Working Group on Risk

"Market Risk Modeling after Basel III : New Challenges for Banks and Supervisors"

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Market Risk Modelling after Basel III: New Challenges for Banks and Supervisors

- Market risks: regulatory outlook
- The rise of historical simulation
- Backtesting and VaR exceptions
- Pointwise volatility estimation: The conundrum
- Assessment of risk models under Basel III
  - Limited usefulness of econometric techniques
  - Hypothetical Portfolio Exercises challenged?
  - Lower decay factors to mitigate disruptions in the computation of Risk Weighted Assets?

Key messages for regulation

- **Hidden** impacts of risk modelling choices on financial stability and pro-cyclicality under Basel III FRTB
  - Even when considering simple exposures (S&P500)
  - And complexity (optional products, correlations) left aside
- Basel backtests poorly discriminates among models
  - Danielsson (2002), Danielsson et al (2016)
  - Focus on VaR exceptions over past year! Minsky moment
- Benchmarking on hypothetical portfolios (EBA, 2017)
  - Unstable ranking of risk models calls for proper averaging
- Promote smart model risk supervision and enhanced disclosure on risk methodologies
  - Ongoing ECB TRIM

Messages for market risk managers

- Favour Volatility Weighted Historical Simulation (VWHS) over Historical Simulation (HS) for VaR/ES computations
- Historical Simulation works poorly in stressed periods
  - Backtesting over current period is useless!
  - Procyclicality: patterns of VaR exceptions under stress and fall-back to costly Standard Approach
- Implementing Volatility Weighted Historical Simulation
  - Consider smaller values of decay factor than .94 Riskmetrics
  - Does not lead to extra-capital charges: Basel III capital metrics based on stressed period only
  - Endogenous stressed period does not depend upon choice of decay factor
  - Lower number of exceptions under stress: greater resilience

Market risks: Basel III regulatory outlook

- Internal Models Approach (IMA) still applicable
  - Stringent constraints on data (modellable risk factors) and processes (P&L eligibility tests)
  - + backtesting at desk level requirements
- IMA based on 97.5% Stressed Expected Shortfall (ES)
  - liquidity horizons : 10 days or more
  - No scaling from 1D to 10D (Danielsson & Zigrand (2006))
  - 1Y stressed period endogeneously computed
    - Is **model dependent**, but in our case study example, was found to be mid June 2008 – mid June 2009

Market Risk Weighted Assets (RWA): Basel III regulatory outlook

- Minimum capital requirements for market risk (January 2016)
    - FRTB: Fundamental Review of the Trading Book
  - Implementation delayed to 2019
- 2016 monitoring exercise: increase of 75% of RWA compared with Basel 2.5
- Bank struggling with operational issues
    - Data quality: Non Modellable Risk Factors (NMRF)
    - Alignment between risk and front office models
    - To a lesser extent, compliance with backtesting requirements
- Market risk RWA might be further inflated…

Basel III regulatory outlook: Market Risk Group reopened in 2017

- Desk eligibility to internal models?
    - Threat of fallback to costly Standard Approach
    - According to ISDA could lead to x6 increase for FX and x4 increase for equity desks
    - Questions the calibration of risk weights in the Standard Approach
- Non Modellable Risk Factors (NMRF) charge
    - Roughly one third of IMA, but large ongoing variability and uncertainty
    - Could be dramatically reduced if banks to use settlement prices in collateral agreements

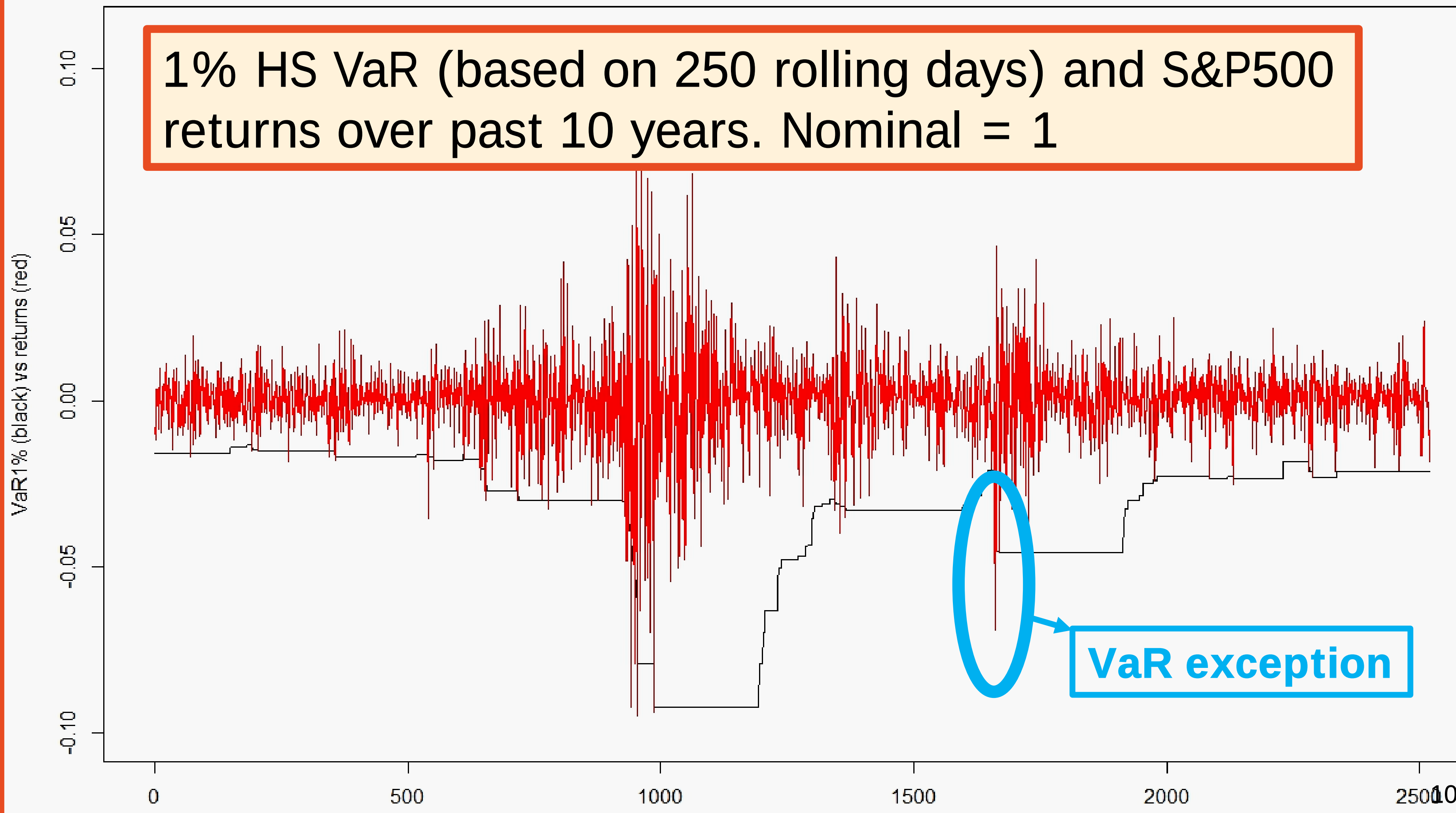
Market Risk Weighted Assets (RWA): EU regulatory outlook

- EU CRR-2 (November 2016)
  - Differences on key points with Basel document
    - Restricted scope of modellable risk factors (MRF)
    - Slightly different backtesting constraints
  - EBA Technical Standards to be issued in 2021
    - Eligibility to Internal Models Approach…
- ECB TRIM (Targeted Review of Internal Models)
    - Still Basel 2.5, but not innocuous regarding pricing models and VaR methodologies
- Impact of ongoing deregulation in the US?

Market risks: Basel III regulatory outlook

- Hypothetical Profit and Loss (HPL)
    - Banks holdings frozen over risk horizon
    - « Uncontaminated P&L »: not accounting for banks' fees (Frésard et al. (2011)).
    - Computed according to all risk factors and pricing tools being used by Front Office (FO)
    - full revaluation is implicit when computing hypothetical P&L
- Backtesting: compare 1 day VaR with daily HPL and daily actual Profit and Loss (P&L)

Market risks: Basel III regulatory outlook



Market risks: Basel III regulatory outlook

- Backtesting based on 97.5% and 99% 1 day VaR
    - Not directly on ES as in Du & Escanciano (2016)
  - Number of VaR exceptions is the max of number of VaR exceptions computed using HPL and number of VaR exceptions using actual P&L (over past year)
  - Allowance for up to 12 breaches for 99% VaR and 30 breaches for 97.5% VaR
  - At trading desk level: Danciulescu (2010), Wied et al. (2015)
  - BCBS QIS and monitoring exercises also requests reporting of 1D 97.5% ES + p −values

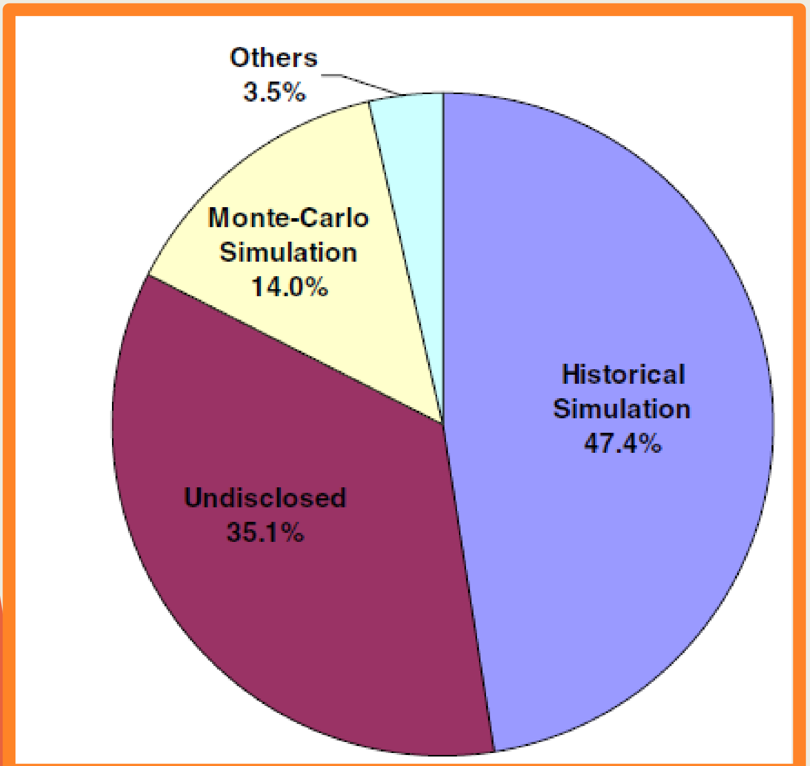
Market risks: Basel III regulatory outlook

- Desk eligibility to IMA (Internal Model
  - Risk-theoretical P&L (RTPL)
    - Changes in P&L according to bank's internal risk model
      - Use of modellable risk factors within risk systems (FRTB/Basel 3)
      - Mapped from risk factors used in Front Office
      - Delta/gamma approximations, PV grids or full revaluation might be used in repricing books
    - **Definition of RTPL is subject to controversy and needs to be clarified**
- **Desk not eligible to IMA if HPL and RTPL are too distant (criteria under scrutiny)**

The rise of historical simulation

- Huge litterature relarted to VaR/ES computations
  - Historical, FHS, VWHS, EWMA, Parametric (multivariate Gaussian), GARCH family, EVT, CAViaR, …
    - To quote a few: Kupiec (1995) Hendricks (1996), Christoffersen (1998), Berkowitz (2001), Berkowitz, & O'Brien (2002), Yamai & Yoshiba (2002) Kerkhof & Melenberg (2004), Yamai & Yoshiba (2005), Campbell (2006), Hurlin & Tokpavi (2008), Alexander (2009), Candelon et al. (2010), Wong (2010), BCBS (2011), Rossignolo et al. (2012), Rossignolo et al. (2013), Abad et al. (2014), Ziggel et al. (2014) Krämer & Wied (2015). Siburg et al. (2015), Pelletier & Wei (2015), Nieto & Ruiz (2016)
- Backtesting performance?
    - Lack of implementation details, choice of backtest portfolios, historical periods make comparisons difficult
- Dealing with operational issues is also of importance
    - large dimensionality: several thousands of risk factors,
    - Costly to price optional products,
    - Data requirements.

The rise of historical simulation



From Perignon & Smith (2010)
based on 2005 data

Market-risk practices at 18 financial institutions, 2011, %

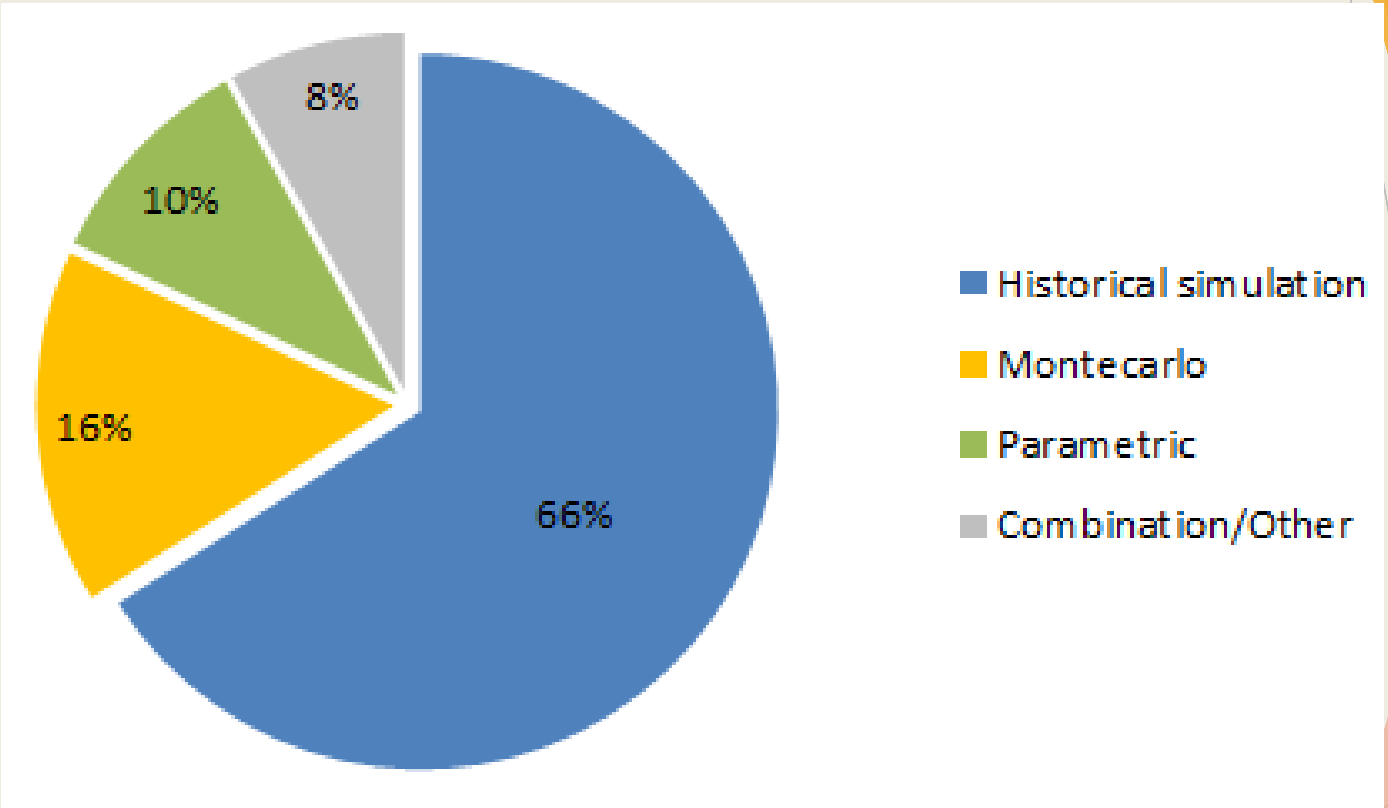
Simulation approach	Valuation approach[1]: Sensitivities	Valuation approach[1]: Hybrid	Valuation approach[1]: Full revaluation
Historical simulation		35	40
Hybrid	5		5
Monte Carlo	15		

1 Banks are deemed to use the sensitivities approach if they use it exclusively, hybrid if they use it at least 30 percent of the time, and full revaluation if less than 30 percent.

Source: McKinsey Market Risk Survey and Benchmarking 2011

Mehta et al (2012)

The rise of historical simulation



EBA (2017) benchmarking exercise conducted over a (heterogeneous) panel of 50 banks with approved internal models

The rise of historical simulation

- Volatility Weighted Historical Simulation (VWHS)
      - Hull & White (1998), Barone-Adesi et al. (1999)
   - Volatility not constant over VaR estimation period
- Rescale returns by ratio of current volatility to past volatility
   - σ_t volatility at time t, r_{t-h} return at $t-h$
   - Rescaled past returns $\frac{\sigma_t}{\sigma_{t-h}} \times r_{t-h}$
   - VWHS: empirical quantile of rescaled returns

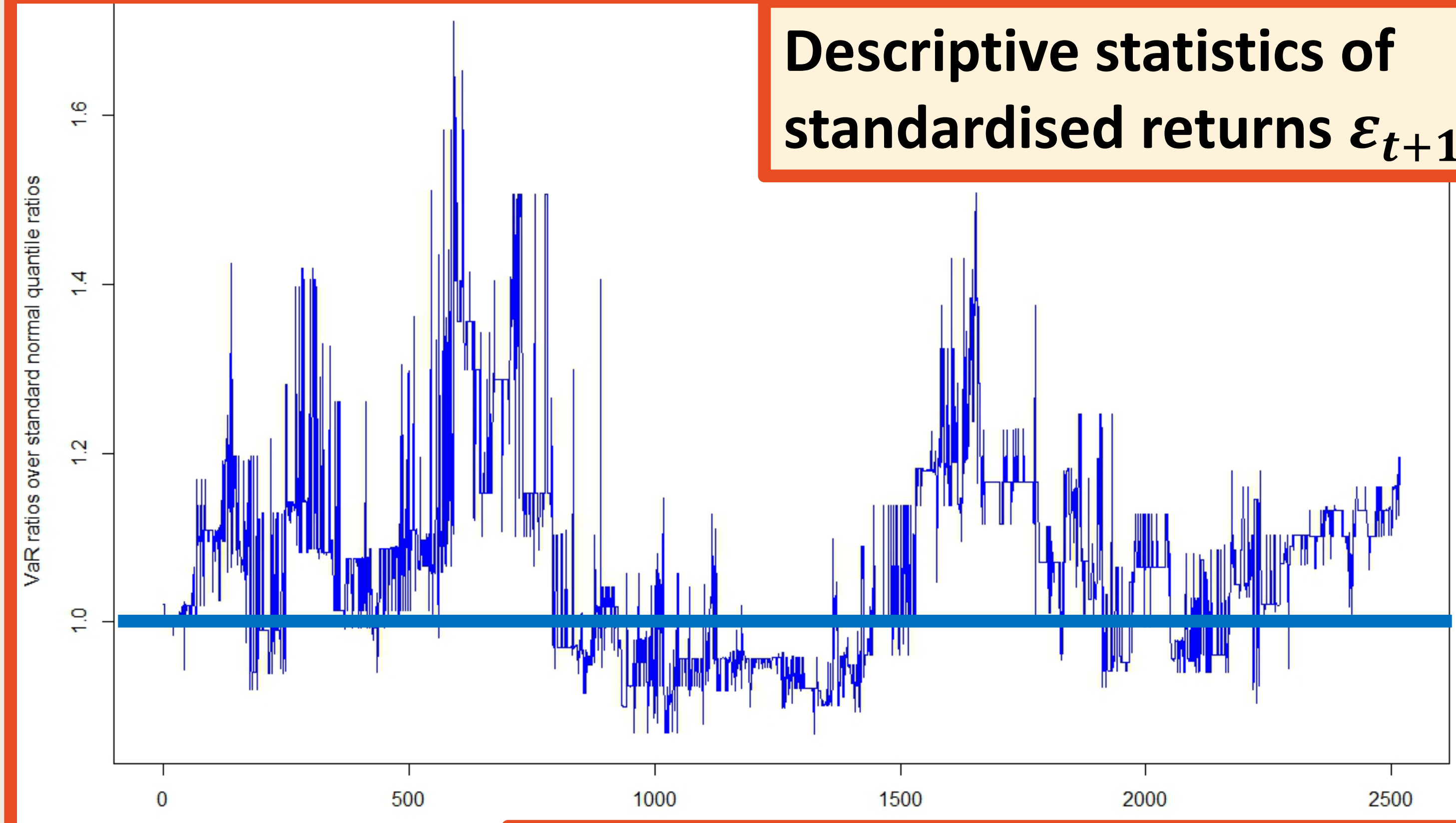
The rise of historical simulation

- (Location) scale models: $r_t = \sigma_t \times \varepsilon_t$
  - GARCH: ε_t has a given stationary distribution
    - Such as $t(\nu)$: parametric approach to ε_t
- VaR: $q_\alpha(r_t) = \sigma_t \times q_\alpha(\varepsilon_t)$
    - EVT could be used to assess $q_\alpha(\varepsilon_t)$, McNeil & Frey (2000), Diebold et al. (2000), Jalal & Rockinger (2008)
- VWHS: same approach to VaR
  - BUT $q_\alpha(\varepsilon_t)$ empirical quantile of standardised returns r_t/σ_t
  - Above decomposition shows two sources of model risk: volatility estimation σ_t, tails of standardized returns ε_t

Practical implementation of VWHS

- Standardised returns $\varepsilon_t = r_t/\sigma_t$ not directly observed
- Since ε_t depends on **unobserved** volatility σ_t
- **Large uncertainty when deriving $\boldsymbol{\sigma_t}$**
- Specific additional issues with GARCH(1,1) modelling: Pritsker (2006)
  - Misspecification of ε_t distribution?
  - Tail dynamics only driven by volatility σ_t

$(\text{Var}1\%/\text{VaR}2.5\%)/\ (\Phi^{-1}(99\%)/\Phi^{-1}\ (97.5\%)$
EWMA volatility estimates, decay factor = .8



Descriptive statistics of standardised returns ε_{t+1}

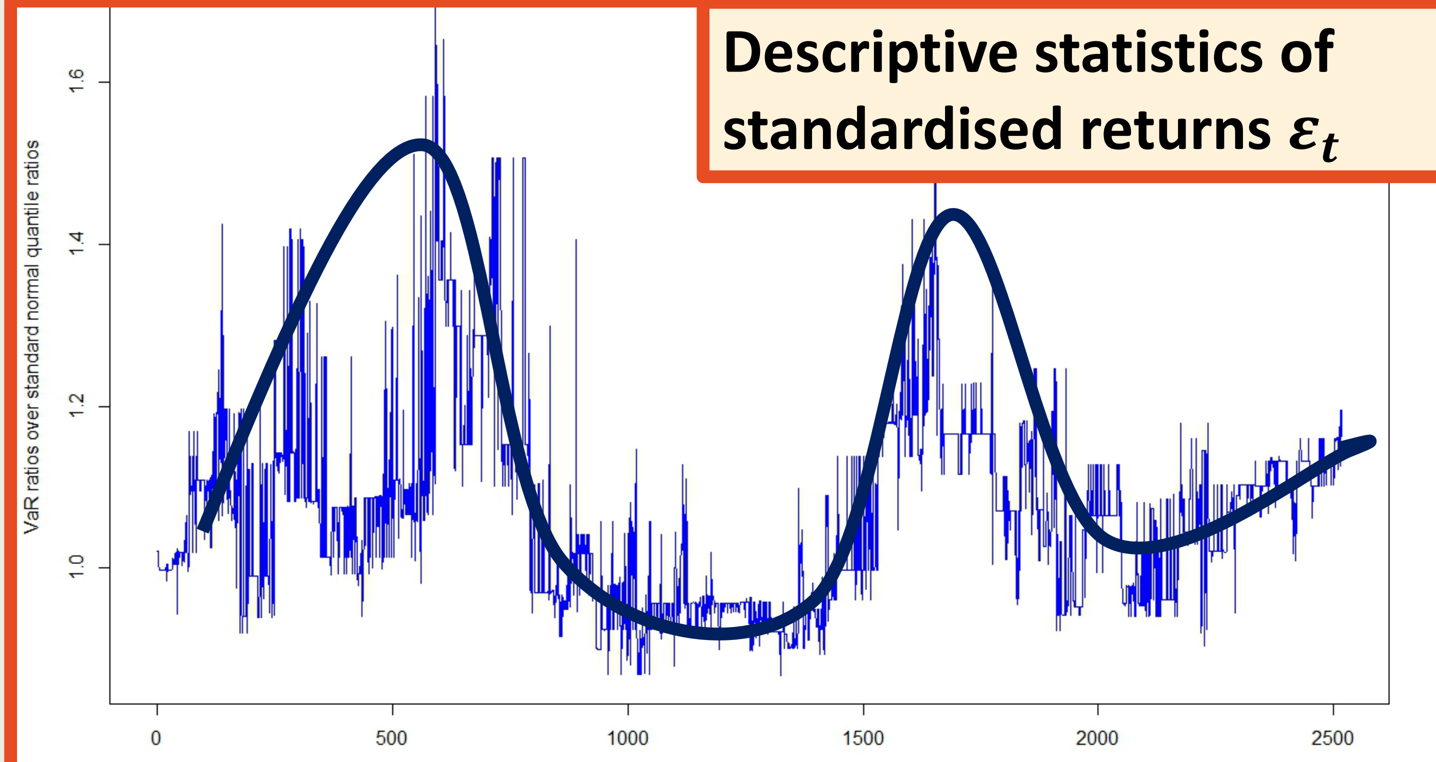
For Gaussian ε_t and well-specified decay factor, ratio should be equal to one

Ratio higher than 1 means fat tails

(Var1%/VaR2.5%)/ (Φ^{-1}(99%)/Φ^{-1} (97.5%) EWMA volatility estimates, decay factor = .8

$\varepsilon_t = r_t/\sigma_t$ **show some left tail dynamics.**

Descriptive statistics of standardised returns ε_t

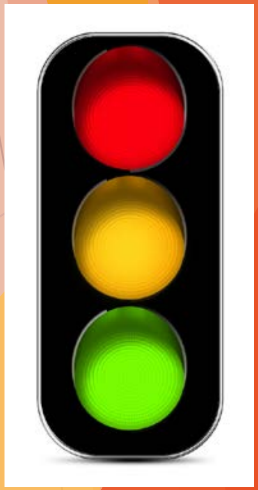


Backtesting and VaR exceptions

- Basel III regulatory reporting
  - 10 days Expected Shortfall (capital requirement)
    - Computed over different subsets of risk factors (partial ES), scaled-up to various time horizons
    - Computed over stressed period, averaged and submitted to multiplier (in between 1.5 and 2)
      - Computation of 10D ES from daily data and VWHS: Giannopoulos & Tunaru (2005), Righi & Ceretta (2015)
  - 1 day 99% and 97.5% VaR (backtesting)
    - $q_{99}(r_t) = \sigma_t \times q_{99}(\varepsilon_t)$
    - $q_{97.5}(r_t) = \sigma_t \times q_{97.5}(\varepsilon_t)$

Backtesting and VaR exceptions

- VaR exception: whenever loss exceeds VaR
- For 250 trading days and 1% VaR, average number of VaR exceptions = 2.5
- For well-specified VaR model, number of VaR exceptions follows a Binomial distribution
  - So-called « unconditional coverage ratios » or **traffic light approach** (Kupiec, 1995, Basel III, 2016)
- Regulatory thresholds at bank's level: green zone, up to 4 exceptions, yellow zone, in between 5 and 9 exceptions, red zone, 10 or above
- At desk level: 12 exceptions at 1%, 30 at 2.5%



Volatily Weigthed Historical Simulation outperforms Historical Simulation

- Number of VaR exceptions over past 10 years (S&P 500)

	1% VaR	2,5% VaR
Historical Simulation	**40**	**89**
Volatility Weighted Historical Simulation (RiskMetrics)	**26**	**68**
Expected	**25**	**63**

Volatility estimation: the conundrum

- EWMA (Exponentially Weighted Moving Average)
- $\sigma_t^2 = \lambda \times \sigma_{t-1}^2 + (1-\lambda) \times r_t^2$
- λ : **decay factor**, $1-\lambda$ speed at which new returns are taken into account for pointwise volatility estimation
  - RiskMetrics (1996), $\boldsymbol{\lambda = 0.94}$ « **Golden number** »
  - Single parameter model
- EWMA is a special case of GARCH(1,1)
  - With no mean reversion of volatility.
  - σ_t^2 is not floored and becomes quite close to zero in calm periods (Murphy et al. (2014))

Volatility estimation: the conundrum

- Numerous techniques to estimate decay factor λ
- RiskMetrics (1996): minimizing the average squared error on variance estimation

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

- Other approaches:
  - Guermat & Harris (2002) to cope with non Gaussian returns
  - Pseudo likelihood: Fan & Gu (2003)
  - Minimization of check-loss function: González-Rivera et al. (2007)

Volatility estimation: the conundrum

- For S&P500, Estimates of decay factor are highly unstable and could range from 0.8 to 0.98 wild around the 0.94 RiskMetrics « golden number »
  - Note that $\lambda = 1$ corresponds to plain HS

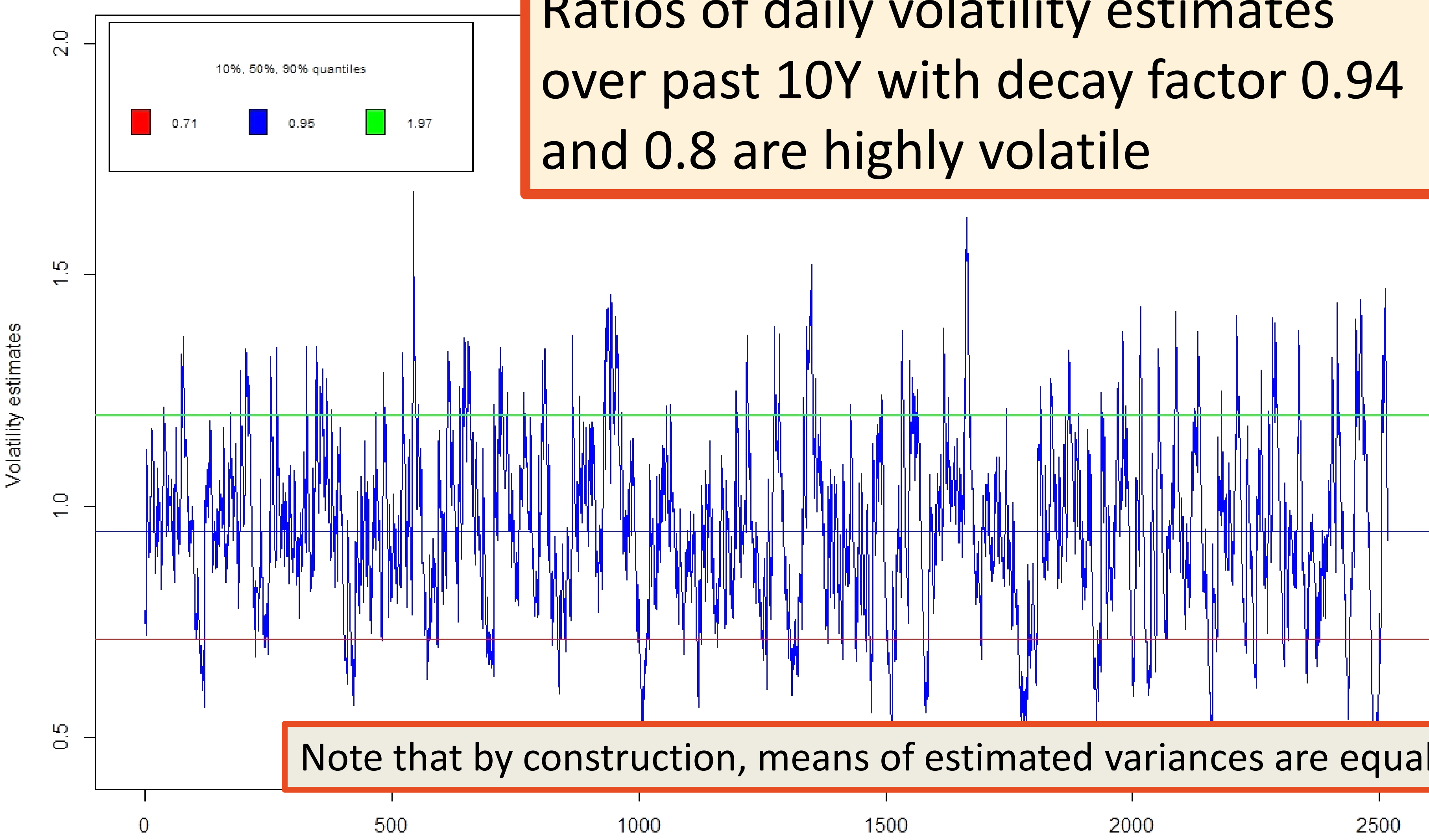
Estimation method/ length of historical data	10 years	First 5 years	Second 5 years
Squared error method	0.8992854	0.8207192	0.9030331
Pseudo likelihood method	0.9331466	0.9525935	0.9146936
Check loss method at 1% level	0.9010942	0.9406649	0.8398029
Check loss method at 2.5% level	0.8829908	0.9557358	0.8634209

- Building volatility filters is even more intricate when considering different risk factors (Davé & Stahl (1998))

Volatility estimation: the conundrum

- Lopez (2001), Christoffersen & Diebold (2000), Angelidis et al. (2007), Gurrola-Perez & Murphy (2015) point out the issues with determining σ_t
- Recall that high values of λ results in slower updates of VaR when volatility increases
  - Murphy et al. (2014) suggest that CCPs typically use high values (.99) for decay factor.
  - In case of Poisson type event risk (no memory), higher values of λ would be a better choice.
  - No obvious way to decide about the optimal λ

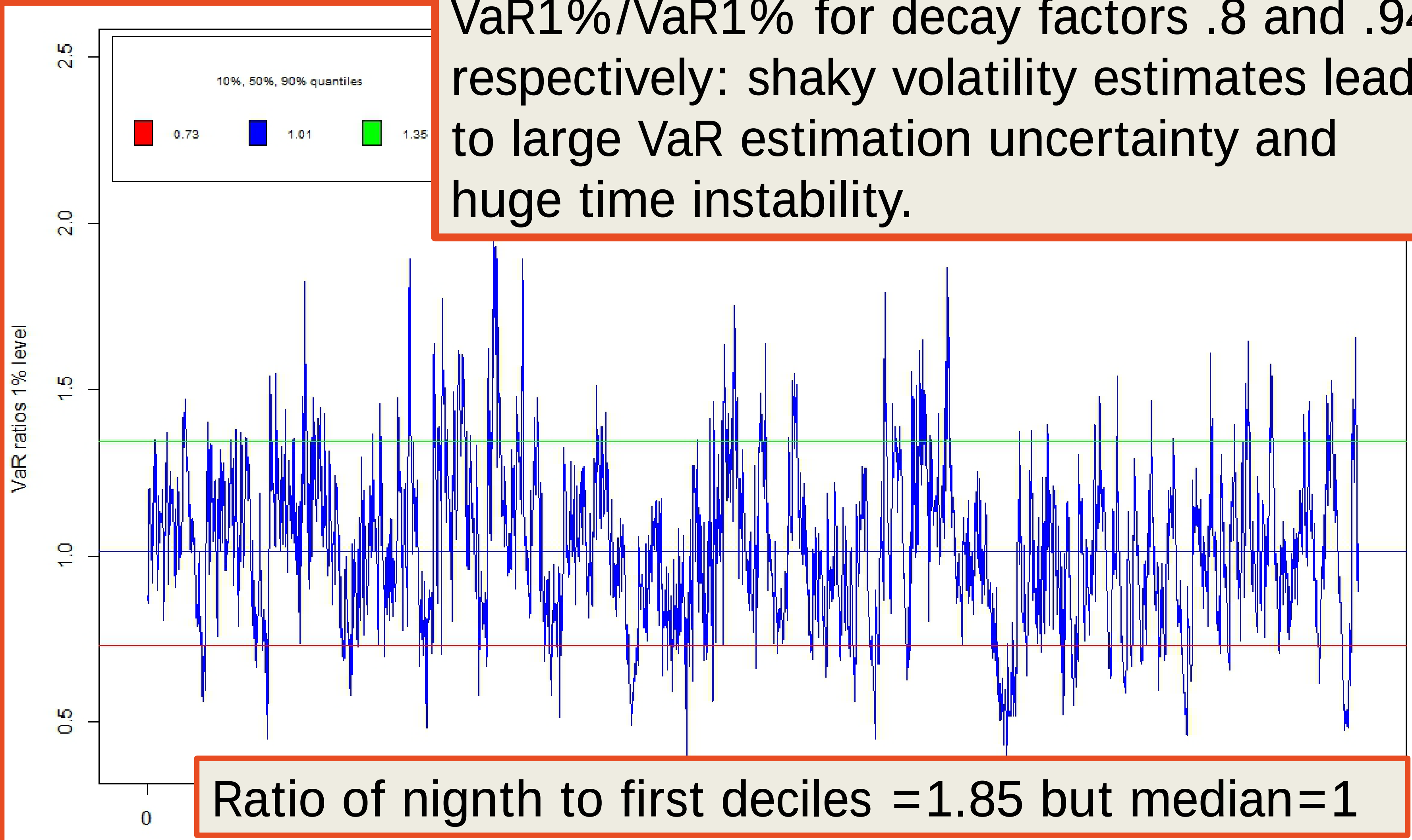
Volatility estimation: the conundrum



Ratios of daily volatility estimates over past 10Y with decay factor 0.94 and 0.8 are highly volatile

Note that by construction, means of estimated variances are equal

Assessment of VaR (risk) models



VaR1%/VaR1% for decay factors .8 and .94 respectively: shaky volatility estimates leads to large VaR estimation uncertainty and huge time instability.

Ratio of nignth to first deciles =1.85 but median=1

Assessment of risk models

- Number of VaR Exceptions over past 10 years (S&P 500)

	1% VaR	2,5% VaR
VWHS $\lambda = 0.8$	28	68
VWHS $\lambda = 0.94$ (RiskMetrics)	26	68
Expected	25	63

- Almost same results for tests based on number of VaR exceptions (unconditional coverage)

Assessment of risk models

- Number of VaR Exceptions over the one year stressed period

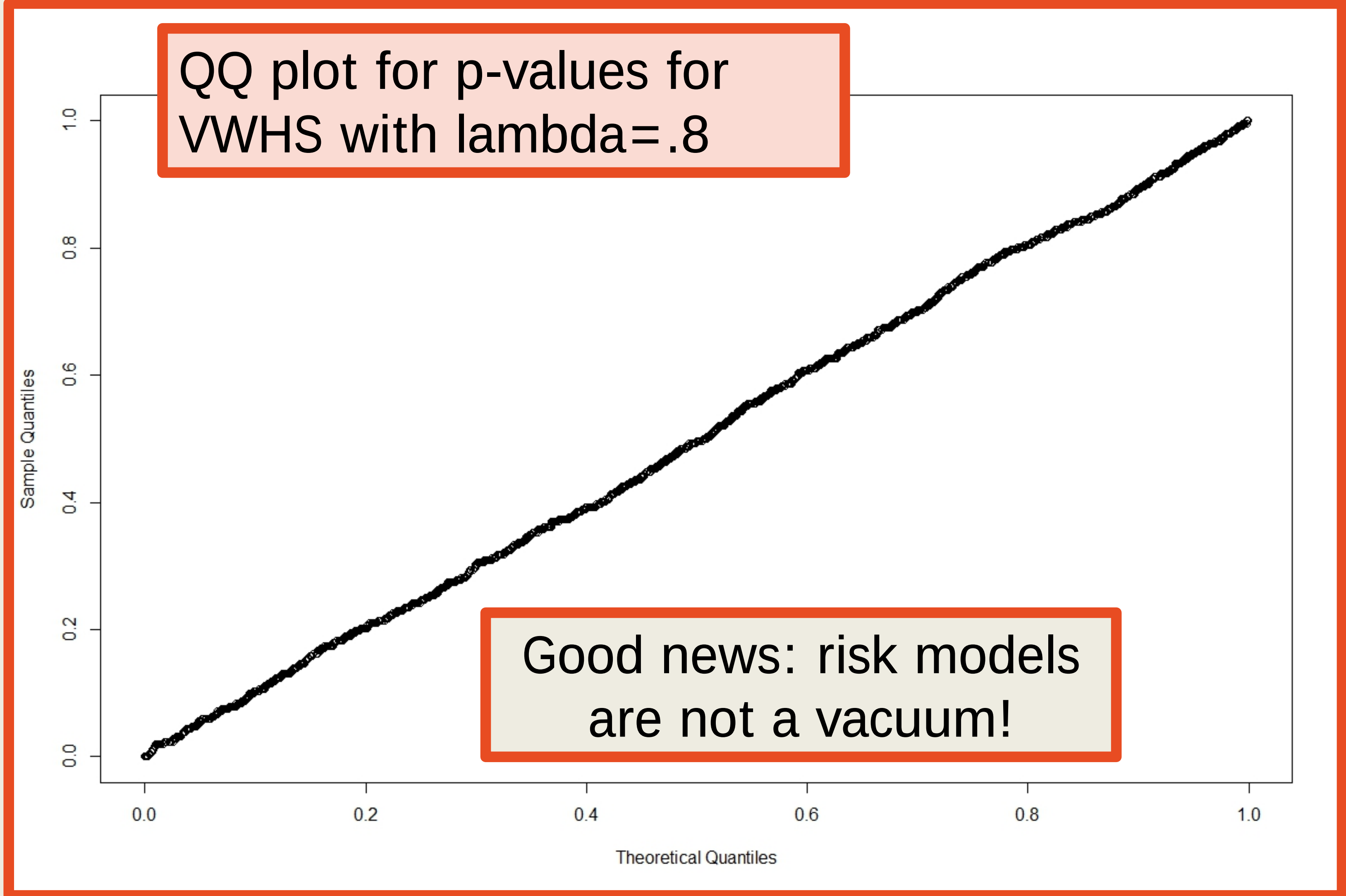
	1% VaR	2,5% VaR
VWHS $\lambda = 0.8$	1	5
VWHS $\lambda = 0.94$ (RiskMetrics)	6	10
Expected	2.5	6

  - Smaller decay factors imply **prompter VaR increases** when volatility rises and better behaviour during stressed period
  - Similar results in Boucher et al. (2014), where plain HS ($\lambda = 1$) provides poor results under stress. See also O'Brien & Szerszen (2014).

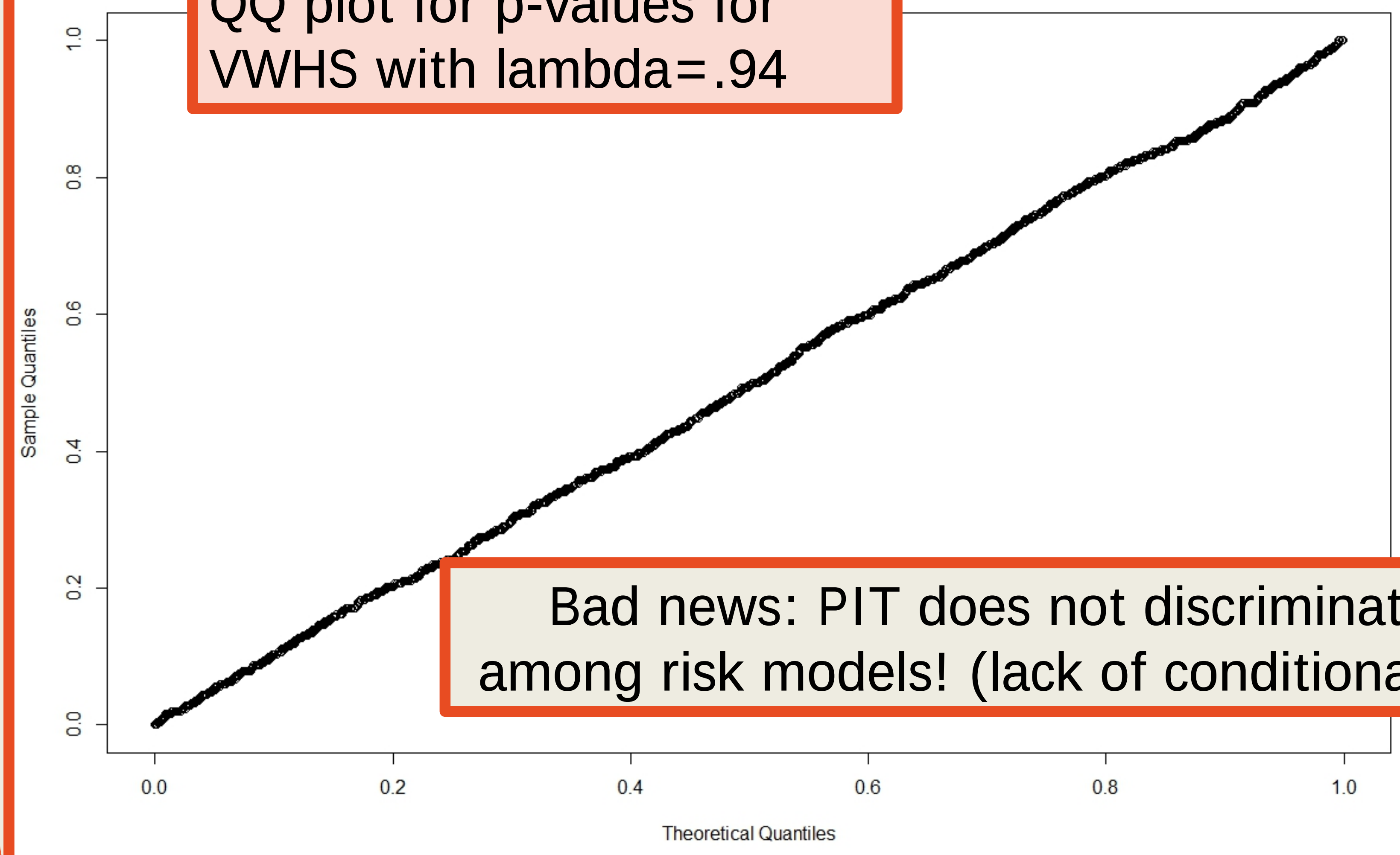
Assessment of risk models

- PIT (Probability Integral Transform) adequacy tests
  - Crnkovic and Drachman (1995), Diebold et al. (1997), Berkowitz (2001)
- Basel Committee Monitoring Exercises
  - Check whether the loss distribution (instead of a single quantile) is well predicted.
  - If F_t is the well-specified (predicted) conditional loss distribution, $F_t(r_{t+1}) \sim U[0,1]$
  - $F_t(r_{t+1})$: *p*-values

PIT adequacy tests



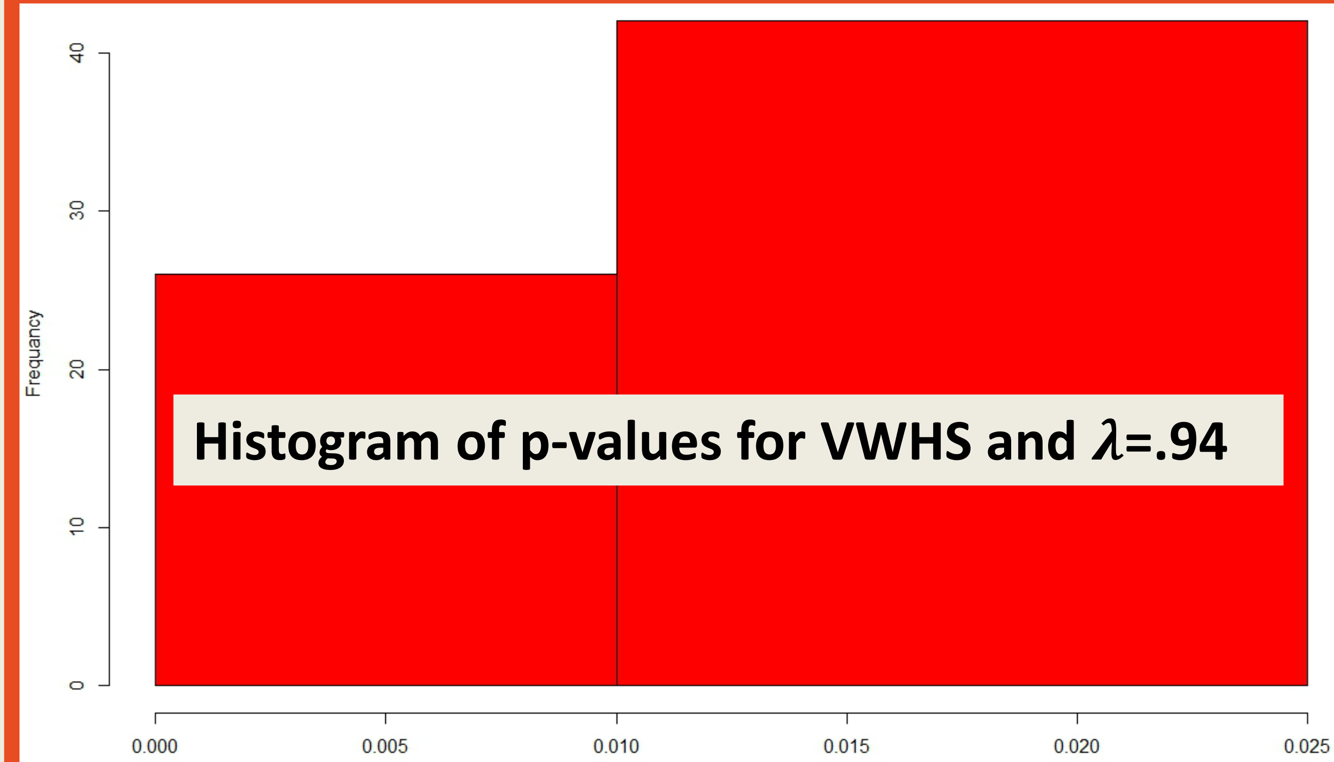
PIT adequacy tests



QQ plot for p-values for VWHS with lambda=.94

Bad news: PIT does not discriminate among risk models! (lack of conditionality)

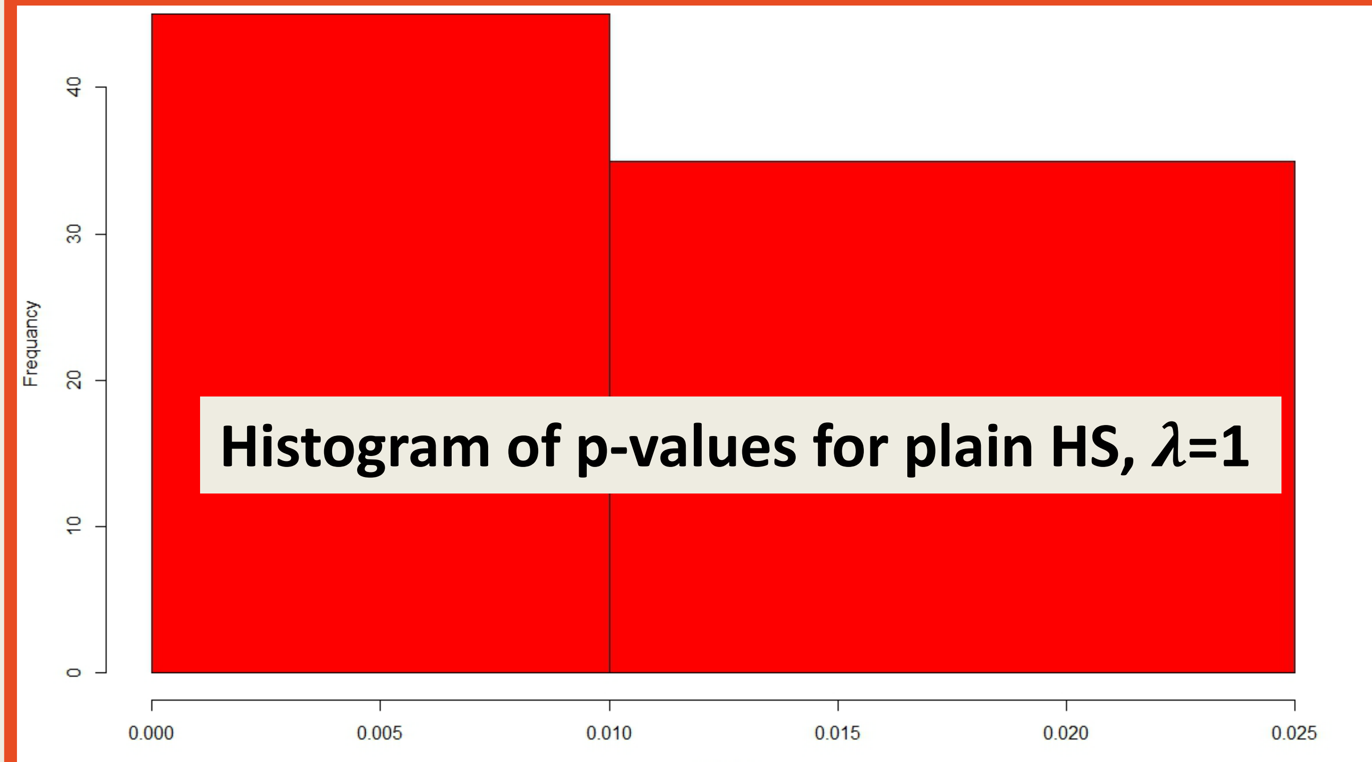
Focusing on tails: VWHS vs plain HS



Expected values: 25 exceptions at 1% level, 38 in between 1% and 2.5%:good fit with VWHS

Hurlin & Tokpavi (2006), Pérignon & Smith (2008), Leccadito, Boffelli, & Urga (2014). Colletaz et al. (2016) for more on the use of different confidence internals

Focusing on tails: VWHS vs plain HS



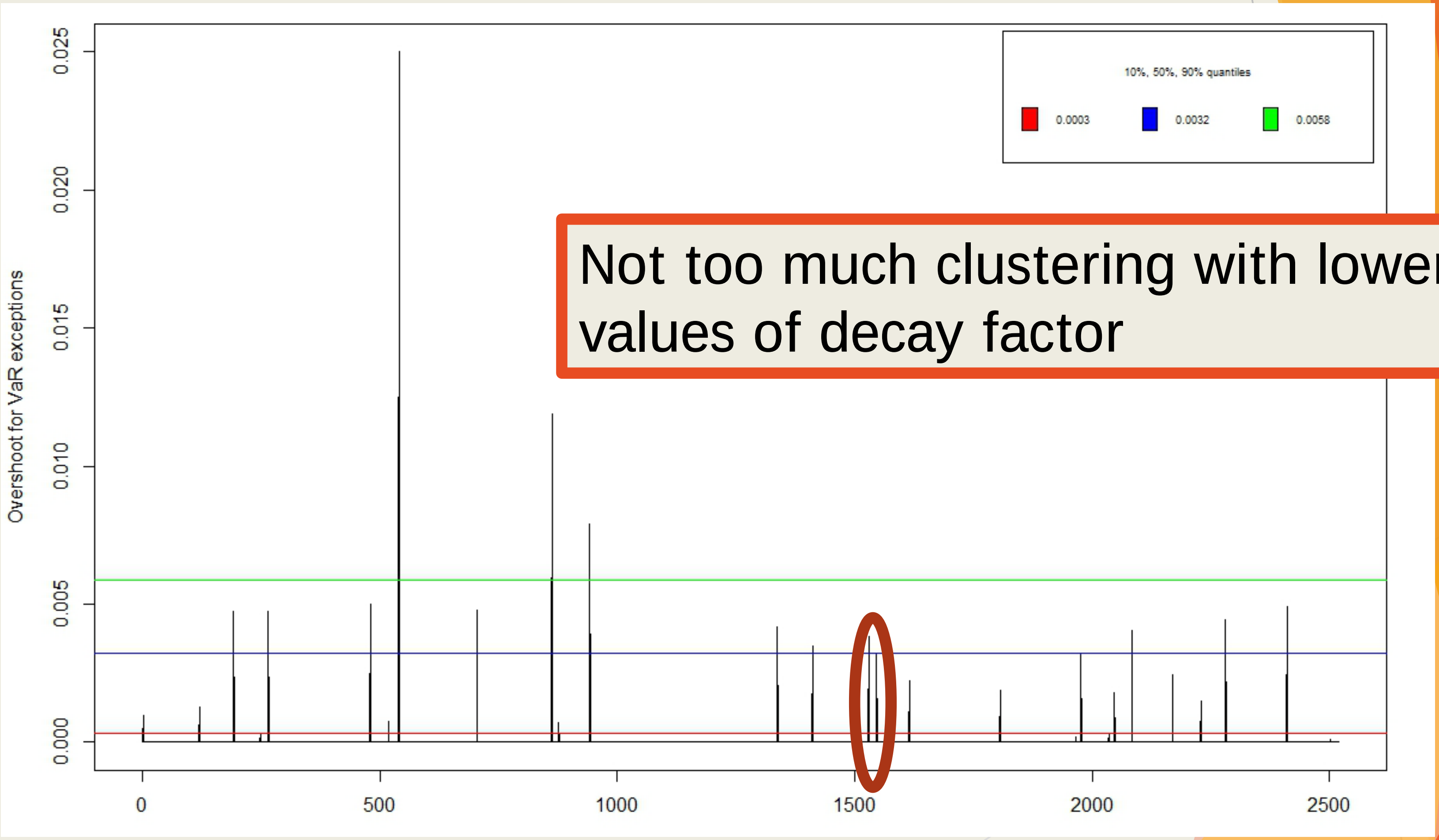
Histogram of p-values for plain HS, λ=1

Expected values: 25 exceptions at 1% level, 38 in between 1% and 2.5%:bad fit with HS

Assessment of risk models

- Clustering of VaR exceptions, i.e. several blows in a row might knock-out bank's capital
- Are VaR exceptions clustered during stressed periods?
  - *"We are seeing things that were 25-standard deviation moves, **several days in a row**"*
    - Quoted from David Viniar, Goldman Sachs CFO, August 2007 in the Financial Times
  - Crotty (2009), Danielsson (2008), Dowd (2009), Dowd et al. (2011)
- Tests based on duration between VaR exceptions
  - Christoffersen & Pelletier (2004), Haas (2005), Candelon et al. (2010)

Overshoots for VaR exceptions using VWHS and lambda=.8 at 1% confidence level



Not too much clustering with lower values of decay factor

Assessment of risk models

- Conditional coverage tests
  - I_t =1,0 depending on occurrence of an exception
  - $E_t[I_{t+1}] = 1\%, 2.5\%$
    - E_t **conditional** expectation
  - Conditional probability of VaR exception consistent with confidence level
      - Engle & Manganelli (2004), Berkowitz et al. (2008), Cenesizoglu & Timmermann (2008), Gaglianone et al. (2012), Dumitrescu et al. (2012), White et al. (2015).
  - Instrumental variables: past VaR exceptions and current + past level of the VIX volatility index
    - Leads to GMM type approach

Assessment of risk models

- $I_t = \alpha_0 + \sum_{i=1}^{I} \alpha_i I_{t-i} + \sum_{j=0}^{K} \beta_j VIX_{t-j} + u_t$
  - Engle & Manganelli (2004)
  - VaR model is well-specified if $\alpha_0 = 1\%, 2.5\%$ and $\beta_j = 0, \alpha_i = 0, i \geq 1$
- **We rather follow the logistic regression approach**
  - Berkowitz et al. (2008)
  - Choosing number of lags I, K is uneasy
    - Number of lags depend on confidence level
    - And considered portfolio/trading desk
    - Bayesian Information Criteria (BIC), backward model selection, partial autocorrelation function (PACF) are not discriminant

Assessment of risk models

- Results for S&P500 2.5% confidence level
  - Red cells are acceptable: no lag for VIX, but lags 2,3,4 or (3,4) for I_{t-i} could be considered

GMM model	(1|0)	(1|1)	(1|2)	(2|0)	(2|1)	(2|2)
BIC	67.18	72.25	69.70	65.07	70.21	67.80
GMM model	(3|0)	(3|1)	(3|2)	(4|0)	(4|1)	(4|2)
BIC	65.07	70.16	67.71	65.07	70.14	67.56
GMM model	(1, 2|0)	(1, 2|1)	(1, 2|2)	(2, 3|0)	(2, 3|1)	(2, 3|2)
BIC	70.33	75.44	73.02	67.86	73.08	70.66
GMM model	(3, 4|0)	(3, 4|1)	(3, 4|2)	(1, 3|0)	(1, 3|1)	(1, 3|2)
BIC	67.86	73.01	70.43	69.97	75.05	72.73

Assessment of risk models

- Preliminary results suggests that $\lambda \leq 0.9$
  - Would reject $\lambda = 0.94$ (Riskmetrics standard)

Parameters (two regressors, I_{t-3}, I_{t-4})	Estimate	Std. Error	z value	$Pr(>\|z\|)$
α_0	-4.0561	0.5043	-8.043	$8.77e-16^{***}$
α_3	2.4467	1.2060	2.029	0.0425^{*}
α_4	2.4467	1.2060	2.029	0.0425^{*}

  - But results of statistical tests are difficult to interpret (depend on the chosen lags)
  - Rejection for lags (3,4) acceptance for lag 3 only

Parameters (one regressor, I_{t-3})	Estimate	Std. Error	z value	$Pr(>\|z\|)$
α_0	-3.8544	0.4519	-8.529	$< 2e-16^{***}$
α_3	2.2450	1.1850	1.894	$0.0582^{\cdot}$

Estimation results based on March 2008 to February 2009 daily data

Assessment of risk models

- Vast litterature on model risk due to parameter uncertainty, choice of estimation method.
  - Christoffersen & Gonçalves (2005), Alexander & Sarabia (2012), Escanciano & Olmo (2012), Escanciano & Pei (2012), Gourieroux & Zakoïan (2013), Boucher & Maillet (2013), Boucher et al. (2014), Danielsson & Zhou (2015), Francq, & Zakoïan (2015), Danielsson, et al. (2016).
- Our focus is more narrow: concentrate on a key parameter left in the shadow, i.e. decay factor, and implications for risk management under Basel III
  - Recall that Historical Simulation, EWMA/Riskmetrics and FHS/VWHS are quite different

Tackling RWA (Risk Weighted Assets) variability

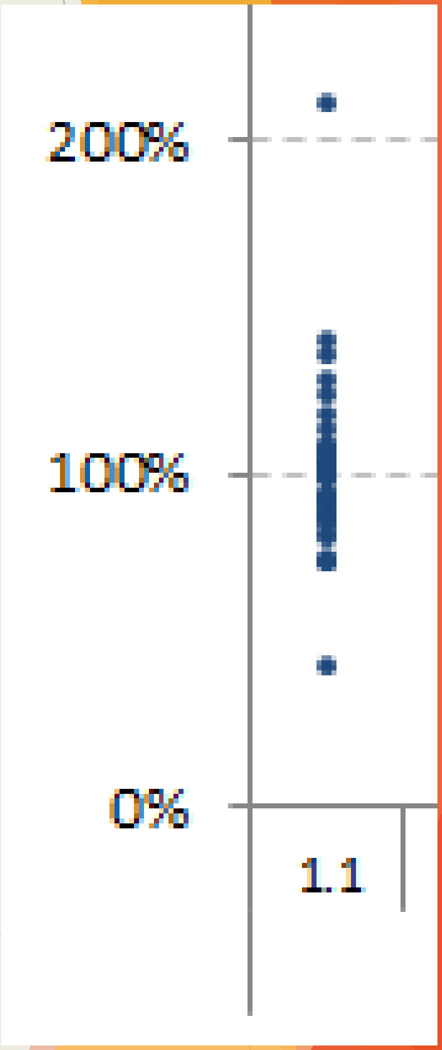
- VaR models with strinkingly different outputs would not fail backtests
    - Not new! But what to do with this?
- This can feed suspicion on internal models
    - Hidden model complexity, tweaked RWAs?
    - Standardized Basel III risk models
    - Floors based on Hypothetical Portfolios Exercises

Floors based on Hypothetical Portfolio Exercises (HPE)?

- Basel 2013 RCAP (Regulatory Consistency Assessment Programme) BCBS240, BCBS267 & EBA (2013), EBA(2017) show large variations across banks regarding VaR outputs for hypothetical portfolios
  - Partly related to discrepancies under various jurisdictions
  - Partly due to modelling choices
    - Lenght of data sample to estimate VaR, relative weights on dates in filtered historical simulation
    - And as shown in our study HS vs VWHS

EBA (2017) benchmarking exercise

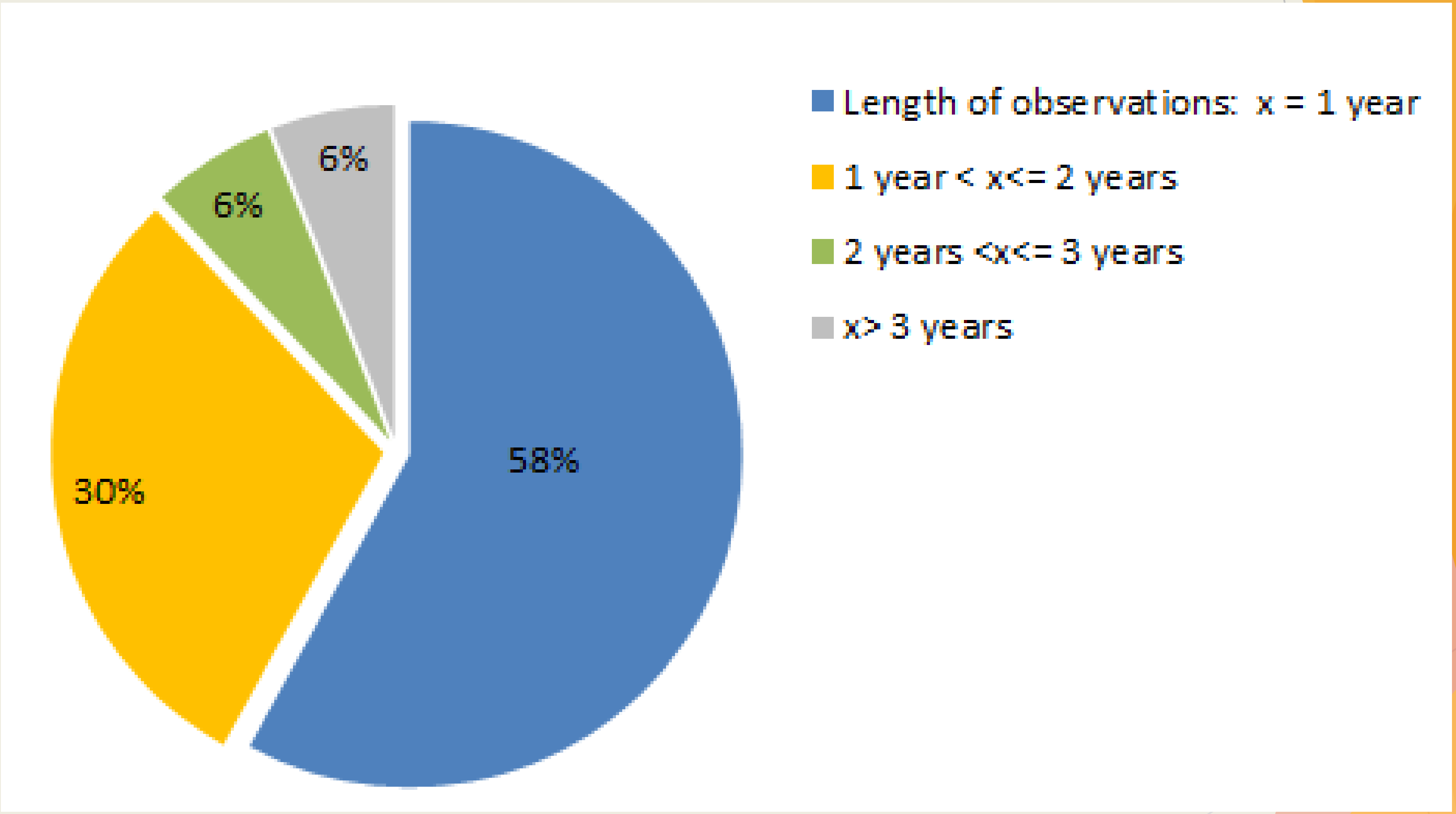
- (Heterogeneous) sample of 50 banks with approved internal models
- On the right, outcome of 99% (current) VaR over 10 days horizon
- Equity index futures trade on FTSE 100
- 41 respondent banks
- How can we analyse variation across banks?



EBA (2017) benchmarking exercise: Reasons for discrepancies between internal models

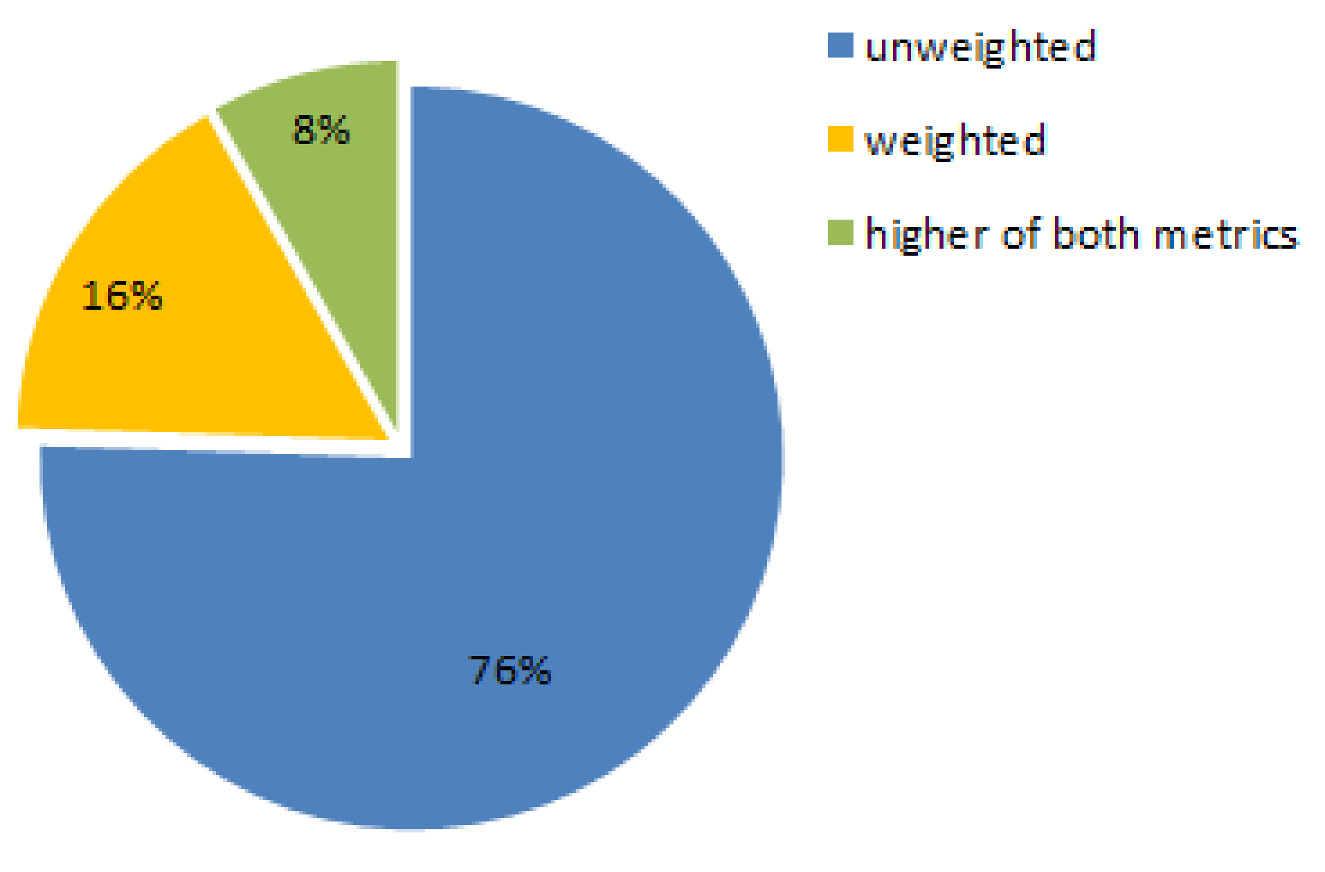
- Poor contributions to the benchmarking exercise!
- Differences in averaging:
  - over two weeks but either with daily or weekly data depending on banks
- Valuation issues for more exotic trades
  - Which model has been used ? full revaluation, approximations made in Risk models
  - Not applicable in disclosed hypothetical portfolio
- Differences in methodologies

Differences in methodologies



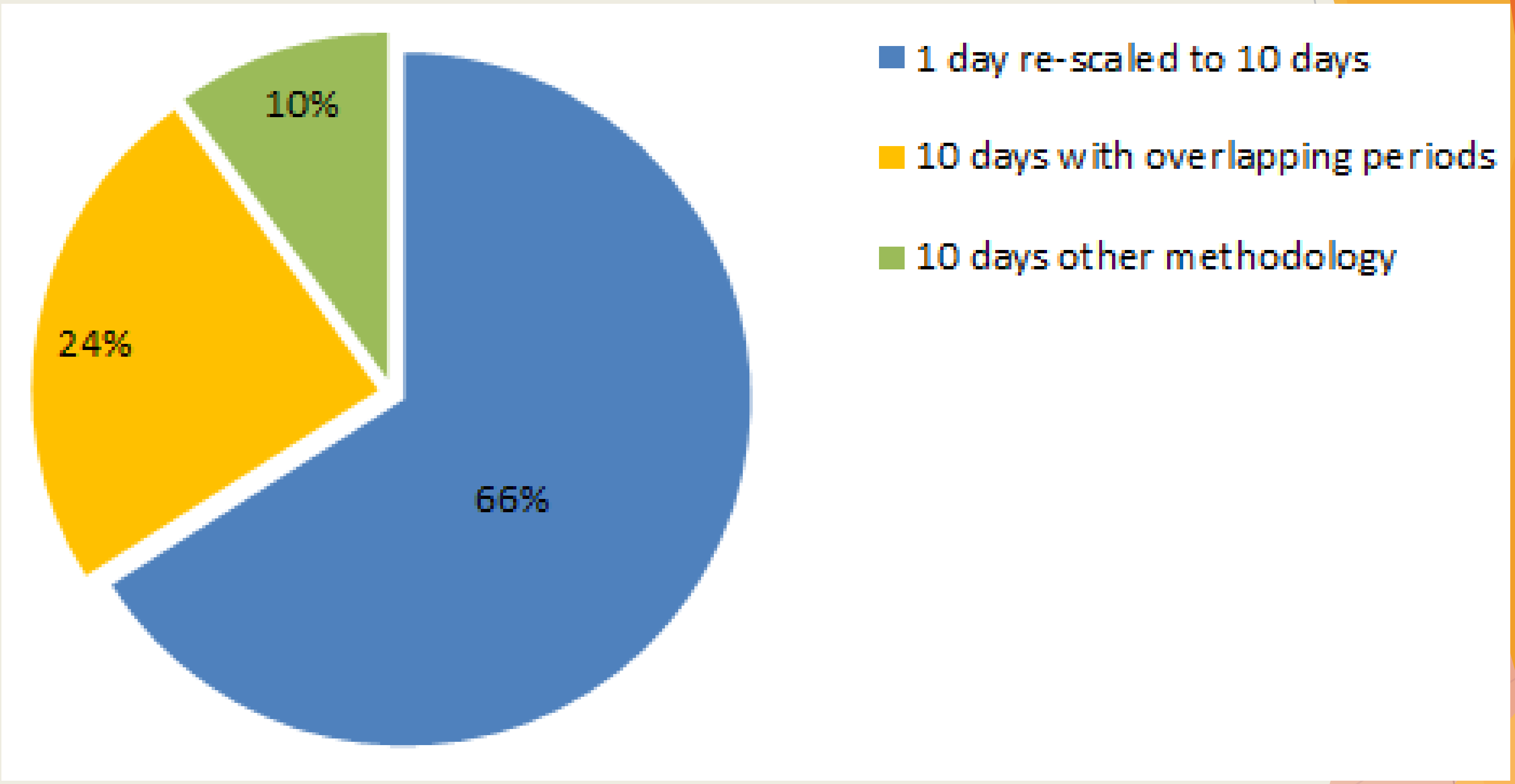
Longer computational period similar to higher decay factor

Differences in methodologies



Most banks in the panel use plain HS (decay factor = 1)

Differences in methodologies



Use of scaling to cope with 10D horizon

Floors based on Hypothetical Portfolio Exercises (HPE)?

- Our controlled experiment shows that ranking of models varies dramatically through time
  - Model A can much more conservative than model B one day, the converse could be observed next day
  - Though in average models A and B provide the same VaRs
- This is problematic regarding the interpretation of HPE and RWA variability
  - Above approach would favour the use of the same possibly misspecified 0.94 golden number…

Tweaking internal models?

- Strategic/opportunistic choice of decay factor?
  - Danielsson (2002), Pérignon et al. (2008), Pérignon & Smith (2010), Colliard (2014), Mariathasan & Merrouche (2014)
- Sticky choice of decay factor: supervisory process
- Does not change average capital requirements
- Could change the pattern of VaR dynamics
  - Higher decay factor leads to smoother patterns and ease management (risk limits)
  - Regulatory capital requirements are based on stressed period only and on averages over past 60 days
  - No procyclicality issue with using smaller decay factors

Undue internal model complexity?

- Haldane and Madouros (2012), Dowd (2016) tackle undue model complexity
- Our approach is simple and widely documented
  - No correlation modelling or pricing models of exotic produts is involved
  - No sophisticated econometric methods
  - However, HS can be fine tuned
- Making things simpler (Standard Approaches, output floors based on SA, leverage ratio) might reduce risk sensitivity

Traps in market risk capital requirements

- Procyclical trap when using today's risk models
  - Ratio of IMA to SA quite large in a number of cases
    - Plain historical simulation or use Riskmetrics decay factor results in large number of VaR exceptions under stress and fallback to SA
    - If a IMA desk is disqualified, huge increase in capital requirements
    - Issue not foreseen: QIS are related to a calm period
  - Use of outfloors based on a percentage of SA would not solve above issue

Traps in market risk capital requirements

- Avoiding the procyclical trap
  - Using lower values of decay factor for prompter updates in volatility prediction
  - Smaller number of VaR exceptions in volatile periods
  - Resilience of internal models against market tantrum
  - Managing reputation (see above Goldman's case study)
- Lowering decay factor should not increase capital requirements
  - No bias in average variance estimates
  - ES computed on a stressed period only + averaging

Traps in market risk capital requirements

- Avoiding the FRTB procyclical trap?
  - Banks are currently faced with other top priorities regarding desk eligibility to IMA
    - Data management to reduce NMRF scope
    - PnL attribution tests: reconciliation of risk and front office risk representations and pricing tools, dealing with reserves and fair value adjustements
    - Threshold number of VaR exceptions at desk level is high.
  - BUT large number of desks (100?) and local or global market tantrums might be devastating
    - Forget about unfrequent recalibration of risk models!

Conclusion

- Focus on decay factor impacts for risk measurement in the new Basel III setting
  - Desk-level validation and back-testing
- Beware of plain historical simulation methods and challenge the .94 golden number
  - Further research with internal bank data might prove useful
  - Lower decay factors for dedicated trading desks
- Challenge the outcomes of Hypothetical Portfolio Exercises on RWA variability

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