficiencies 1 and 4 listed in previous slide
- Cannot be manipulated as easily as linear correlation, resulting in analytical difficulties when calculating variance of a portfolio's return
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- Best way to model dependency between risks! ✓