The best and the worst of VaR in a Basel III context

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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
- Backtesting / Quantitative Impact Studies poorly discriminates among models under calm periods
  - Danielsson (2002)
- Questionable benchmarking on hypothetical portfolios
  - Highly unstable ranking of risk models
- Promote smart supervision, model risk validation and enhanced disclosure on risk methodologies
  - Fed SR 11-7 (2011), BCBS239 (2013)

Messages for market risk managers

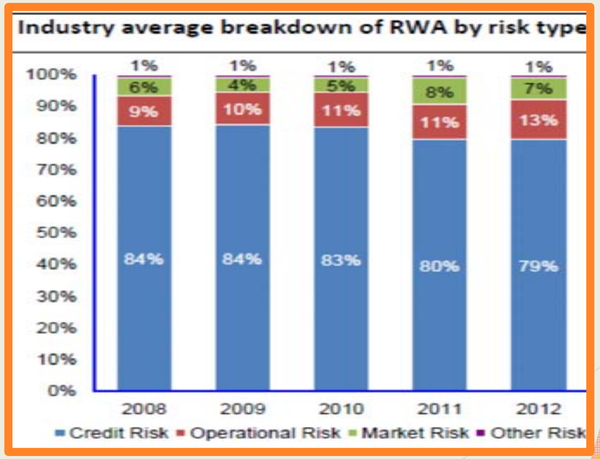
- Favour Volatility Weighted Historical Simulation (VWHS) over Historical Simulation (HS) for VaR and Expected Shortfall computations?
  - Standard backtesting procedures are of little help
- Historical Simulation works poorly in stressed periods
  - Hidden procyclicality: patterns of VaR exceptions under stress and fall-back to costly Standard Approach
- BUT large estimation errors when computing the decay factor in VWHS
  - Challenge the .94 golden risk number?
  - Consider smaller values of decay factor(s)?

The best and worse out of VaR in a Basel III context: outlook

- 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 useless?
  - Lower decay factors to mitigate disruptions in the computation of Risk Weighted Assets?

Market risks: regulatory outlook

- Market risks are not the main driver of banks' risks
  - But are prominent for large dealer banks



Ames, Schuermann, & Scott (2015)

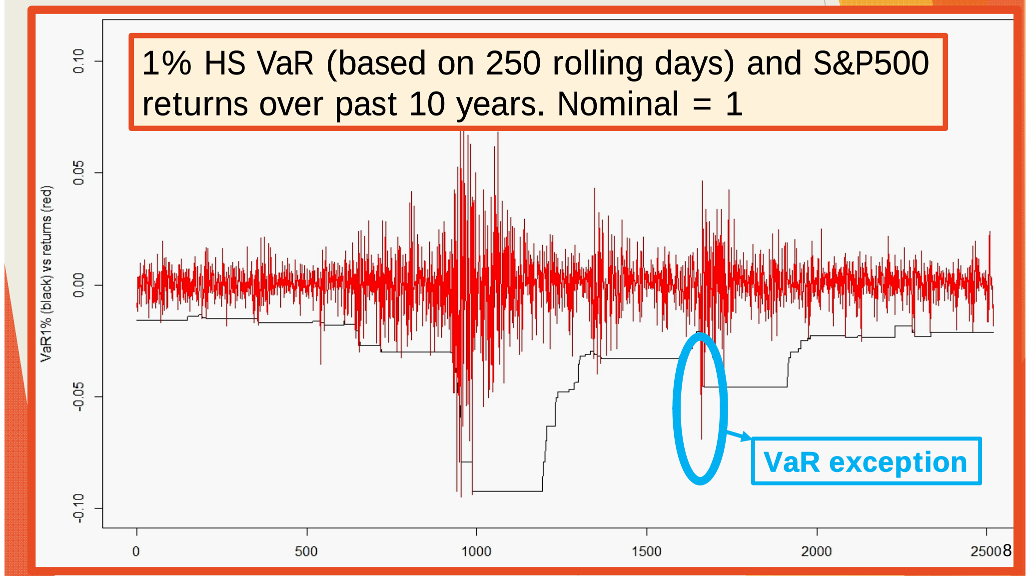
Market risks: regulatory outlook

- Computing market RWA (Risk Weighed Assets)
  - Basel amendment for market risks (1996)
  - JP Morgan's RiskMetrics (1996)
  - Fixing Basel II after 2008 turmoil
    - Stressed VaR based on year 2008
    - Credit risk: IRC, CRM, VaR on CVA, …
  - Minimum capital requirements for market risk (2016)
    - Implementation scheduled in 2019
    - Laurent (2016) for an overview of ongoing issues

Market risks: regulatory outlook

- Basel III: Internal Models Approach (IMA) still applicable
- 97.5% Stressed Expected Shortfall (ES)
  - liquidity horizons : 10 days or more
    - No scaling from 1D to 10D (Danielsson & Zigrand (2006))
- Backtesting based on 97.5% and 99% 1 day VaR
    - Not directly on ES as in Du & Escanciano (2016)
  - Number of VaR exceptions over past year
  - At trading desk level: Danciulescu (2010), Wied et al. (2015)
    - VaR exception if « loss » greater than VaR
  - BCBS QIS also requests reporting of 1D 97.5% ES + p −values

The rise of Historical Simulation (HS)



The rise of historical simulation

- Backtesting: compare 1 day VaR with both hypothetical and actual daily Profit and Loss (P&L)
  - Hypothetical P&L
    - 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

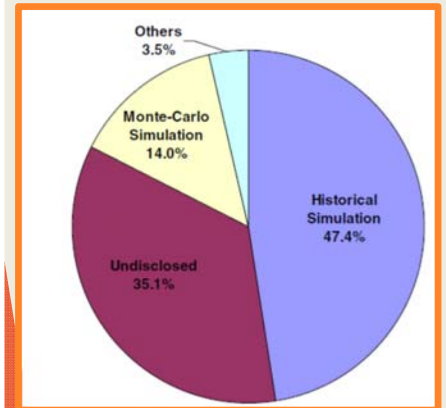
The rise of historical simulation

- Use of risk-theoretical P&L to compute VaR
  - Changes in P&L according to bank's internal risk model (which includes risk representation and pricing tools)
    - Use of modellable risk factors within risk systems (FRTB/Basel 3) or risks in VaR when applicable
    - Subset of risk factors used in Front Office systems.
    - Delta/gamma approximations, PV grids or full revaluation might be used in repricing books
- Rank daily P&L over past 250 trading days (1Y)
  - In between 2nd and 3rd worst loss provides 99% VaR

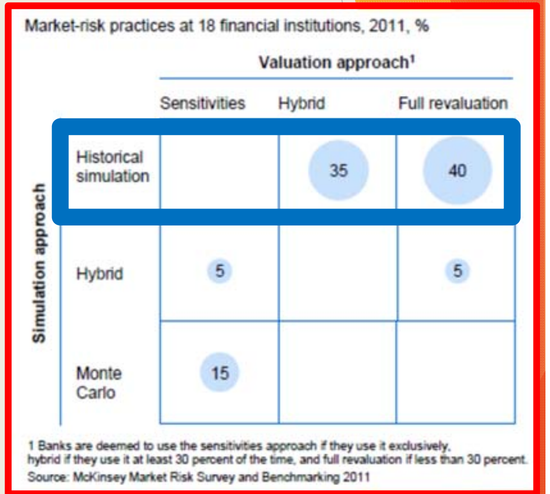
The rise of historical simulation

- Huge litterature to compare approaches to VaR/ES
  - 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)
  - Focus on 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



Mehta et al (2012)

The rise of historical simulation

- Volatility Weighted Historical Simulation (VWHS)
    - Hull & White (1998), Barone-Adesi et al. (1999), not to be confused with Boudoukh et al. (1998)
  - 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

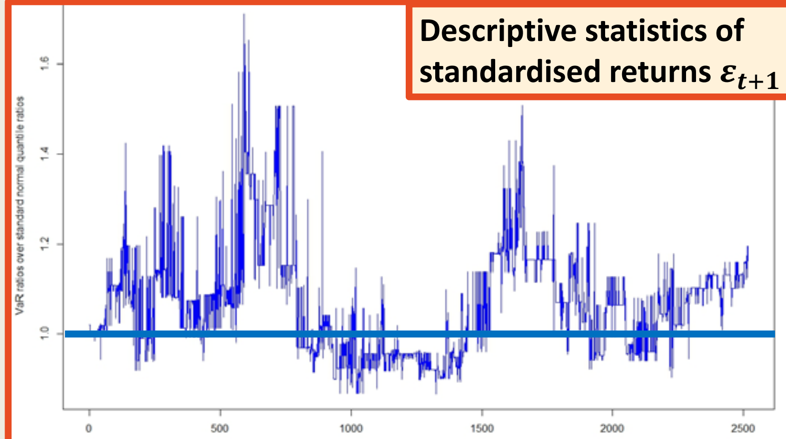
- (Location) scale models: $r_t = \sigma_t \times \varepsilon_t$
  - GARCH: ε_t has a given stationary distribution
    - Such as $t(\nu)$: parametric approach to ε_t
- VaR: $q_\alpha(r_t) = \sigma_t \times q_\alpha(\varepsilon_t)$
    - EVT could be used to assess $q_\alpha(\varepsilon_t)$, McNeil & 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

The rise of historical simulation

- Issues with previous approaches
  - Standardised returns $\varepsilon_t = r_t/\sigma_t$ not directly observed
    - Since ε_t depends on volatility estimates σ_t
    - Use of Diebold & Mariano (2002) to compare predictive accuracy questionable.
  - Large uncertainty when deriving σ_t?
    - See page 29 when using EWMA
  - Issues with GARCH(1,1) modelling: Pritsker (2006)
    - Misspecification of ε_t distribution?
    - Tail dynamics only driven by volatility σ_t

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

Descriptive statistics of standardised returns ε_{t+1}

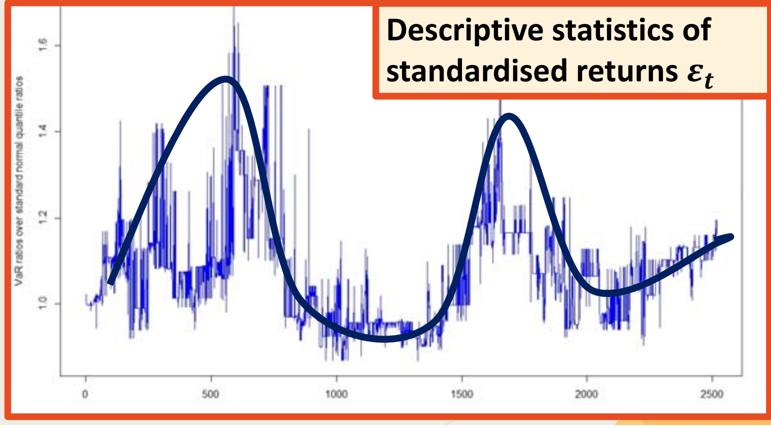


For Gaussian ε_t and well-specified decay factor, ratio should be equal to one

Ratio higher than 1 means fat tails

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

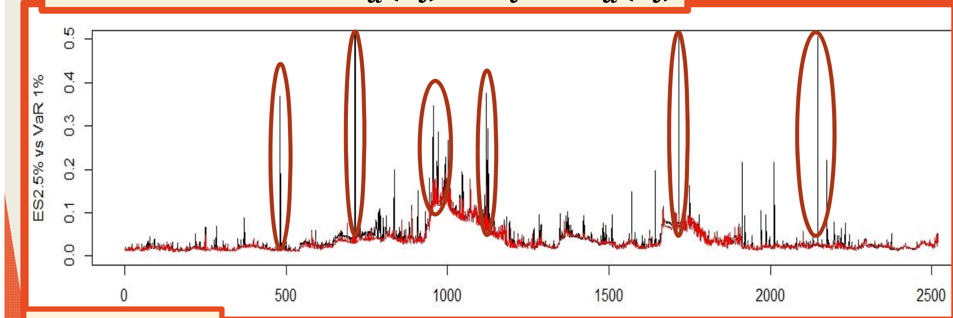
$\varepsilon_t = r_t/\sigma_t$ **show some left tail dynamics.**



Descriptive statistics of standardised returns ε_t

Daily 97.5% ES (black) vs 99% VaR (red), λ=.97

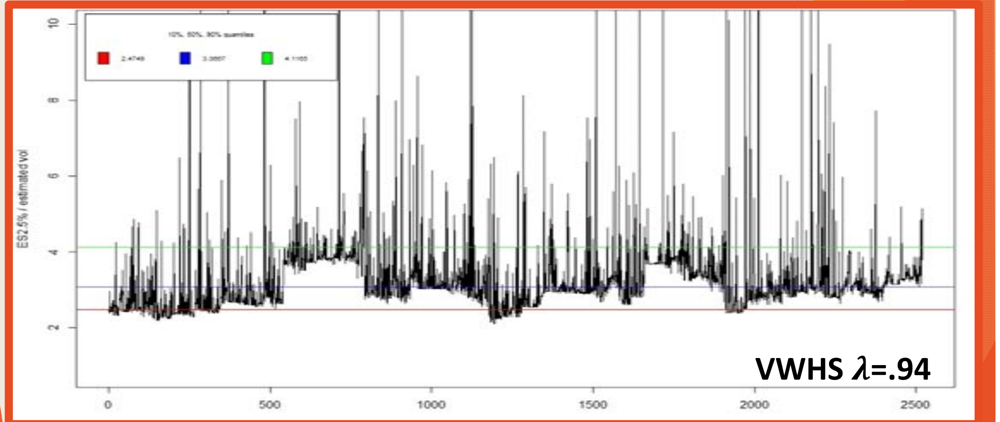
Expected Shortfall computations:
$$ES_\alpha(r_t) = \sigma_t \times ES_\alpha(\varepsilon_t)$$



VWHS λ=.97

Over past 10 years, patterns are similar, but ES is less stable than VaR due to outliers

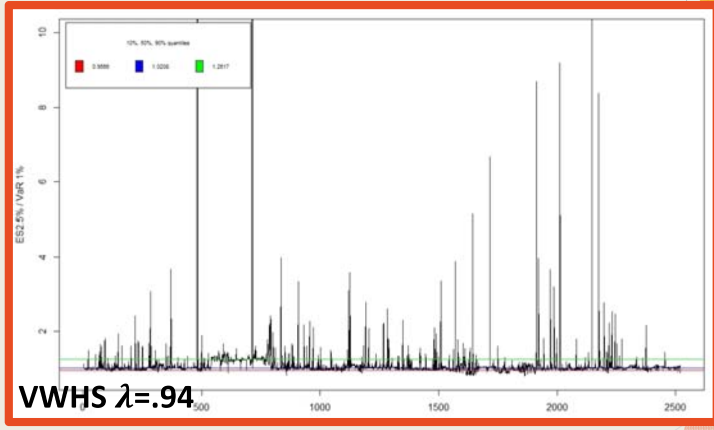
Daily Expected Shortfall of Standardised returns



VWHS λ=.94

$ES_{97.5}(\varepsilon_t)$ is unstable over past 10 years
Median (3.1), 1st decile (2.5), 9th decile (4.1) with peaks up to 10

Ratio of 97.5% ES to 99% VaR (λ=.94)



VWHS λ=.94

Daily ES unstability confirmed by considering ratio of ES to VaR

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

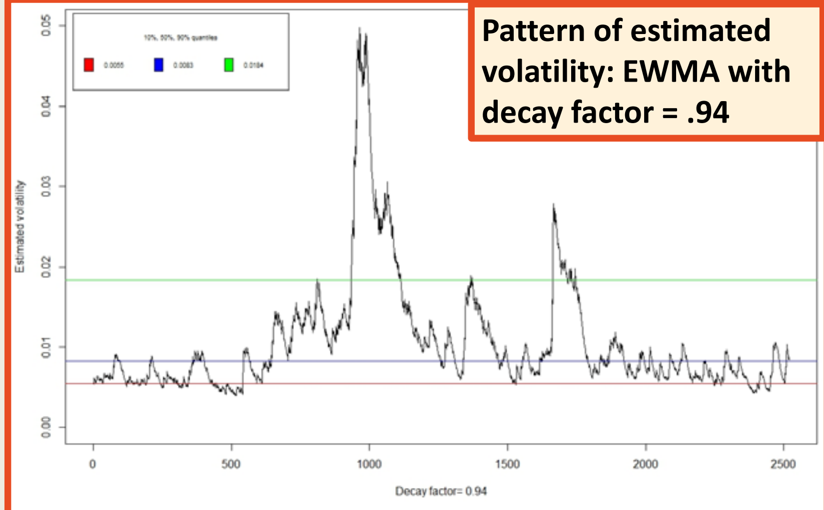
- Number of VaR exceptions over past 10 years (S&P 500)

	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 become quite close to zero in calm periods (Murphy et al. (2014))

Volatility estimation: the conundrum



Pattern of estimated volatility: EWMA with decay factor = .94

Volatility estimation: the conundrum

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

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

- 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

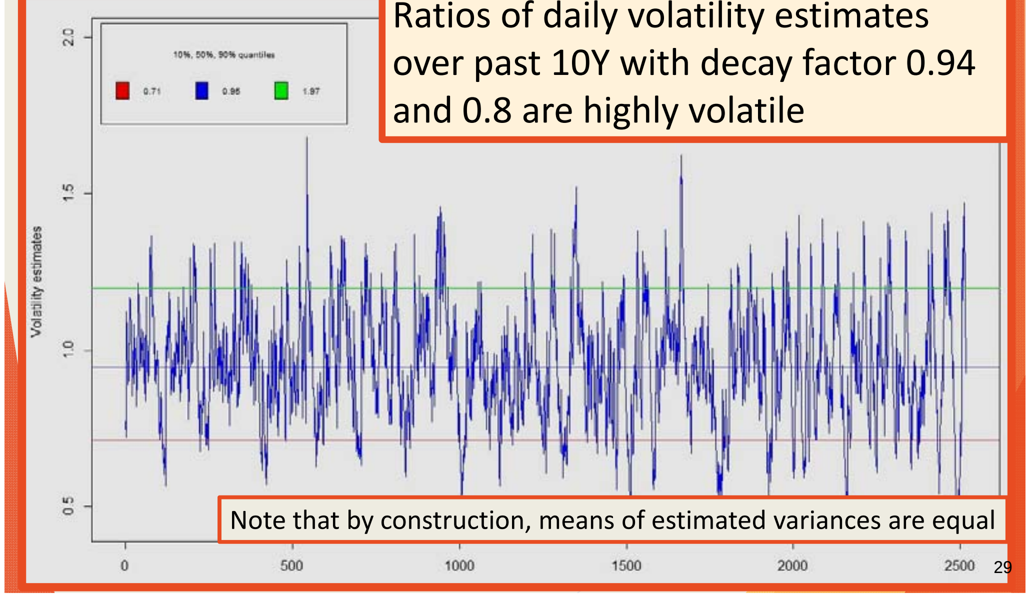
Estimation method/ length of historical data	10 years	First 5 years	Second 5 years
Squared error method	0.8992854	0.8207192	0.9030331
Pseudo likelihood method	0.9331466	0.9525935	0.9146936
Check loss method at 1% level	0.9010942	0.9406649	0.8398029
Check loss method at 2.5% level	0.8829908	0.9557358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

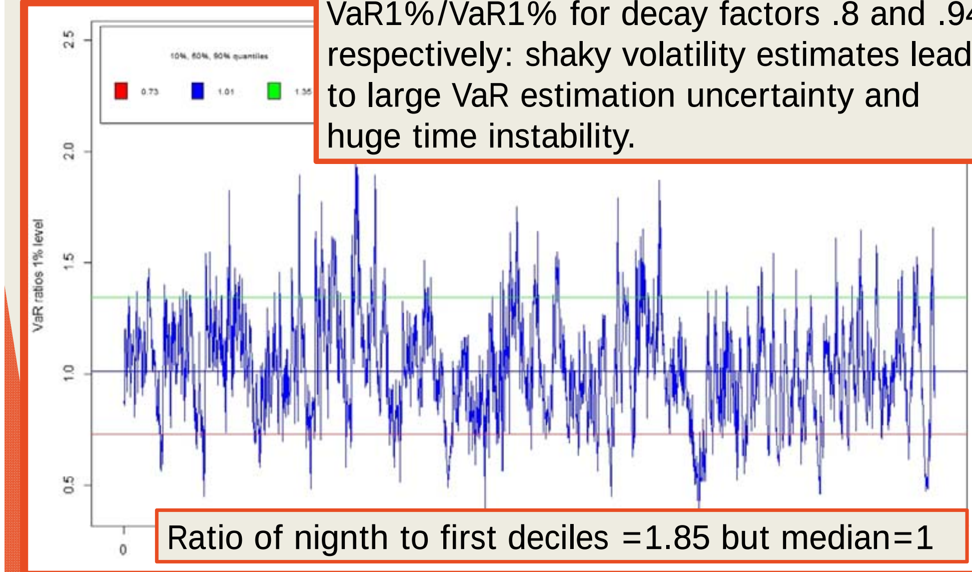
Volatility estimation: the conundrum



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)

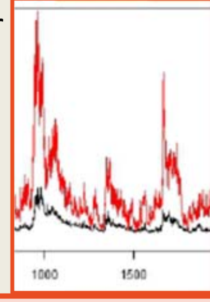
	1% VaR	2,5% VaR
VWHS $\lambda = 0.8$	28	68
VWHS $\lambda = 0.94$ (RiskMetrics)	26	68
Expected	25	63

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

Assessment of risk models

- Smaller decay factors imply **prompter VaR increases** when volatility rises and slightly better behaviour during stressed periods

VWHS	Number of Exceptions for 99% VaR over period January 2008 – January 2011
$\lambda = 0.8$	5
$\lambda = 0.94$	8
$\lambda = 0.97$	11



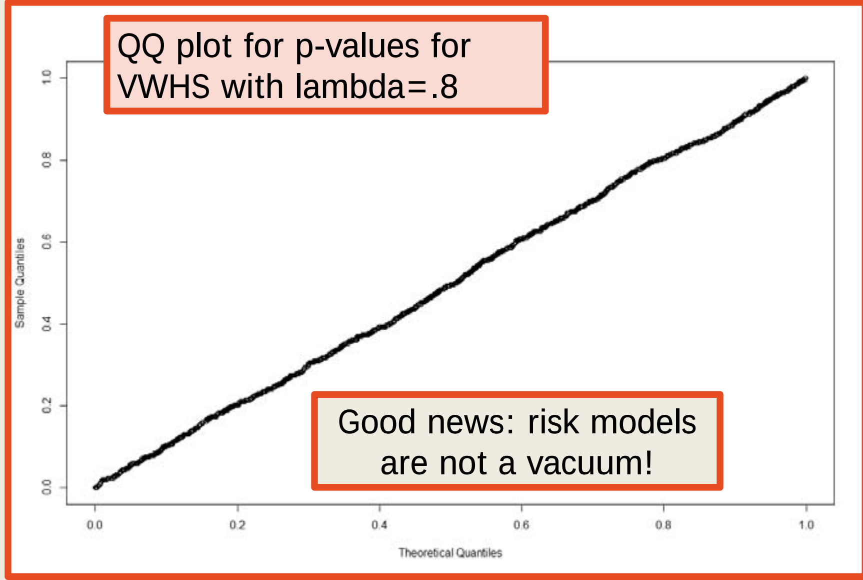
Note: Stressed period based on high levels of VaR and of VIX

  - Similar results in Boucher et al. (2014), where plain HS ($\lambda = 1$) provides poor results under stress. See also O'Brien & Szerszen (2014).

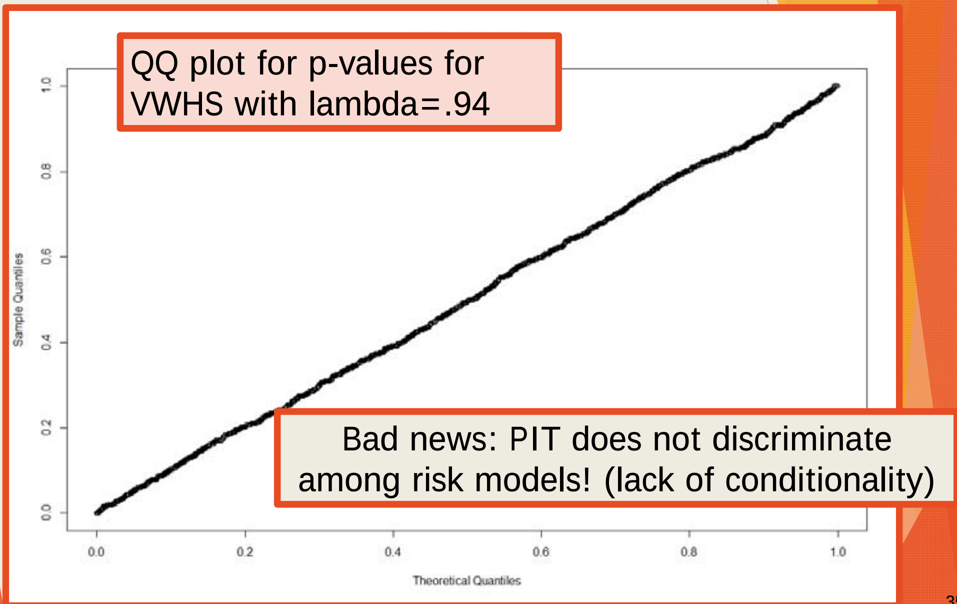
Assessment of risk models

- PIT (Probability Integral Transform) adequacy tests
  - Crnkovic and Drachman (1995), Diebold et al. (1997), Berkowitz (2001)
- Regulators: Fed, ongoing BCBS QIS
  - 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

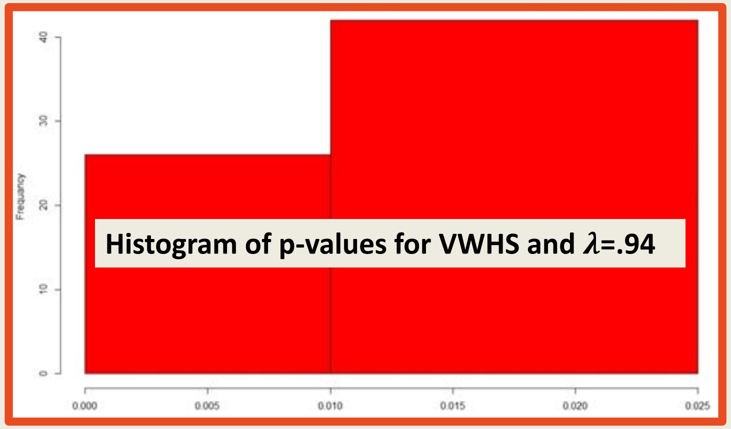
PIT adequacy tests



PIT adequacy tests



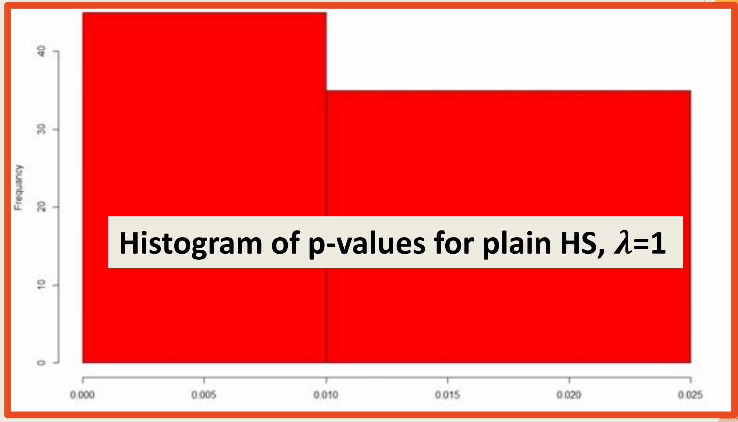
Focusing on tails: VWHS vs plain HS



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

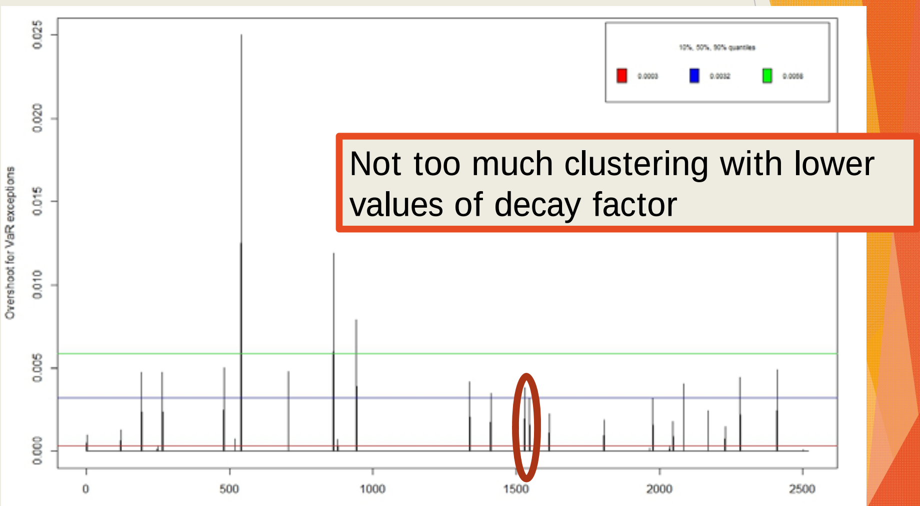


Expected values: 25 exceptions at 1% level, 38 in between 1% and 2.5%:bad fit with HS

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



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·

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) 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

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

References

- BCBS, 2011. Messages from the Academic Literature on Risk Measurement for the Trading Book.
- Fed, 2011, Supervisory Guidance on Model Risk Management.
- BCBS, 2013, Principles for effective risk data aggregation and risk reporting.
- BCBS, 2013. Regulatory consistency assessment program (RCAP) - Analysis of risk-weighted assets for market risk.
- BCBS, 2013. Regulatory consistency assessment program (RCAP) – Second report on risk-weighted assets for market risk in the trading book.
- EBA, 2013, Report on variability of Risk Weighted Assets for Market Risk Portfolios.
- BCBS, 2016, Minimum capital requirements for market risk.
- *Riskmetrics: technical document*. Morgan Guaranty Trust Company of New York, 1996.

References

- Abad, P., Benito, S., & López, C. (2014). A comprehensive review of Value at Risk methodologies. *The Spanish Review of Financial Economics*, 12(1), 15-32.
- Alexander, C. (2009). *Market Risk Analysis, Value at Risk Models* (Vol. 4). John Wiley & Sons.
- Alexander, C., & Sarabia, J. M. (2012). Quantile Uncertainty and Value-at-Risk Model Risk. *Risk Analysis*, 32(8), 1293-1308.
- Ames, M., Schuermann, T., & Scott, H. S. (2015). Bank capital for operational risk: A tale of fragility and instability. *Journal of Risk Management in Financial Institutions*, 8(3), 227-243.
- Angelidis, T., Benos, A., & Degiannakis, S. (2007). A robust VaR model under different time periods and weighting schemes. *Review of Quantitative Finance and Accounting*, *28*(2), 187-201.
- Barone-Adesi, G., Giannopoulos, K., & Vosper, L. (1999). VaR without correlations for portfolio of derivative securities. Università della Svizzera italiana.

References

- Bhattacharyya, M., & Ritolia, G. (2008). Conditional VaR using EVT–Towards a planned margin scheme. *International Review of Financial Analysis*, *17*(2), 382-395.
- Berkowitz, J. (2001). Testing density forecasts, with applications to risk management. *Journal of Business & Economic Statistics*, *19*(4), 465-474.
- Berkowitz, J., Christoffersen, P., & Pelletier, D. (2011). Evaluating value-at-risk models with desk-level data. *Management Science*, *57*(12), 2213-2227.
- Berkowitz, J., & O’Brien, J. (2002). How accurate are value-at-risk models at commercial banks?. *The Journal of Finance*, *57*(3), 1093-1111.
- Boucher, C. M., & Maillet, B. B. (2013). Learning by Failing: A Simple VaR Buffer. *Financial Markets, Institutions & Instruments*, *22*(2), 113-127.

References

- Boucher, C. M., Daníelsson, J., Kouontchou, P. S., & Maillet, B. B. (2014). Risk models-at-risk. *Journal of Banking & Finance*, *44*, 72-92.
- Boudoukh, J., Richardson, M., & Whitelaw, R. (1998). The best of both worlds. *Risk*, *11*(5), 64-67.
- Campbell, S. D. (2006). A review of backtesting and backtesting procedures. *The Journal of Risk*, *9*(2), 1.
- Candelon, B., Colletaz, G., Hurlin, C., & Tokpavi, S. (2010). Backtesting value-at-risk: a GMM duration-based test. *Journal of Financial Econometrics*.
- Cenesizoglu, T., & Timmermann, A. G. (2008). Is the distribution of stock returns predictable?. *Available at SSRN 1107185*.
- Christoffersen, P. F. (1998). Evaluating interval forecasts. *International economic review*, 841-862.
- Christoffersen, P., & Pelletier, D. (2004). Backtesting value-at-risk: A duration-based approach. *Journal of Financial Econometrics*, *2*(1), 84-108.

References

- Christoffersen, P. F., & Diebold, F. X. (2000). How relevant is volatility forecasting for financial risk management?. *Review of Economics and Statistics*, *82*(1), 12-22.
- Colletaz, G., Hurlin, C., & Pérignon, C. (2013). The Risk Map: A new tool for validating risk models. *Journal of Banking & Finance*, *37*(10), 3843-3854.
- Colliard, J. E. (2014). Strategic selection of risk models and bank capital regulation. *Available at SSRN 2170459*.
- Crnkovic, C., & Drachman, J. (1996). Presenting a quantitative tool for evaluating market risk measurement systems. *RISK-LONDON-RISK MAGAZINE LIMITED-*, *9*, 138-144.
- Christoffersen, P., & Gonçalves, S. (2005). Estimation risk in financial risk management. The Journal of Risk, 7(3), 1.
- Crotty, J. (2009). Structural causes of the global financial crisis: a critical assessment of the ‘new financial architecture’. *Cambridge Journal of Economics*, *33*(4), 563-580.

References

- Danielsson, J. (2002). The emperor has no clothes: Limits to risk modelling. *Journal of Banking & Finance*, *26*(7), 1273-1296.
- Danielsson, J. (2008). Blame the models. *Journal of Financial Stability*, *4*(4), 321-328.
- Danielsson, J., & Zigrand, J. P. (2006). On time-scaling of risk and the square-root-of-time rule. *Journal of Banking & Finance*, *30*(10), 2701-2713.
- Danielsson, J., & Zhou, C. (2015). Why risk is so hard to measure.
- Danielsson, J., James, K. R., Valenzuela, M., & Zer, I. (2016). Model risk of risk models. *Journal of Financial Stability*, *23*, 79-91.
- Danciulescu, C. (2010). Backtesting value-at-risk models: A multivariate approach. *Center for Applied Economics & Policy Research Working Paper*, (004-2010).

References

- Dave, R. D., & Stahl, G. (1998). On the accuracy of VaR estimates based on the variance-covariance approach. In Risk Measurement, Econometrics and Neural Networks (pp. 189-232). Physica-Verlag HD.
- Diebold, F. X., Gunther, T. A., & Tay, A. S. (1997). Evaluating density forecasts.
- Diebold, F. X., Schuermann, T., & Stroughair, J. D. (2000). Pitfalls and opportunities in the use of extreme value theory in risk management. *The Journal of Risk Finance*, *1*(2), 30-35.
- Diebold, F. X., & Mariano, R. S. (2002). Comparing predictive accuracy. *Journal of Business & economic statistics*.
- Dowd, K. (2009). Moral hazard and the financial crisis. *Cato J.*, *29*, 141.
- Dowd, K., Cotter, J., Humphrey, C., & Woods, M. (2011). How unlucky is 25-sigma?. *arXiv preprint arXiv:1103.5672*.

References

- Dowd, K. (2016). Math Gone Mad: Regulatory Risk Modeling by the Federal Reserve. *Policy Perspectives*.
- Du, Z., & Escanciano, J. C. (2016). Backtesting expected shortfall: accounting for tail risk. *Management Science*.
- Dumitrescu, E. I., Hurlin, C., & Pham, V. (2012). Backtesting value-at-risk: from dynamic quantile to dynamic binary tests. *Finance*, *33*(1), 79-112.
- Engle, R. F., & Manganelli, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic Statistics*, *22*(4), 367-381.
- Escanciano, J. C., & Olmo, J. (2012). Backtesting parametric value-at-risk with estimation risk. *Journal of Business & Economic Statistics*.
- Escanciano, J. C., & Pei, P. (2012). Pitfalls in backtesting historical simulation VaR models. *Journal of Banking & Finance, 36*(8), 2233-2244.

References

- Fan, J., & Gu, J. (2003). Semiparametric estimation of Value at Risk. *The Econometrics Journal*, *6*(2), 261-290.
- Francq, C., & Zakoïan, J. M. (2015). Risk-parameter estimation in volatility models. *Journal of Econometrics*, *184*(1), 158-173.
- Frésard, L., Pérignon, C., & Wilhelmsson, A. (2011). The pernicious effects of contaminated data in risk management. *Journal of Banking & Finance*, *35*(10), 2569-2583.
- Gaglianone, W. P., Lima, L. R., Linton, O., & Smith, D. R. (2012). Evaluating value-at-risk models via quantile regression. *Journal of Business & Economic Statistics*.
- Giannopoulos, K., & Tunaru, R. (2005). Coherent risk measures under filtered historical simulation. *Journal of Banking & Finance, 29*(4), 979-996.
- González-Rivera, G., Lee, T. H., & Yoldas, E. (2007). Optimality of the RiskMetrics VaR model. *Finance Research Letters*, *4*(3), 137-145.

References

- Gourieroux, C., & Zakoïan, J. M. (2013). Estimation-Adjusted VaR. *Econometric Theory*, *29*(04), 735-770.
- Guermat, C., & Harris, R. D. (2002). Robust conditional variance estimation and value-at-risk. *Journal of Risk*, *4*, 25-42.
- Gurrola-Perez, P., & Murphy, D. (2015). Filtered historical simulation Value-at-Risk models and their competitors.
- Haldane, A. G., & Madouros, V. (2012). The dog and the frisbee. *Revista de Economía Institucional*, *14*(27), 13-56.
- Haas, M. (2005). Improved duration-based backtesting of value-at-risk. *Journal of Risk*, *8*(2), 17.
- Hendricks, D. (1996). Evaluation of value-at-risk models using historical data (digest summary). *Economic Policy Review Federal Reserve Bank of New York*, *2*(1), 39-67.

References

- Hull, J., & White, A. (1998). Incorporating volatility updating into the historical simulation method for value-at-risk. *Journal of Risk*, *1*(1), 5-19.
- Hurlin, C., & Tokpavi, S. (2006). Backtesting value-at-risk accuracy: a simple new test. *The Journal of Risk*, *9*(2), 19.
- Hurlin, C., & Tokpavi, S. (2008). Une évaluation des procédures de Backtesting. *Finance*, *29*(1), 53-80.
- Jalal, A., & Rockinger, M. (2008). Predicting tail-related risk measures: The consequences of using GARCH filters for non-GARCH data. *Journal of Empirical Finance*, *15*(5), 868-877.
- Kerkhof, J., & Melenberg, B. (2004). Backtesting for risk-based regulatory capital. *Journal of Banking & Finance*, *28*(8), 1845-1865.
- Krämer, W., & Wied, D. (2015). A simple and focused backtest of value at risk. *Economics Letters*, 137, 29-31.
- Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *The J. of Derivatives*, *3*(2).

References

- Leccadito, A., Boffelli, S., & Urga, G. (2014). Evaluating the accuracy of value-at-risk forecasts: New multilevel tests. *International Journal of Forecasting*, *30*(2), 206-216.
- Laurent, J. P. (2016). The Knowns and the Known Unknowns of Capital Requirements for Market Risks.
- Lopez, J. A. (2001). Evaluating the predictive accuracy of volatility models. *Journal of Forecasting*, *20*(2), 87-109.
- Mariathasan, M., & Merrouche, O. (2014). The manipulation of Basel risk-weights. *Journal of Financial Intermediation*, *23*(3), 300-321.
- McNeil, A. J., & Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *Journal of empirical finance*, *7*(3), 271-300.
- Mehta, A., Neukirchen, M., Pfetsch, S., & Poppensieker, T. (2012). Managing market risk: today and tomorrow. McKinsey & Company McKinsey Working Papers on Risk, (32), 24.

References

- Murphy, D., Vasios, M., & Vause, N. (2014). An investigation into the procyclicality of risk-based initial margin models. Bank of England Financial Stability Paper, (29).
- Nieto, M. R., & Ruiz, E. (2016). Frontiers in VaR forecasting and backtesting. *International Journal of Forecasting*, *32*(2), 475-501.
- O'Brien, J. M., & Szerszen, P. (2014). An evaluation of bank var measures for market risk during and before the financial crisis.
- Pelletier, D., & Wei, W. (2015). The Geometric-VaR Backtesting Method. *Journal of Financial Econometrics*, 2015.
- Pérignon, C., Deng, Z. Y., & Wang, Z. J. (2008). Do banks overstate their Value-at-Risk?. *Journal of Banking & Finance*, *32*(5), 783-794.
- Pérignon, C., & Smith, D. R. (2008). A new approach to comparing VaR estimation methods. *Journal of Derivatives*, 16(2), 54-66.

References

- Pérignon, C., & Smith, D. R. (2010). Diversification and value-at-risk. *Journal of Banking & Finance*, *34*(1), 55-66.
- Pérignon, C., & Smith, D. R. (2010). The level and quality of Value-at-Risk disclosure by commercial banks. *Journal of Banking & Finance*, *34*(2), 362-377.
- Pritsker, M. (2006). The hidden dangers of historical simulation. *Journal of Banking & Finance*, *30*(2), 561-582.
- Righi, M. B., & Ceretta, P. S. (2015). A comparison of Expected Shortfall estimation models. *Journal of Economics and Business*, *78*, 14-47.
- Rossignolo, A. F., Fethi, M. D., & Shaban, M. (2012). Value-at-Risk models and Basel capital charges: Evidence from Emerging and Frontier stock markets. Journal of Financial Stability, 8(4), 303-319.
- Rossignolo, A. F., Fethi, M. D., & Shaban, M. (2013). Market crises and Basel capital requirements: Could Basel III have been different? Evidence from Portugal, Ireland, Greece and Spain (PIGS). *Journal of Banking & Finance*, *37*(5), 1323-1339.

References

- Siburg, K. F., Stoimenov, P., & Weiß, G. N. (2015). Forecasting portfolio-Value-at-Risk with nonparametric lower tail dependence estimates. Journal of Banking & Finance, 54, 129-140.
- Wied, D., Weiss, G. N., & Ziggel, D. (2015). Evaluating Value-at-Risk Forecasts: A New Set of Multivariate Backtests. *Available at SSRN 2593526*.
- White, H., Kim, T. H., & Manganelli, S. (2015). VAR for VaR: Measuring tail dependence using multivariate regression quantiles. *Journal of Econometrics*, *187*(1), 169-188.
- Wong, W. K. (2010). Backtesting value-at-risk based on tail losses. *Journal of Empirical Finance*, 17(3), 526-538.
- Yamai, Y., & Yoshiba, T. (2002). Comparative analyses of expected shortfall and value-at-risk: their estimation error, decomposition, and optimization. *Monetary and economic studies*, *20*(1), 87-121.
- Yamai, Y., & Yoshiba, T. (2005). Value-at-risk versus expected shortfall: A practical perspective. *Journal of Banking & Finance*, *29*(4), 997-1015.
- Ziggel, D., Berens, T., Weiß, G. N., & Wied, D. (2014). A new set of improved Value-at-Risk backtests. *Journal of Banking & Finance*, *48*, 29-41.