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A series of studies on liquidity management have appeared during the financial crisis, many of them comparing the funding liquidity with the market liquidity. The paper offers a dynamic image about the liquidity in the Romanian banking sector and its integration with the market risk, comparing the Value at Risk approach with the Liquidity at Risk approach. The research also wants to highlight the most significant features to consider in order to implement an effective liquidity risk management and to achieve a more integrated supervisory framework.

Key words: liquidity risk, market crisis, liquidity limits, Value at Risk, Liquidity at Risk

JEL code: G01, G21, G32, C63.

1.Introduction

This paper analyze market risk behavior in periods characterized by extreme events and propose a liquidity model in order to quantify and manage the risk that arise from the trading book. The most used model for quantifying the market risk is Value at Risk (VaR) initiated by Jorion (1997), Dowd (1998), and Saunders (1999). Even though it replaced less standardized techniques such as Asset and Liability Management and Stress-testing, it lacks a rigorous treatment of liquidity risk. The liquidity risk has two main parts: funding liquidity risk and market liquidity risk. The first one has received the most attention from the banks for its significance. But, the market liquidity risk, described as the risk that a bank cannot easily offset or eliminate a position without significantly affecting the market price because of inadequate market depth or market disruption (ECB, 2002) has gained more attention in the latest years.

A problem of the VaR models is that they don't take account of market liquidity risk, because they assume that the positions (currency rates, interest rates, stock index values, option volatilities) could be sold at a fixed market place, the midpoint quote, within a fixed period time (Laorence and Robinson, 1995). There are many studies in the related literature of incorporating market liquidity risk n the VaR models. Almgren and Chriss (2000) and Bangia et al (1999) proposed a dependent model strategy. Dubil (2001) proposed a model for determining optimal liquidation periods for different assets. Shamroukh (2000) highlight that scaling the holding period to account for orderly liquidation can only be justified if the holding period actually represents the liquidation period. Jarrow and Subramanian (1997) proposed a liquidity adjusted VaR measure that incorporates the liquidity discount, volatility of liquidity discount and the volatility of time horizon to liquidation, considering the effect of trade size and execution lag on the liquidation value of the portfolio.

In this article we present a framework for incorporating the liquidity risk into the VaR models. Section 2 presents the Value at Risk methodology, in accordance with the Basel II requirements. Section 3 describes the Liquidity at Risk methodology and reviews the techniques used to model the distribution of the returns. In section 4 is presented a case study which models the daily bid-ask spread for three important banks from the Romanian banking system, listed on the Bucharest Stock Exchange and section 5 concludes.

2.The Value at Risk methodology

Financial institutions have developed models for quantifying, comparing and aggregating the risk connected with different positions and portfolios. One of the most used methods is Value at Risk, which is defined as the expected maximum loss of a portfolio over some time period and for some level of probability. From a statistical point of view, VaR entails the estimation of the quantile of the returns' distribution. In other words, Value at Risk is the probability that returns or losses (ξ) are smaller than –VaR over a period of time (T):

$$P_{VaR} = P(\xi < -VaR) = \int_{-\infty}^{-VaR} P_T \cdot \xi \cdot d\xi \quad (1),$$

where P_T is the probability distribution of returns over the time horizon T.

For a 99% confidence level the worst value is:

$$P_{99\%} = P_t \cdot e^{[E(r_t) - 2.33\sigma_t]} \ (2),$$

where E(r_t) and σ_t^2 are the first two moments of the asset returns' distribution.

In order to compute the VaR for a portfolio first we have to mark-to-market the portfolio and then to estimate the distribution of the portfolio's returns, which is a very challenging statistical problem. When the returns are normal, which is very rarely in practice, it is used the variance-covariance approach. When risk is recurrent VaR can be estimated by using historical time series and for new situations it should be modeled through EWMA and GARCH models. When risk is sensitive to rare events it is preferred the Extreme Value Theory. The main limitation of the VaR methodology is that the assumption of normal distribution can lead to large underestimation of the probability of extreme events, which affects the capital requirements. Also, the estimated distribution tends to fit central observations, while falling in fitting the extreme observations. The accuracy of VaR depends on how well the underlying markets have been simulated and how well each security has been modeled. Recent studies propose to analyze only the distribution of extreme returns, instead of describing the behavior of all of the returns (Ferreira and Lopez, 2004; Burns, 2002; Rombouts and Verbeek, 2004). Related to these studies is the EVT, introduced in finance by Embrechts (1997), although the basics were initiated by Fisher and Tippett (1928) when proposing the Generalized Extreme Value (GEV) distribution. The modeling of the financial variables through EVT was also studied by McNeil and Frail (2000), by Danielsson and De Vries (1997) which computed a model for calculating the VaR, taking into account the inconsistency of extreme values and by Huisman et al. (1997) which proposed a new estimator for the tail index.

3.The Liquidity at Risk methodology

Banks should possess a funding liquidity contingency plan in order to prevent insolvency, pass through stressful situations and maintain their reputation and credit rating. From all the proposed definitions of funding liquidity and market liquidity the next two ones are promising. Funding liquidity is the ability of a bank to maintain a prospective equilibrium between cash inflows and outflows, ensuring appropriate coverage of payments on the bank's liabilities (Erzegovesi, 2002). Market liquidity is the discounted expected price concession required for an immediate transformation of an asset into cash or cash into an asset under a specific trading strategy (Neuman and Demsetz, 1968). Jarrow and Subramanian (1997) consider the effect of trade size and execution lag on the liquidation value of the portfolio, proposing a liquidity adjusted VaR that incorporates the volatility of liquidity discount.

In order to incorporate the liquidity risk into the VaR models we would make an assumption that in stressed market conditions extreme events in returns and extreme events in spreads happen concurrently. So, in calculating liquidity-risk adjusted VaR we incorporate both a 99[th] percentile movement in the underlying and a 99[th] percentile movement in the spread:

$$P_{99\%} = P_t \cdot e^{(-2.33\sigma_t)} - \frac{1}{2}\left[P_t\left(\overline{S} + a\widetilde{\sigma}\right)\right] \quad (3)$$

Assuming that the expected return $E(r_t)$ is zero, that the Liquidity at Risk can be written as follows:

$$LaR - VaR = P_t \cdot \left(1 - e^{(-2.33\theta\sigma_t)}\right) + \frac{1}{2}\left[P_t\left(\overline{S} + a\widetilde{\sigma}\right)\right] \qquad (4)$$

where S_T is the relative medium spread ((Ask-Bid)/Mid) over the time horizon T, $\widetilde{\sigma}$ is the volatility of the medium spread and a is the scaling factor, a multiple of the spread volatility, in order to achieve 99% probability coverage and θ is a correction factor that take into account the fat-tailed distribution.

4.Empirical study: analyzing the market risk and the liquidity risk in the Romanian banking system

In order do determine the VaR and the LaR we have modeled the daily data of the stock prices for three important banks in the Romanian banking system, listed on the stock exchange: Erste Bank (EBS), BRD Group Societe Generale (BRD) and Transilvania Bank (TLV), from 01.01.2007 to 31.03.2010. The observations of the closing price, bid and ask spread, are available on a period longer than that we took in consideration, but we have considered that the recent observations provides a better estimation on the risk of the portfolio. Also, we divided the data into two samples: the first sample is from 01.01.2007 to 31.08.2009 representing the "pre crisis" period and the second sample is from 01.09.2009 to 31.03.2010 representing the "post crisis" period.

The daily rentabilities were determined by logarithmation of the series of closing prices and present a lot of extreme variations that took place on the stock exchange market. Applying the Jarque Berra Test we will observe that the normal hypothesis is rejected. The distributions are leptokurtic, more sharpen than the normal ones, for all of the samples, a fact shown by the kurtosis coefficient. Analyzing the skewness coefficient we will observe that the distributions are shifted to the left, compared with the normal distribution. Applying the ADF and the Philipe-Peron tests it will be observed that the series composed of the closing prices values have one unit roots, which means that it is needed a first order differentiation in order to become stationary.

Table 1: The moments of the distributions

	EBS sample I	EBS sample II	BRD sample I	BRD sample II	TLV sample I	TLV sample II
Observations	265	323	403	323	403	323
Mean	-0.000359	-0.000202	-0.000136	-0.000241	-0.001671	0.001543
Median	0.000080	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.051403	00.51403	0.113482	0.139762	0.062160	1.434721
Minimum	-0.369786	-0.468803	-0.099820	-0.158523	-0.501279	-0.501279
Std. Dev.	0.037123	0.060703	0.017438	0.027437	0.025827	0.060477
Skewness	-0.975164	-0.784071	-0.057078	-0.565357	-11.15595	17.00904
Kurtosis	98.41873	54.69923	9.606578	11.33078	200.8467	427.6909
Jarque-Bera	342687.5	30483.70	1366.191	2211.710	1240438	5680052
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

According to all these factors, the distribution of the rentabilities presents fat tails, which correspond to the extreme variations that took place on the money market. Using the historical simulation method can lead to an overestimation of VaR, especially that the method describes the maximum expected loss. Here appears the "volatility clustering" phenomena, which can be remedied by the heteroscedasticity models GARCH.
In order to eliminate the linear structure we propose some ARMA models studying the residuals' correlogram, for which the AIC and BIC criterions are minimum. In the pre-crisis period we found ARMA(7) for EBS, ARMA(3) for BRD and ARMA(4) for TLV and in the post-crisis period we found ARMA(5) for EBS, ARMA(6) for BRD and ARMA(7) for TLV. The remained residuals have a non-linear structure which was detected by the BDS test elaborated in 1987 by Brock, Dechert and Scheinkman, in order to check the stochastic non-linearity. The BDS test's values are strong, which sustains the rejection of the normal hypothesis. This tendency reflects a degree of heteroscedasticity, which means that the present volatility depends on the previous volatility. Unless the data is filtered, this dependence will undermine the value of VaR. In order to eliminate the correlation between residuals we had to find some GARCH models. The best models identified were: GARCH(2,3) for EBS, TGARCH for BRD, GARCH(2,4) for TLV in the pre-crisis period and GARCH(1,2) for EBS, GARCH(2,3) for BRD, GARCH(3,4) for TLV in the post-crisis period.
In order to calculate the banks' exposure to liquidity and market risk, we have incorporated the liquidity components into the VaR approach. It is observed that during the financial crisis the liquidity component has a higher contribution in the level of VaR. The results for the two samples taken into consideration are the following:

Table 2: Market and liquidity risk for the pre-crisis period

	EBS	BRD	TLV
Price on 31.08.2009	144.10	12.5	0.288
Return volatility (σ_t)	0.037123	0.060703	0.017438
Fat tail factor (θ)	1.2	1.3	1.25
Market component (VaR) $P_t \cdot \left(1-e^{(-2.33\theta\sigma_t)}\right)$	4.3796	2.5634	0.0937
Liquidity component of (LaR) $\frac{1}{2}\left[P_t\left(\overline{S}+a\widetilde{\sigma}\right)\right]$	0.0816	0.1043	0.0034
Total Adjusted Value at Risk	4.4612	2.6677	0.0971
% of liquidity component	1.8291%	3.9097%	3.5015%

Table3: Market and liquidity risk for the post-crisis period

	EBS	BRD	TLV
Price on 31.03.2010	125.10	15.6	2.31
Return volatility (σ_t)	0.027437	0.025827	0.060477
Fat tail factor (θ)	1.4	1.65	1.55
Market component (VaR) $P_t \cdot \left(1-e^{(-2.33\theta\sigma_t)}\right)$	4.9872	3.0105	0.1032
Liquidity component of (LaR) $\frac{1}{2}\left[P_t\left(\overline{S}+a\widetilde{\sigma}\right)\right]$	0.1207	0.2032	0.0048

Total Adjusted Value at Risk	5.1079	3.2137	0.108
% of liquidity component	2.3630%	6.3229%	4.4444%

In order to test the post efficiency of the methodologies we have used the back-testing, by simulating the stress scenarios for the least 245 days. We have applied the quadratic loss function approach, calculating how many times the VaR has been exceeded. The results are presented below:

Table 4: Backtesting results for the market portfolio with and without liquidity risk

	Pre-crisis		Post-crisis	
Exceptions from of $VaR_{99\%}$	Market risk	Market risk & Liquidity risk	Market risk	Market risk & Liquidity risk
EBS	4	3	6	4
BRD	6	4	6	4
TLV	5	2	5	3

The best methods, which are in the minimum risk zone (which means that VaR has been exceeded for no more that 4 times), are those that take into consideration the market liquidity risk. The other models that count only the bank's exposure to the market risk are in the medium safety zone (from 5 to 9 violations of VaR), which means that the banks need more capital allocation in order to satisfy the Basel II Accord requirements.

5.Conclusion

We confirmed our hypothesis that only advanced VaR models that incorporate the liquidity risk (LaR) could adequately measure exposure of the bank to market risk and satisfy the BCBS criteria in periods characterized by extreme events. Also, in forecasting VaR for exposures in crisis periods it should be used a shorter sample of data, the most recent one, in order to capture the large movements on the market. With regard to accuracy, the risk managers should be concerned with whether the model's ex-post performance is compatible with the theoretically desired level, applying permanently back-testing criteria.

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