Portfolio Value at Risk and Expected Shortfall using high-frequency data

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The main objective of this thesis is to investigate whether multivariate models using high-frequency data provide significantly more accurate forecasts of Value at Risk (VaR) and Expected Shortfall (ES) than do multivariate models using only daily data. We employ a parsimonious HAR model and its asymmetric version that uses high-frequency data for modelling of the realised covariance matrix. The selected benchmark models are the well-established DCC-GARCH and EWMA. The computation of VaR and ES is done through parametric, semi-parametric and Monte Carlo simulations. The loss distributions are represented by multivariate Gaussian, multivariate Student's t, multivariate distributions simulated by Copula functions, and multivariate filtered historical simulations. The following univariate loss distributions are used: GPD from EVT; empirical and standard parametric distributions. The main finding is that the VaR forecasting accuracy of the HAR model using high-frequency data is superior, or at least equal, to that of benchmark models based on daily data. Finally, backtesting of ES remains very challenging; the forecasts were not credibly validated by the applied Test I and Test II.

Motivation

The recent financial crisis in 2007-2009 showed that neither Value at Risk (VaR) that is in effect only the lower or upper quantile of the loss distribution nor just using daily closing prices is sufficient risk approach. The academic research was aware of these main issues, and hence since 1997 there has been proposed the alternative to VaR called Expected Shortfall (ES) that studies the average of loss distribution given that VaR was exceeded. Thus, ES is more informative about the possible risk according to certain probability. Simultaneously to ES, since 1998, there has been started a deep research about the utilization of prices sampled with higher frequency than one day until the finest frequency that is transaction by transaction also for risk management purposes. The importance of ES has been recently even magnified as Basel Committee in 2013 announced that ES is going to replace VaR measure for calculation of capital requirements. In case of high-frequency data (HFD), meaning prices, the rapid technological progress allowed to boost significantly the computation power resulting in the substantial volume of trading. Many markets turned to such liquidity that intraday information become statistically relevant also for the measurement of volatility and covariance that is currently known as realized measures. These events give the main motivation for this master thesis to investigate ES besides of VaR. Additionally, our investigation is from the portfolio perspective because we are usually interested in various assets at least for the diversification purposes in practice as basic technique to minimize the risk. The main objectives of this thesis are to investigate whether multivariate models using High-frequency data provide significantly more accurate forecasts of VaR and ES than multivariate models using only daily data. The investigation will be carried out through answering following questions: What model and approach provides the most accurate forecasts of VaR and ES? Does the best model and approach of VaR perform similarly also in the forecasting of ES? What is the difference between the two approaches for various market volatility periods (stable versus turbulent period)?

Our contribution according to review of literature is that there has not been published or found by author yet an article which investigate the application of high-frequency data in terms of realized measure in multivariate space in order to estimate ES measure. Furthermore, we provide a comprehensive comparison of the difference between high-frequency and daily data according to all standard methods of calculation VaR and ES. Such scope has not been conducted yet to the best author's knowledge.

However, the conducted research is limited in the certain areas. The first limitation lies in the type of products used in the portfolio. The portfolio consists of only linear products such as futures and spot prices. The reason is that applied models do not capture correctly nonlinear dependency between the price of product and the underlying variables. The second limitation is that the agent using VaR and ES measures is a price taker and he is able to close out its entire position for the market price from the used data set. Therefore, the liquidity adjustment of VaR and ES is omitted. The third limitation is that we investigate only passive risk management application and we do not study the active one such as incremental, marginal and component VaR and ES. Another limitation is an assumption that circuit breakers applied on futures products in our portfolio will remain in the same structure also for the future implying that we do not expect the structural change from the regulator.[2] The last limitation is in the size of port-

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2 *The latest example how such an assumption can be strong is the unexpected exit of peg on Swiss franc by Swiss National Bank. It caused the unseen volatility in the entire history of currency trading since the floating regime was established.*

folio and variety of assets since the used portfolio contains only four and low correlated assets. In the case of larger portfolio or high correlated assets, the different approaches or models would be more suitable.

LITERATURE REVIEW

Daily realized volatility and covariance are estimated, in their naive version, as the sum of the squared intraday returns and the sum of the products of intraday returns, respectively. Based on this methodology, realized volatility and covariance are, in principle, observable and estimators become non-parametric (model-free). The new paradigm of volatility and covariance estimators perceived as realized ones was introduced in the seminal work of Andersen & Bollerslev (1998) and Andersen et al. (1999). The theoretical framework of realized volatility and covariance can be found in Andersen et al. (2003), Barndorff-Nielsen & Shephard (2004) and comprehensive summary in McAleer & Medeiros (2008) and Bauwens et al. (2012).

An essential property of forecasted covariance matrix for computation of VaR is the Positive Semi-Defniteness (PSD). This property is not guaranteed from the naive version of realized covariance due to market microstructure noise and hence, one of the proposed augmented realized covariance estimators satisfying mentioned property is multivariate realized kernel of Barndorff-Nielsen et al. (2011). The other methods insuring PSD property include the Matrix Logarithm transformation of realized covariance of Bauer & Vorkink (2007) and adapting long-memory univariate model Heterogeneous Autoregression (HAR) of realized volatility of Corsi (2009) on the individual elements of transformed realized covariance matrix. The similar technique is used by Chiriac & Voev (2011) which applies Cholesky decomposition of realized covariance and forecasting Cholesky factors by a multivariate long-memory Vector Autoregressive Fractionally Integrated Moving Average (VARFIMA) model and univariate HAR model. The drawback of previous two approaches was a loss of interactions between variances and covariances. In a different approach Gourieroux et al. (2009) modeled entire realized covariance matrix by the Wishart Autoregression (WAR) and further extensions by block WAR and HAR-WAR can be found in Bonato et al. (2009) or asymmetric version of WAR in Jin & Maheu (2010). The dynamic generalization of the models of Gourieroux et al. (2009) and Jin & Maheu (2010) was proposed by Golosnoy et al. (2012) as a Conditional Autoregressive Wishart (CAW). A new class of multivariate models modeling realized covariance matrix can be considered also a High-frEquency-bAsed VolatilitY (HEAVY) model of Noureldin et al. (2012).

Finally, we assess the literature of papers investigating potential benefits of high-frequency data in estimation of portfolio VaR and ES in a multivariate dimension. We can divide papers in two groups, those do compare the performance against daily data based models and those that do not.

Let's start with the first group initiated by McMillan et al. (2008) who found the preferred model is univariate GARCH estimated on the raw intraday portfolio returns to multivariate Vector Autoregression (VAR) model using the same type of data or other models using daily data. Following innovative report of Fengler & Okhrin (2012) showed that proposed realized copula managed to adopt quickly to volatile events thanks to utilization of high-frequency data and enabled sufficient capturing of non-trivial tail-dependence structures in comparison with Gaussian copulas and hence, realized copulas were superior to other models. Another very comprehensive comparison is due to Candila (2013) where he evaluated rolling realized covariance, CAW models versus BEKK, DCC-GARCH and Generalized Orthogonal GARCH (GO-GARCH) models without finding the significant difference of forecasting portfolio VaR. The only one result considering the most appropriate models such as DCC-GARCH and RiskMetrics™ based on daily is in the master thesis of Čech (2013). Even though he included not only basic multivariate HAR model based on Cholesky decomposition but also more advanced WAR models of Bonato *et al.* (2009). The biggest sample of data consisting of 52 stocks of the largest U.S. financial institutions is in Boudt et al. (2014) with the most accurate VaR forecasts recorded by model utilizing high-frequency data by corrected realized Dynamic Conditional Correlation (cRDCC) on Cholesky decomposed realized covariance (Liquidity sorting type) using Autoregressive Fractionally Integrated Moving Average (ARFIMA) model. Generally, cRDCC performed good and Scalar-BEKK or HEAVY significantly worse in comparison cRDCC or cDCC. The last one comparing article is Fengler & Okhrin (2016) with the same conclusion as in Fengler & Okhrin (2012) namely with Cholesky decomposition irrespective to marginal distribution or type of realized copula but in the context of additional high-frequency and daily data models.

The second group of papers that did not assess performance of portfolio VaR between high-frequency and daily data models can serve as the inspiration for further assessment, specifically Bonato et al. (2009), Bauwens et al. (2014) and Brechmann et al. (2015). To the best knowledge of author, there is only one paper of estimating VaR and ES portfolio Ubukata & Watanabe (2015) but entirely for purposes of hedging performance and not risk management one.

METHODOLOGY AND DATA

Our benchmark models for modeling of covariance matrix use daily prices represented be the Exponential weighted moving average (EWMA) model with estimated parameter $\lambda = 0.94$ by RiskMetrics J.P.Morgan (1996) and well established Dynamic Conditional Correlation (DCC)-Generalized Autoregressive Conditional Heterosckedasticity (GARCH) of Engle (2000) with its asymmetric version ADCC introduced by Cappiello et al. (2006) and GJR introduced by Glosten et al. (1993). The representation of model using high-frequency data is multivariate Heterogeneous Autoregression (HAR) of Chiriac & Voev (2011) inspired by univariate HAR model suggested by Corsi (2009) and simplified asymmetric HAR of DARV-HAR suggest by Allen et al. (2014) that has the same construction as the asymmetric GJR-GARCH(1,1). Realized (co)variance in its naive version on day *t* and a number of intraday returns M is defined as

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2 \;\; RCOV_t = \sum_{j=1}^{M} r_{t,j} r'_{t,j} \quad (1)$$

HAR model suggested by Corsi (2009)

$$RV_{t+1}^{(d)} = c + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \nu_t, \nu_t \overset{iid}{\sim} (N, \sigma_\nu^2) \quad (2)$$

We implement all standard methods of calculation of VaR and ES meaning parametric, semi-parametric and non-parametric. Parametric method is represented by elliptical distributions, specifically multivariate Gaussian and Student's *t*. The Filtered Historical Simulations belongs to class of semi-parametric method of calculation of VaR and ES and it was suggested by Barone-Adesi et al. (1998) and Barone-Adesi et al. (1999). The last method uses an advanced econometric approach such as Gaussian and *t* copula which parameters are estimated in two steps. First step is to estimate parameters for margins (parametrically using univariate Gaussian and Student's *t* probability distribution, semi-parametrically using Generealized Pareto Distribution via Extreme Value Theory (EVT) with peaks-over-threshold approach and non-parametrically using empirical distribution function). Second step is to estimate a parameter for copula function.

We understand under the term backtesting as quantitative check of the significance of the forecasts from the out-of-sample against the realization of the losses. Nonetheless, backtesting methods do not pick up the best model from the set of candidate models, given data. Therefore, we introduce also the methods for model selection using loss functions. In case of VaR, we applied following backtests: Unconditional Coverate Test (UC) of (Kupiec, 1995), Conditional Coverage Test (CC) of (Christoffersen, 1998), Dynamic Quantile Test (DQ) of (Engle and Manganelli, 2004) and model selection methods: Regulator Loss Function (RLF) of (Lopez, 1998), Firm Loss Function (FLF) of (Jondeau et al., 2007, p. 343) and Asymmetric Loss Function (ALF) of (González-Rivera et al., 2004). In our case, we are going to apply RLF and FLF with γ = 2 and instead of constant interest rate i, we choose classical risk premium from Capital Asset Pricing Model (CAPM) as the difference between market return[3] and risk free return[4] representing an opportunity cost of reserved capital for VaR measure. Moreover, we assume zero transaction cost.

In case of backesting of ES, the scholars brought on light a fundamental question whether ES is backtestable since Gneiting (2011) showed that ES lacks a mathematical property called *elicitability* while VaR does have it. Gneiting (2011) showed it is not possible to find minimizing scoring function for ES and hence, ES is not elicitable. This sparked a new global discussion among scholars, research and practitioners about ES backtesting because Basel Committee did not suggest that time any backtesting method (neither if it exists) for ES but to keep backtesting 99% and 97:5% VaRs. These circumstances motivated research to investigate how and if ES can be backtested. As Acerbi & Szekely (2014a) points out that the most of people understood Gneiting (2011) that ES is not backtestable at all and they explain it was further strengthen by statement of Embrecht *"ES cannot be back-tested because it fails to satisfy elicitability ... If you held a gun to my head and said: 'We have to decide by the end of the day if Basel 3.5 should move to ES, or do we stick with VaR,' I would say: 'Stick with VaR' "* said in 2013 at Imperial College. The opposition to these statements was formalized in the article of Acerbi & Szekely (2014b) where the authors firstly argue that the property of elicitability has to do only with model selection in order to choose the best model among competitors and additional argument is that currentlyVaR is backtested without exploiting its elicitability property. Therefore, they suggested three ES non-parametric tests using Monte-Carlo simulations even with missing elicitability property because it is not needed for backtesting of ES. Another insightful article of Emmer et al. (2015) showed that ES is conditionally elicitable and proposed another non-parametric without need of Monte-Carlo simulations.

The great overview of ES backtesting methods is written in the master thesis of Wimmerstedt (2015) including implementation of four of them. The others were not chosen due to their parametric assumptions and requirement of large out-of-sample samples. The conclusion of that master thesis is that

Table 1 Chosen models

	High-frequency	Daily
Variance-Covariance	HAR.Chol	EWMA (λ = 0.94)
Models	LHAR.Chol	DCC.GARCH(1,1)
		DCC.GJR.GARCH(1,1)
		aDCC.GJR.GARCH(1,1)
Method	**Distribution**	
Parametric	MV-Normal	
	MV-t	
Semi-parametric	FHS	
Monte Carlo	GaussCopula Normal-Normal	
	GaussCopula Empirical-Normal	
	GaussCopula GPD+Kernel	
	tCopula t-t	
	tCopula Empirical-t	
	tCopula GPD+Kernel	

Source: Author's computation.

3 *Daily log return of settlement prices of continuous front month futures ES1.*

4 *Daily log return of settlement prices of continuous front month US Treasury notes futures TU1 with maturity 2 years.*

backtesting of ES is possible but the complexity is significantly higher compared to the backtesting of VaR and further research is needed. Nonetheless, the author prefers the test of Emmer et al. (2015) where ES is backtested through approximation of several VaR levels. We are going to implement first two tests proposed by Acerbi & Szekely (2014b) due to their non-parametric, simulation properties and possibility to backtest on just one confidence level contrary to test of Emmer et al. (2015) which is designed for four or even more confidence levels what increase computational burden.

In order to assess our predictive models, we use cross-validation technique in our backtests. We use the proportion for each in-sample 67% of data and out-of-sample remaining 33%. We characterize three scenarios as *Full* sample from January 3, 2008 until June 12, 2015 consisting of 1,844 business days. The second one is a subsample of time period with *High* volatility from January 2,

Table 2 VaR and ES Test I results for Full sample and significant models

Model	VR	UC pv	CC pv	DQ pv	RLF	RLF %	FLF	FLF %	ALF	ALF %	Z1	Z1 pv
Best 3												
HAR.Chol.RCOV.N	1.3	0.22	0.44	0.62	0.019	0	0.243	100	0.039	73	-0.27	0.58
HAR.Chol.RCOV.t	1.2	0.46	0.64	0.66	0.018	15	0.244	94	0.039	73	-0.18	0.48
HAR.tC.e	1.1	0.82	0.72	0.61	0.019	0	0.248	61	0.039	73	-0.22	0.27
Worst 3												
LHAR.nC.n	0.6	0.09	0.07	0.14	0.015	61	0.256	18	0.042	6	-0.42	0.12
LHAR.Chol.RCOV.N	0.6	0.09	0.07	0.15	0.012	97	0.262	3	0.043	0	-0.29	0.34
LHAR.Chol.RCOV.FHS	0.6	0.09	0.07	0.15	0.012	97	0.264	0	0.043	0	-0.09	0.27

Source: Author's computation.
Note: VR stands for violation ratio. The perfect VR should be equal to 1. UC, CC and DQ stand for Unconditional Coverage test, Conditional Coverage test and Dynamic Quantile test (only p-values are presented). RLF, FLF, ALF stand for average value of Regulator, Firm and Asymmetric Loss Function. RLF, FLF, ALF with symbol % stand for percentile value. Z1 stands for test statistics of Test I and Z1 pv for its p-value. If p-value of Z1 test obtains value (-) it means that it could not be computed.

Table 3 VaR and ES Test I results for High sample and significant models

Model	VR	UC pv	CC pv	DQ pv	RLF	RLF %	FLF	FLF %	ALF	ALF %	Z1	Z1 pv
Best 3												
HAR.tC.gpd	1.8	0.08	0.17	0.42	0.014	67	0.835	37	0.059	93	-0.01	0.95
LHAR.tC.gpd	1.0	0.93	0.86	0.99	0.006	100	0.861	4	0.059	93	0.05	-
LHAR.nC.gpd	0.8	0.61	0.79	0.99	0.007	93	0.856	7	0.059	93	-0.03	-
Worst 3												
GARCH.nC.n	1.6	0.16	0.24	0.43	0.028	0	0.787	100	0.065	7	-0.28	0.47
DCC.GARCH.COV.t	1.8	0.08	0.17	0.36	0.028	0	0.801	67	0.066	0	-0.15	0.59
GARCH.tC.t	1.6	0.16	0.24	0.40	0.027	7	0.792	81	0.066	0	-0.15	0.54

Source: Author's computation.
Note: VR stands for violation ratio. The perfect VR should be equal to 1. UC, CC and DQ stand for Unconditional Coverage test, Conditional Coverage test and Dynamic Quantile test (only p-values are presented). RLF, FLF, ALF stand for average value of Regulator, Firm and Asymmetric Loss Function. RLF, FLF, ALF with symbol % stand for percentile value. Z1 stands for test statistics of Test I and Z1 pv for its p-value. If p-value of Z1 test obtains value (-) it means that it could not be computed.

Table 4 VaR and ES Test I results for Low sample and significant models

Model	VR	UC pv	CC pv	DQ pv	RLF	RLF %	FLF	FLF %	ALF	ALF %	Z1	Z1 pv
Best 3												
HAR.Chol.RCOV.N	1.1	0.74	0.77	0.53	0.004	0	0.201	24	0.028	83	-0.21	0.70
HAR.Chol.RCOV.t	1.1	0.74	0.77	0.53	0.004	0	0.203	17	0.028	83	-0.09	0.74
DCC.GJR.GARCH.COV.N	0.8	0.62	0.80	0.29	0.002	31	0.193	69	0.028	83	-0.10	0.84
Worst 3												
GARCH.nC.n	1.1	0.74	0.77	0.06	0.002	31	0.189	90	0.030	3	-0.07	-
GARCH.nC.gpd	0.8	0.62	0.80	0.39	0.002	31	0.193	69	0.030	3	-0.03	-
DCC.GJR.GARCH.COV.FHS	0.8	0.62	0.80	0.41	0.003	10	0.187	93	0.031	0	0.10	-

Source: Author's computation.
Note: VR stands for violation ratio. The perfect VR should be equal to 1. UC, CC and DQ stand for Unconditional Coverage test, Conditional Coverage test and Dynamic Quantile test (only p-values are presented). RLF, FLF, ALF stand for average value of Regulator, Firm and Asymmetric Loss Function. RLF, FLF, ALF with symbol % stand for percentile value. Z1 stands for test statistics of Test I and Z1 pv for its p-value. If p-value of Z1 test obtains value (-) it means that it could not be computed.

2009 until December 30, 2011 consisting of 750 business days with some stress events and the third one is a subsample of time period with *Low* volatility from January 3, 2012 until December 31, 2014 consisting of 742 business days. Our portfolio consists of the most liquid representatives of major financial asset classes denominated in the U.S. dollars. Specifically, the data employed in this thesis are E-mini futures S&P 500, Light Crude Oil futures, Spot gold and spot EURUSD for the time period from January 3, 2008 to June 12, 2015.

Conclusions

Regarding to data analysis, we implemented the naive estimator of realized covariance constructed by homogeneously spaced returns on 20 minutes frequency (volatility and relatively also covariance is stabilized around this frequency on signature covariance plot), synchronization according to fixed time when all assets were traded and omitting the overnight returns. We found that overnight returns were only significant between Friday closing and Monday opening on CL and XAUUSD asset. Our synchronization technique resulted in high reduction of data as we had left only 69 observations per business day. Moreover, the long-memory effect was confirmed on all elements of realized covariance matrix that provided the support for our multivariate HAR model. Overall, the estimation of realized covariance matrix is still relatively in its infancy period and hence, the more advanced methods are very sophisticated with little documentation of their implementation in practice. From the practical point of view, one thinking about HFD sampled with very high frequencies must be also aware of substantial increased demand of computation power. Subsequent modeling of realized covariance matrix was very efficient due to the parsimony and stability of multivariate HAR models. We tried to apply also ARFIMA model in the same fashion as multivariate HAR but it was very unstable estimation returning many errors during estimation in R. The estimation of multivariate distributions through copula functions is very well-documented and implemented also in R. The challenging point was the determination of threshold level for the GPD. Based on the Monte Carlo experiment in McNeil et al. (2015, pp. 161-162) where they concluded that optimal choice of the threshold level would be from the sample of 100-150 exceedances, we decided to set the threshold to such percentage of observations in order to get around 100 observations that should provide stable estimates of GPD.

Table 5 ES Test II results for 2 models with the closest and the furthest Z2 statistics from zero for all scenarios

Scenario	Model	Z2	pv
Full			
	DCC.GARCH.COV.FHS	0.02	0.85
	aDCC.GJR.GARCH.COV.N	-0.02	0.91
	HAR.Chol.RCOV.N	-0.67	0.95
	EWMA.COV.t	0.58	0.43
High			
	LHAR.Chol.RCOV.FHS	0.01	0.54
	LHAR.tC.gpd	0.08	0.76
	EWMA.COV.FHS	-1.61	0.44
	HAR.nC.e	-1.66	0.72
Low			
	EWMA.COV.t	0.00	0.38
	GARCH.tC.e	-0.09	0.72
	LHAR.tC.gpd	0.72	0.96
	LHAR.nC.gpd	0.70	0.97

Source: Author's computation.

Regarding to answers to our main objective and following questions, we are going to answer through our empirical results of our backtesting and model selection methods (the position of models were determined by the asymmetric loss function). All empirical results are derived for full sample called *Full* scenario and subsamples containing periods of high volatility called *High* scenario and low volatility called *Low* scenario. The first question was *"What model and approach provides the most accurate forecasts of VaR and ES?"* The answer is that the most robust performance was achieved by utilization of HFD through univariate HAR using copula function either Gaussian or *t* in terms of forecasts of VaR. The second question was *"Does the best model and approach of VaR perform similarly also in the forecasting of ES?"* Unfortunately, we are not able to answer this question. The reason is that backtests of ES did not give credible results since both tests did not reject any model on significance level 5%. Moreover, the Test I did not even calculate p-value on some models because the simulation via bootstrapping resulted in calculation of p-value that would include division by zero what is undefined mathematical operation. The both tests were rather disappointing and probably the backtesting approach by approximation of ES by VaR for different confidence levels can be better alternative as it was suggested by Emmer et al. (2015). The third question was *"What is the difference between the two approaches for various market volatility periods (stable versus turbulent period)?"* The answer is there is significant difference. When we have a look on top models in High scenario in Table 2, we can find the best performing model asymmetric version of univariate HAR called LHAR with Gaussian or *t* copula using GPD as marginal distribution. These models coped with the fat tails the best. Anyway, asymmetric version of univariate HAR was an excellent model in all its variations in High scenario. Another interesting result is from Low scenario where all models either using HFD or daily data performed relatively the same. It tells us that backtesting and selecting the models based on this scenario is very low robust. The final answer for our main objective is that Heterogeneous Autoregression model using high-frequency data delivered superior or at least the same accuracy of forecasts of VaR to benchmark models (DCC-GARCH or EWMA) based on daily data. Nevertheless, EWMA model was the worst performing model from all because it was rejected in all scenarios and therefore it was not included in model selection. The model selection based on loss functions revealed also interesting information. The regulatory loss function was giving more or less inverse preference of models than firm loss function. This was the reason why we implemented asymmetric loss function as our decisive criterion to define the order of preference of models. Another important finding about backtesting of ES is that depending on the definition of "backtesting", the backtesting might not exist or at least the model selection does not exist due to lack of elicitability what means there does not exist scoring function such as loss functions applied in the model selection of VaR. Overall, backtesting of ES remains very challenging; the forecasts were not credibly validated by the applied Test I and Test II.

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