On the market risk measurement and Basel Accords

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Advanced Methods in Mathematical Finance
Angers

1. Laboratory of Excellence for Financial Regulation

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- **Commodity risk** : the risk of changing in commodity prices (crude oil price, silver, etc.).
- **Credit spread risk** : the risk due to changes in credit spread.

Market risk and Basel III

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2. Stressed calibration. Using the most severe 12-month stress period in computing ES.

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4. Computing Expected Shortfall for both modellable and non-modellable risk factors.

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2. non parametric approaches. Historical simulation (HS) and BRW methods (Boudoukh et al. 1998).
3. semi parametric approaches. Filter historical simulation (FHS) (Barone et al., 1999 and Gurrola-Perez et al., 2015) and volatility-weighted historical simulation (VWHS) models (Hull and White, 1998).

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3. mostly assume the returns for risk factors are normal distribution (or generally elliptical distributions). ! ! (See Chicheportiche 2012)

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4. Both HS and BRW do not consider upper tail of returns (Pritsker, 2006).

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The combination of EWMA model with VWHS or variance-covariance method (RiskMetrics approach) are the most used models between banks for computing market risk. (Alexander 2008)

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Volatilitites are estimated using the EWMA model :

$$\sigma_{t+1}^2 = \lambda \sigma_t^2 + (1-\lambda) r_t^2, \tag{2}$$

where $\lambda \in (0, 1)$ is called *decay factor* and has to be estimated from historical data.

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Example

In the RiskMetrics of J.P. Morgan (1996) approach, the decay factor is fixed and $\lambda = 0.94$ for daily returns and $\lambda = 0.97$ for monthly returns. Moreover, a normality assumption of the return process is assumed.

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The EWMA estimator is based on the *maximum likelihood estimator of the variance of the normal distribution*, and is therefore optimal when returns are conditionally normal (see Nelson and Foster, 1996).

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3. Which method is robust in estimating decay factors ?
4. The effect of choosing different estimation methods for estimating decay factors on VaR backtesting ?
5. In the case of rejection at desk level, what is the cost for falling back to the standardized approach ?

Challenges related to the EWMA model

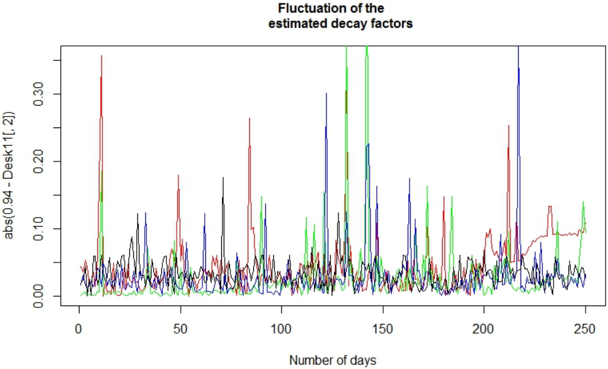

FIGURE: Fluctuations of the estimated decay factors for 3 different assets and for the desk composed of linear combinations of these 3 assets for a sample from $17/12/2012$ to $31/12/2013$.

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Pritsker in his article (Pritsker, 2006) discusses about drawbacks of tests for **correct conditional coverage** (independence of VaR exceptions) property for exceptions and shows that the power of tests for correct conditional coverage is **very low**.

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Example : Consider the VaR model (1). In the case of an increasing in volatility, assume that lambda parameter in (2) is not well estimated, then it is very likely that there will be a clustering of exceptions, due to high persistence of volatility. In this case, if number of historical data window will be short enough, then it is likely to have conditional coverage property while in practice there is autocorrelations between exceptions.

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How about choosing an alternative EWMA estimator which is robust to non normality in returns ? (See Harris and Guermat, 2002).

$$\sigma_{t+1}^2 = \{\lambda\sigma_t + (1-\lambda)\sqrt{2}|r_t|\}^2, \tag{3}$$

Challenges related to the EWMA model

In RiskMetrics approach, the decay factor is recommended to be estimated using minimizing the squared error loss function. i.e.,

$$\hat{\lambda} = \underset{\lambda \in (0,1)}{arg\min} \frac{1}{T} \sum_{i=1}^{T} [\sigma_i^2(\lambda) - r_i^2]^2, \tag{4}$$

where $\sigma_i^2(\lambda)$ follows equation (2).

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Our evidence suggests that the estimator (4) is not robust ! !

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$$\hat{\lambda} = -\underset{\lambda \in (0,1)}{arg \min} \sum_{i=1}^{T} (log(\sigma_i^2) + \frac{r_i^2}{\sigma_i^2}), \tag{5}$$

where r_i is the ith return in historical data window and σ_i^2 is obtained from equation (2).

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where $e_i = r_i - q_{\alpha,i}$, and $\rho_\alpha(e_i) = (\alpha - \mathbf{1}_{\{e_i<0\}})e_i$ for $\alpha \in (0,1)$. $q_{\alpha,i}$ is the quantile function at confidence level α.

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is a method based on statistical tools which compares actual profits and losses with VaR estimates.

Backtesting

Christoffersen,P., (Christoffersen, 1998) has shown that a VaR model is valid if and only if the following two conditions are satisfied :

1. the unconditional coverage property. i.e, $\mathbb{E}(I_t) = \alpha$, where $I_t = \mathbf{1}_{\{r_t < -VaR_\alpha(r_t)\}}$,
2. the independence condition. i.e, for all $s \neq t$, I_s and I_t are independent,

where r_t is the return or P&L of a risk factor.

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6. the geometric-VaR test (Pelletier, 2014).

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If we assume ρ_k the univariate exceptions sequence autocorrelation of order k, then to test if $\rho_k = 0$ holds for the first K autocorrelations, we have

$$Q = 63000 \sum_{k=1}^{K} \frac{\rho_k^2}{250 - k}. \tag{7}$$

Under null hypothesis, $\rho_k = 0$ holds for the first K autocorrelations, Q follows a $\chi^2_{(K)}$.

Traffic light approach used by BCBS

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If a model is accurate, then the violations (exceptions) distribution should follow Bin$(250, \alpha)$ for $\alpha = 0.025$ and $\alpha = 0, 01$.

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If a model is accurate, then the violations (exceptions) distribution should follow Bin$(250, \alpha)$ for $\alpha = 0.025$ and $\alpha = 0, 01$.

$$P(X = k) = \binom{250}{k} \alpha^k (1 - \alpha)^{250-k}, \tag{8}$$

where k is the number of exceptions.

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2. Yellow zone : The range from 5 to 9 exceptions constitutes the yellow zone. Outcomes in this range are plausible for both accurate and inaccurate models (BCBS 1998).
3. Red zone : Outcomes in the red zone $(10$ or more exceptions$)$ should generally lead to an automatic presumption that a problem exists with a bank's model (BCBS 1998).

Backtesting at desk level under Basel III framework

"Backtesting requirements are based on comparing each desk's 1-day static value-at-risk measure at both the 97.5th percentile and the 99th percentile, using at least one year of current observations of the desk's one-day P&L" (FRTB October 2013).

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"If any given desk experiences either more than [12] exceptions at the 99th percentile or [30] exceptions at the 97.5th percentile in the most recent 12-month period, all of its positions must be capitalized using the standardized approach" (FRTB October 2013).

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1. The mean of the difference between the risk-theoretical and hypothetical P&L (unexplained P&L) divided by the standard deviation of the hypothetical P&L should be in $[-10\%, 10\%]$; and
2. The variance of the unexplained P&L divided by the variance of the hypothetical P&L should be less than 20%.

Questions

Thanks for your attention !

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