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Capital adequacy in the context of markets turmoil♣

Claudia Ioana VLAD♥
Faculty of Finance, Insurance, Bankingand Stock Exchange, Corporate Finance Master Program , Bucharest, University of Economic Studies
Ana-Maria RADA♥
Faculty of Finance, Insurance, Bankingand Stock Exchange, Risk Management and Actuarial Science Master Program , Bucharest, University of Economic Studies

Andreea-Florentina RADA♥
Faculty of Finance, Insurance, Bankingand Stock Exchange, Risk Management and Actuarial Science Master Program , Bucharest, University of Economic Studies

ABSTRACT

Financial stability is the key objective that sustains and empowers investments and economic groth, or scatters the opportunities when lacking. As growth translates to profitability, and profitability is dependent upon solvalibility, the need for a deep knowledge of all potential risks surfaces. This scope is seeken through all the reglementations of the financial markets. Since the last major financial crisis had a less devastating impact on the insurance market and the losses suffered by the insurance companies were smaller than the losses of banks, we will focus on the risk valuation apllied by these insurance companies. The proper valuation of risks is mirrored in the Solvency Capital Requirement calculated,which under Solvency II framework,corresponds to Value-at-Risk of the basic own funds subjected to a confidence level of 99.5% over a one-year period.

Keywords: Financial stability, Insurance market, Solvency Capital Requirement, Risk measurement, Value-at-Risk

JEL Codes: G22, G28

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1.Introduction

In the context of current financial markets where the stability is often tested,as a result of the previous market turmoil, there can be said that is of utmost importance to properly identify and evaluate risks. On a macroeconomic level, the stability is seaken through the fiscal, budgetary and monetary policies, and also through the reglementary frameworks of financial markets. Hence, by treating and being aware of the system weaknessenses, the role of risk management is highlighted, which through an accurate approach can lead to a decrease of the overall financial crisis risk. As previously proved, the insurance sector is not the first to be affected during a financial crisis and not the one that suffers the largest losses, due among others to a better valuation of risks and capital adequacy.

The purpose of this paper is to evaluate the risks that a general insurance company faces, according to the regulatory framework Solvency II. Based upon this, we aim to calculate the required capital to be held, in order to meet all future contingencies on a time horizon of one year, assuming a 0.5% probability of failure.

The calculation method is both complying with the general standards on the most part, and also original because it it has a different approach for the evaluation of market risk. Basically, for the Value-at-Risk calculation, we based our approach on a stochastic evaluation of the unconditional volatility associated to currency risk and interest rate risk.

The practical utility of this paper consists in the understanding facilitated by the review regarding the main risks that a property-casuality insurance company faces and also in the valuation methods used in practice.All of these, are generally developed accordindg to transparency and disclosure standards.

The article is structured in five sections. The first one covers the introduction, Section 2 describes the main regulatory frameworks on the financial markets and their interaction regardingcapital adequacy, Section 3 presents the main risk cathegories, their significance and how can be evaluated, Section 4 containts the necessary capital requirement calculation and the results obtained, as well as agregationg the risks, while the final section summarizes the conclusions.

2. Solvency II – the most significant regulatory change for theEuropean insurance market

As financial institutions continue to face complex economic, regulatory, and social environments, it is now more important than ever for senior executives to takea holistic view in understanding their organization and positioning it for future profitability and growth.

The main reglementary framework on the insurance market is Solvency II, which forces insurance companies to comply with a more accurate valuation of capital requirements and stricter reporting standards. Hence, the purpose is to harmonize the regulatory framework among the states members of European Union. Basically, in the case of small companies it provides a standard formula for the calculation of the solvency capital requirement, allowing the others to develop their own characteristic model.

Solvency II aims to implement solvency requirements that better reflect the risks that companies faceand deliver a supervisory system that is consistent across all member states, having a dynamic risk based approach, which allows for a 0.5% probability of failure. The challenge of preparing for and implementing Solvency II calls for a multidisciplinary approach. Therefore, the main goal of Solvency II is to establish a single regulatory framework within theEU to protect insurers' policy holders via adequate capital and consistent risk management standards.

The European Insuranceand Occupational Pensions Authority (EIOPA) defines the three pillars as a way of grouping Solvency II requirements. Pillar 1covers all the quantitative requirements and aims to ensure firms areadequately capitalized with risk-based capital. All valuations in this pillar are to be done in a prudent and market-consistent manner. Under Solvency I, capital requirements were determined based on profit and lossaccount measures (premiums and claims). In contrast, Solvency II adopts a balance sheet focused approach, with the SCR consisting of a series of stresses against the key risks affecting all balance sheet components (assets, as well as insurance liabilities), together with a charge in respect of operational risk. Solvency margins are structured around two main figures: one, which we could consider as economic capital (associated with the risk bearing) -this is what is called the Solvency Capital Requirement (SCR); the second one, which we could consider as legal capital which would be the minimum required amount – it is called Minimum Capital Requirement (MCR). The SCR level is a first action level, that is, supervisory action will be triggered if resources fall below its level. The MCR is a severeaction level monitored by the control authority, which can include company closure to new business (Egidio dos Reis et al., 2010). The SCR is a going-concern risk measure, targeting a 99.5% Value-at-Risk. The SCR is based on four major risk categories: market risks, credit risks, operational risks and underwriting risks. Each of these categories is further subcategorized as indicated by the International Association of Actuaries (IAA, 2004).

Companies may use either the Standard Formula approach or an internal model approach to determinate the required risk capital for a one-year time horizon. However, many insurers are struggling with the implementation, thus, many companies rely on standard models, which are usually not able to accurately reflect an insurer's risk situation and may lead to deficient outcomes (Reusset al., 2010 and Ronkainen et al., 2007). Still, any internal model alternative would have to accomplish legal requirements, provide greater added value to shareholders when risk management processes are included, and be subject to approval by the control authorities (Liebwein, 2006).

While Pillar I focuses on quantitative requirements, Pillar IIdefines more qualitative requirements and supplements the first. It imposes higher standards of risk management and governance within a firm's organization. Pillar 3 aims to achieve greater levels of transparency to their supervisors and the public so that firms are more disciplined in their actions. This pillar focuses on disclosure requirements to ensure the transparency of the regimeand that supervisors have the necessary information to ensure compliance with Solvency II.

As widely noted, Solvency II is similar in structure to the Basel II regulation for the banking industry. Both are based on three pillars that include quantitative, qualitative requirements, market discipline, and also specific components that focus on capital, risk, supervision, and disclosure. However, it is important to acknowledge that banking and insuranceare distinctly different industries. Therefore, the implementation process for Solvency II cannot just mirror the one of Basel II. Each represents a unique process into itself as they deal with very different business models and different types of risk. While similarities surely exist, thereare considerable differences in the requirements, application, and impact of each pillar (KPMG, 2011).

Such a difference derives from the fact that while Basel has only applicability purpose, without being compulsory, Solvency II has a binding basis across the UE, Iceland, Norway and Lichtenstein. Still, Solvency II implications are not limited to Europe, its influence on the international standards being developed by the International Association of Insurance Supervisors (IAIS). This is an advantage for external insurance groups , which cand be able to operate easier on foreign markets if there is an equivalence between Solvency II and their home regulatory framework (Al-Darwishet al.,2011).As a similarity, both frameworks have a risk based approach for the valuation of minimal capital requirement.

Going only to the insurance market, we noticed that in parallel with the Solvency II process, a number of other initiatives have been taken to update various regulatory frameworks such as Internal Capital Assessment Standards (ICAS) in the U.K., the Swiss Solvency Test (SST) and the Financial Assessment Framework (FTK) in the Netherlands. Also, the International Association of Insurance Supervisors (IAIS) started up various initiatives with the objective of convergence of the context of insurance solvency systems. All four frameworks include capital requirements for market, credit, underwriting and operational risks. Of these, Solvency II is the most important, because firstly it is a concrete legal framework rather than principles and secondly it will apply to a large and important insurance market (i.e. Europe) (Doff, 2008). Even so, we cannot ignore the SST because it brings another way of modeling the Solvency Capital Requirement, using the Tail-Value-at-Risk, also called Expected Shortfall (ES), at a 99% confidence level. The main difference is that ES consider all tail values not, like VaR, only the threshold. In their study, M. Elingand D. Pankoke (2010), found that using ES as a risk measure instead of VaR leads to very comparable results.

To date, there have been fivequality impact studies: the most recent, QIS5 ran from August to November 2010, being used to develop the Standard Formula, for the Solvency Capital Requirement (SCR) of all EU insurers not using an approved Internal Model. All insurers were strongly encouraged to participate in this exercise, as it assisted them in determining the likely impact of Solvency II on their capital requirements. In some locations, e.g., in the UK, the regulator has indicated that all firms that intend to apply an internal model must take part in QIS5.

3. Methodology

There is well known that financial series data manifest fatter tails than a normal distribution (excess of kurtosis), volatility clustering (shock persistence, indicated by squared returns, which often are significantly autocorrelated), leverage effects (volatility tends to react differently on good and bad news) and long memory (near unit root behavior in the conditional variance process).

When determining the Value-at Risk, choosing the method for calculation is of upmost importance, since it can lead to an accurate value if done properly, or to a weak estimate. In order to obtain a significant result, we studied the performance of different VaR models, based on the conditional volatility, modeled by GARCH.

Conditional variance of the portofolio is one of the key ingredients required by Value at Risk. For this purpose, thereare different classical methods, such as Historical simulation, Variance – Covariance, Monte Carlo simulation and J. P. Morgan's RiskMetrics® Methodology. The last one, introduced in 1994 and based on the exponentially weighted moving average (EWMA), brought the use of VaR into mainstream business practice. (Dowd, 1998)

Historical Simulation method consists of ranking the observations from worst to best; Var-Covar approach assumes a normal distribution and the Monte Carlo Simulation is based on a Geometric Brownian Motion. The focus is currently shifting from classical methods, which in essence represent a time-series analysis, to ARCH/GARCH models, considering that often the time series show time-dependent volatility. Considering the fact that volatility is rather heteroskedastic process, it is not optimum to apply equal weights, considering more relevant the recent events. The ARCH model, by letting the weights be parameters, estimates the most appropriate value in order to forecast the variance.

Thus, following the seminal contributions of Engle (1982) and Bollerslev (1986), modeling of financial asset returns has been cast in the generalized autoregressive conditional heteroskedasticity framework. The GARCH models have been proved capable to capture leptokurtosis, skewnessand volatility clustering, which are commonly observed in high frequency financial time series data.

3.1. Market risk

Generally, the market risk comprises the volatility of the portfolio due to own exposure on the financial markets on currency risk, interest rate risk, equity risk and credit risk. The currency risk arises from the volatility of the currencies exchange rates, when the insurer's assets and liabilities are denominated in a different currency than the national one. The exposure on interest rate risk is based on the sensitive change in the value of fixed income investments, insurance liabilities, loans, etc. The credit risk can be measured by the yield difference between corporate bonds which coupons may miss the payments and government bonds. As far as equity risk in concerned, which is divided into specific and systematic risk, this occurs when the insurer's portfolio contains investments in financial market instruments.

The starting point of studies regarding the dynamics of foreign currency exchange returns was the work of Mandelbrot (1963) and Fama (1965), which observed a non-linear temporal dependence. A few years later, Fama (1965), arrived to the conclusion that the distribution of the exchange rate of returns is leptokurtic and Friedman and Vandersteel (1982) found that it is bell-shaped, symmetric and fat-tailed and also that largeand small changes obey the volatility clustering effect over time.

Beside theexcess of kurtosis of financial data, Black (1976) concludes that there is a negative correlation between the current return and the estimated volatility, which is considered a leverage effect. According to this, a downfall in stock prices leads to an increase of leverage (debt/equity), which leads further to a higher risk (a higher volatility) for the next period. In other words, the volatility is higher when reflecting a negative shock compared to an equal positive change.

Hsieh (1989) was the first to model the exchange rate based on an Autoregressive Conditional Heteroskedasticity, following the works of Engle (1982) and Bollerslev (1986). In a study published one year later, he found that even though the daily changes in five major foreign exchange rates do not contain any linear correlation, evidence indicates the presence of a significant nonlinearity, in a multiplicative rather than an additive form and that a GARCH model can model a significant part of nonlinearities.

Frances (1987) found that in order to analyze the volatility over a long period, a model witha small lag, such as GARCH (1,1) provide satisfying results.

Nelson(1991), based on theargument that a GARCH model even though can remove theexcess kurtosis in returns, is expected to be biased for skewed time series, introduced theExponential GARCH, which according to his analysis proves to be the best for stock indices time series. This model is able to estimate the leverageeffect by capturing small positive shocks with a more significant impact on conditional variance than small negative shocks and large negative shocks with a greater impact than large positive shocks.

Engle (1987), considering the hypothesis that an increase in the volatility will result in a higher expected return, developed the GARCH in Mean model (GARCH-M), which formulates the conditional mean as a function of the conditional volatility and as an autoregressive function of the past values.

Glosten, Jagannathanand Runkle (1993) extended the GARCH model to assess possibleasymmetries between theeffects of positiveand negative shocks of the same magnitude on the conditional volatility.

Choo *et al (*1999), analyzing the volatility forecasting performance on stock prices, arrived to a few significant conclusions, such as: the long memory GARCH model is preferable to a short memory and high order ARCH method; the GARCH-M is the best in fitting the historical dataand theEGARCH proves to be the best in one-step-ahead forecasting and also that IGARCH is the least efficient in both aspects.

Combining the conclusions previously mentioned, Choo *et al* (2002) studied the efficiency of forecasting the currency exchange rate volatility and arrived to the conclusion that a Stationary GARCH (SGARCH(1,1)) has the best results, followed by GARCH-M(1,1) and that generally GARCH in mean models outperform the ordinary models.

Vee*et al* (2011) conducted a study regarding the forecasting performance of GARCH models based upon two underlying fat-tailed distributions: Student-t and GeneralisedErrors. They found that both models lead to good results, witha slight advantage for GED distribution. Previously conducted studies showed a preference for Student t distribution (Bollerslev, 1987 and Baillie, 1989) and for GED distribution (Nelson, 1991 amd Kaiser,1996).

The confidence level explains how often the portfolio returns may exceed the Value-at-Risk. The pitfall of normal assumption is that financial time series tend to have fatter tails than accounted for by the normal distribution, which may lead to an underestimated VaR. There have been used other approaches such as the Student-t, which can account for fatter tails or by using the Historical Simulation method, which does not assume for any kind of distribution (Dowd, 1998).

Dowd (2002) points that the problem with VaR is the failure of subadditivity, which means that the risk measure for two portfolios after they have been merged should be no greater than the sum of their risk measures before they were merged. This is a propriety that would normally be regarded as absolutely basic to any respectable measure of financial risk, however VaR, in general, does not satisfy the coherent risk measure.

3.2. Underwriting risk

Solvency II represents a new and different assessment of tehnical provisions for premiums and outstanding claims. This new approach highlights the need to calculate liabilities on a consistent-market basis. In fact, Solvency II introduces a total balance sheet approach, where technical provisions are the most important liabilities for a non-life insurance company. Thus, the SII framework says that the calculation of the best estimate provisions for premiums outstanding claims should be managed separately. The valuations should be based on the exit value and may use data supplied by financial markets in addition to the company's own data. Under SII, the Best Estimate Liability method (BEL) and the Risk Margin (RM) are the most important in approximation of the market value of liabilities.

The best estimate shall correspond to the probability-weighted average of future cash-flows, taking account of the time value of money (expected present value of future cash-flows), using the relevant risk-free interest rate term structure. The best estimate is calculated in gross terms, without deducting the amounts recoverable from reinsurance contracts (CEIOPS, 2009).

The Risk Margin can be interpreted as a loading for non- hedgeable risk and has to "ensure that the value of technical provisions is equivalent to theamount that (re)insurance undertakings would beexpected to require to take over and meet the (re)insurance obligations" (CEIOPS, 2009).Thus, in case of a company's insolvency, the Risk Margin should belargeenough for another company to guarantee the proper run-off of the portfolio of contracts. It is computed viaa cost of capital approach (CEIOPS, 2009) and reflects the required return in excess of the risk-free return on assets backing future SCRs.

The insurance activity leads us directly to the underwrinting risk. The non-life underwriting risk is coming from the non-life insurance obligations due to the risks covered and the business management. Non-life underwriting risk also arises from the uncertainty included in assumptions about the policyholder options such as renewal or ending options.

The non-life underwriting risk modulehas the following sub-modules: the non-life premium and reserve risk, the non-life lapse risk and the non-lifecatastrophe risk (QIS5, 2010). To be noted that we analyze the premium and reserve risk in the context of this study.

3.3. Counterparty default risk

Starting 2008, financial tumult and catastrophic damages have shocked the insurance and reinsurance markets. From that point, the major players have focused on the topic of reinsurance counterparty risk, because all insurance companies are highly exposed to reinsurance failure and their protential fragility. Thus, was born the need to control and reglementate this type of risk in the context of complex markets.

Counterparty default risk is one of the core components of the SCR. In the QIS 5 final report, EIOPA noted that this module received the most criticism for the "overly complex approach" relative to the materiality of counterparty default risk within the overall risk-based capital requirement-(EIOPA, 2011). Under Solvency II insurers will be able to retain lower capital due to the risk they have passed on to the reinsurer, but they will also need to holdan appropriate amount of capital for the default risk they are exposed to.

We noticed that there is a problem with counterparty risk approach identified by QIS 5 participants. This problem refers to difficulties in establishing the mitigate risk for the programs where exists more than one counterparty. EIOPA will consider a variety of ways to simplify this mode to address these issues before implementing.

3.4. Operational risk

Besides quantitative requirements for SII, insurers must face with operational risks to which they are exposed and which must be quantified. The operational risk that insurers are facing has become more potentially devastating and more difficult toanticipate. Operational risk is defined as the capital charge for "the risk of loss arising from inadequate or failed internal processes, people, systems or external events". It also indicates that operational risk losses result from complex and non-linear interactions between risk and business processes- (RMA/ PWC, 1999).

In operational risk category we can include: internal fraud(claim fabrication, employee theft), external fraud (claim fraud, falsifying information), employment practicies and workplaces safety(repetitive stress, discrimination), damage to physical assets(physical damage to own office, own automobile fleets),clients, products and businesses practices (client privacy, bad faith, redlining), business disruption and system failures (processing centre downtime, system interruptions), according to Thirlwell (2010).

A proper risk management will separate the operational risk from other risks to help improve future results. This is true both for higher and lower damages.

4. Results

The GARCH models allow the conditional variance to change over timeas a function of past errors and volatility, leaving the unconditional (long-run) variance constant. Under these models, the returns process is generated as $r_t = \mu + \varepsilon_t$, where$r_t$ is the returns process, μ the conditional mean, which may include autoregressiveand moving average terms, and εt is the error term, which can be decomposed as $\varepsilon_t = z_t * \sqrt{\sigma_t^2}$such that σ_t^2 is the conditional volatility process to be estimated.The GARCH(p,q) model is written under the form:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \propto_i \times r_{t-1}^2 + \sum_{j=1}^{p} \beta_j x \sigma_{t-1}^2 \quad (1)$$

In order toensure wide sense stationarity, Ling and McAleer (2002) established the following constraint for the parameters: $(\alpha_i + \beta_j)$<1, which means that the impact of shocks on volatility is decreasing over timeand insignificant asymptotically. Thus, the unconditional variance becomes existent and is calculated as(Hamilton, 1994):

$$Var\,(\varepsilon_t) = \frac{\omega}{1 - (\alpha_i + \beta_j)} \quad (2)$$

For $(\alpha_i + \beta_j) > 1$, the unconditional volatility is undefined, thus, we deal with non-stationary variance, which means that theeffect on future volatility is not decreasing over time, and remains persistent. If $\alpha_i + \beta_j = 1$, the model required is an integrated GARCH (IGARCH) because the second moment of process which describes the dynamics of return series is infinite, meaning that shocks havea permanent effect on volatility atany time horizon. This fact holds a great influence on volatility forecasting since the current information maintains its weight constant.

In the case of GJR model, the constraint for theexistence of the second moment is

$\alpha_i + \beta_j + \frac{\gamma}{2} < 1$ and the unconditional variance is $\sigma^2 = \frac{\omega}{1-\alpha-\frac{\gamma}{2}-\beta}$. (3)

4.1. Market risk

Theexposure of the insurer's portfolio in our case follows only the volatility of currencies and interest rate. There is no spread or credit risk beacause the company is not exposed to credit worthiness of some financial products issued by corporations and no equity risk to to the lack of investments in others company's stocks.

As far as **currency risk** is concerned, the balance sheet reflects an exposure of 36.48% on EUR volatility, 4.61% on CHF varianceand a small fraction percentage of 0.33% on USD exchange rate.

Based on the daily returns exchange rate of the three currencies since January, the 1st, 2005 (2092 observations), we estimated the exposure of the portofolio based on various stochastic models.

In order to estimate the Value-at Risk, we have to accurately forecast the volatility. This step must be based on a previously determination of the ARCH signature, using the Autocorrelation function and the Partial autocorrelation function or Ljung-Box *Q*-Test and Engle's ARCH Test (Table 2, Appendix).

In the case of Ljung Box test, when the Q-Statistic value is large, thearea under the Chi Square distribution that exceeds this value is less than 0.05; in consequence, since the calculated statistics are higher than the critical value (32.801), we reject the null hypothesis that errors are not correlated in the case of all three currencies. The conclusion is supported by the null probability associated. The pattern of autocorrelation coefficiens of the currency exchange rate of return and their significance suggest that they follow an autoregressive/moving average process.

In order to detect the presence of Arch, Engel in his seminal paper (1982) suggests the use of the Lagrange multiplier or the Arch LM Test. The methodology involves to fit ε_t^2 by the regression of these squared residuals founded in the right model on a constant and on the k lagged values (2 in our case). If thereare no Arch effects, theestimated value of the coefficients should be zero, but in our case, since the estimated parameters of the regression arestatiscally significant and probability associated is null, we reject the null hypothesis of no Arch effects. Hence, this regression has also little explanatory power so that the coefficient of determination, R^2, are quite low.

On the other hand, we have to make sure that the series are stationary, because only then the mean, the volatility and the autocorrelations are accurately approximated. Mainly, in the case of a stationary process, the effect of shocks is temporary and the series return to the initial trend and the time series converge to the unconditional mean. For this purpose, there are unit root tests, such as Augmented Dicky Fuller or Phillips-Perron. The null hypothesis of Augmented Dickey Fuller test states that the serie has a unit root (non stationarity) and according to the higher level of statistics then the critical threshold, we reject the null hypothesis and accept that all three currencies return series are stationary.

Also, by verifying the distribution of the errors distribution using the Jarque-Bera test, we conclude that in all three currencies don't follow a normal distribution, having mainly an excess of kurtosis and a significant skewness.

Considering that we determined the presence of heteroskedasticity, we conclude to use a GARCH model for the conditional volatility, since high volatility periods alternate with low volatility. As for the main equation, based on theAutocorrelation Function and Partial Autocorrelation Function discussed previously, after testing various models, the minimum Akaike, Schwarz and Hannan-Quinn criteria led to an AR(1) model for USD returns, an AR(3) for CHF and to ARMA(1,3) for EUR.

In the matter of conditional volatility, based on various simulation, we selected as optimum a GARCH(1,1) based on a Normal distribution of USD volatility, a bivariate GJR-GARCH(1,2) model based on a normal distribution for CHF and a GJR-GARCH(0,2) model based a Student distribution for EUR series. All three models respect the stationarity constraint, thus the unconditional volatility is defined (Table 3, Appendix).

The unconditional volatilities determined based upon are 0.0077% for USD, 0.004% for EUR and 0.0029% for CHF.

Regarding **the interest rate risk**, we considered the daily average return of ROBID and ROBOR for an equally large sample, sinceJanuary, the 1st 2005 (2092 observations) untill present.

The return time series respect the stationary constraint, according to Augmented Dickey Fuller statistic, which is significantly lower than the 5% threshold. Also, based on the correlogram of the residues, the Ljung-Box statistic reveals the significance of autocorrelation coefficients, suggesting in the same timean autoregressive/moving average process (Table 1, Appendix).

The errors are not normally distributed, The Jarque-Bera statistic being higher than the chi square distribution threshold, the distribution presents excess of kurtosis, which means there is a higher probability for extremeevents and a left asymmetry.

The Arch test confirmed the presence of ARCH effects, which led to the decision to model the data series according to GARCH method. The return serie follows an autoregressive process of order 1 and 5, and the conditional volatility a GARCH (2, 1) process, based upon a Student's t error distribution. This conclusion is sustained by Akaike, Schwarz and Hannan-Quinn minimum value criteria, after previous analysis of various model, such as: EGARCH, TARCH, ARCH, IGARCH and the available error distributions.

The unconditional volatility estimated based upon this model for the interest rate return is 0.0005%.

4.2. Underwriting risk

On what concerns premium and reserve risk, QIS5 standard approach rely on two measures: a premium volume measure (PVM) and a reserve volume measure (RVM) and in evaluating the variations of such measures to compute their volatilities.

In our case-study we use the following input information: capital requirement for non-life premium and reserve risk, to obtain the final output capital requirement for non-life underwriting risk.

As QIS5 specifies, premium risk comes out from variations in the timing, frequency and severity of insured events, premium risk relates to policies to be written (including renewals) during the period, and to unexpired risks on existing contracts. Premium risk includes the risk that premium provisions turn out to be insufficient to compensate claims or need to be increased. Reserve risk results from fluctuations in the timing and amount of claim settlements.

In order to carry out the non-life premium and reserve risk calculation we determined the volume measure and standard deviations for each Line of business (LoB). Our company has an exposure on the following lines: accident insurance, health, motor hull, cargo insurance, property (fire and natural disasters), property (other than fire), general third party liability and travel health.

The volume measure PVM and RVM and the combined standard deviation, σ, for the overall non-life insurance portfolio was determined in two steps as follows: first of all we calculated the standard deviations and volume measures for both premium risk and reserve risk per LoB, than the results of the standard deviations and volume measures for the premium risk and the reserve risk in the individual LoBs were aggregated in order to obtain an overall volume measure and a combined standard deviation, σ.

The volume measure for premium risk in the individual LoB was determined by using the formula below:

$$PVM_{LoB} = \max\left(P_{LoB}^{t,written}, P_{LoB}^{t,earned}, P_{LoB}^{t-1,written}\right) + P_{LoB}^{PP} \qquad (4)$$

To calculate the volume measure for premium risk we used data such as: estimate of net written premium for each LoB during the forthcoming year ($P_{LoB}^{t,\ written}$). We consideredan increase of 5% on the actual net premiums, estimates of net earned premium for each LoB during the forthcoming year($P_{LoB}^{t,\ earned}$), Net written premium for each LoB during the previous year ($P_{LoB}^{t-1,\ written}$) and Present value of net premiums of existing contracts which are expected to be earned after the following year for each LoBs(P_{LoB}^{PP}). The term P_{LoB}^{PP} is only relevant for contracts with a coverage period that exceeds the following year. For annual contracts without renewal options P_{LoB}^{PP} is zero (mentioned in QIS5).

The volume measure for reserve risk in the individual LoB was determined as follows:

$$RVM_{LoB} = PCO_{LoB} \qquad (5)$$

We considered PCO_{LoB}as best estimate for claims outstanding for each LoB (QIS 5, 2010). This amount does not include the amount recoverable from reinsurance and special purpose vehicles. We used for the estimation of outstanding claims reserves the Chain Ladder Method. We used this method for the next classes of insurance: accident insurance, motor hull and property (fire and natural disasters). For the others classes of insurance we used the Bornhuetter-Ferguson method.

After the aggregation of volume measures and volatilities we obtained the capital requirement for the combined premium risk and reserve risk (VaR), as follows:

$$VaR = F(\sigma) \times V\ , \tag{6}$$

where V-volume measure, $V = PVM + RVM$

σ- combined standard deviation, $\sigma = (PVM \times RVM \times \sigma^{or} \times \sigma^{res})/V^2$

$$\mathrm{F}(\sigma) = \frac{\exp(N_{0.995} * \sqrt{log(\sigma^2+1)})}{\sqrt{\sigma^2+1}} - 1, \tag{7}$$

Where $N_{0.995}$ is 99.5% quantile of the standard normal distribution.

The function F(σ) is set such that, assuming a lognormal distribution of the underlying risk, a risk capital requirement consistent with theVaR 99.5% calibration objective is produced (QIS5, 2010)

In order to estimate the underwriting risk, we considered a sample of net claims reserves, net premiums and net earned premiums, consisting of monthly data during the previous four years, organized by lines of business. These series are stationary, but since there is no heteroskedastic volatility, we chose the QIS5 approach in spite of a stochastic one.

For this purpose, we separated the lines of business in several categories, as follows: Motor and other classes (line 2), Marine, aviation and transport (line 3), Fire and other property damages (line 4), third party liability (line 5) and credit (line 6). Thus, we determined the premium volume measure, standard deviation for premium risk, the reserve volume measure and the standard deviation for reserve risk for these lines of business (Table 5, Appendix).

In order to cuantify the overall standard deviation, there was implemented the correlation matrix CorrLob and determined the function of the combined standard deviation, obtaining the Value-at-Risk for the underwriting risk, which is equivalent to the Solvency Capital Requirement for this risk (Table 4, Appendix).

Table 1 Capital requirement for non-life underwriting risk

Volume measure	28,812,811	SCR UW	7,015,392
σ overall	233,778		
F(σ)	0.24		
VaR	7,015,392		

Source: *own calculations*

4.3 Counterparty default risk

Regarding QIS5, there are two types of exposure: type 1- includes contracts with partners like banks, reinsurers, securitization counterparties; they are likely to have credit ratings which determine the probability of default and affect the exposure; type 2 includes intermediaries, policyholders and others unrated.

In our case-study, reinsurance counterparty risks are considered to be the most important (type1 exposure). The QIS5 specification wants to quantify the replacement cost of an exposure allowing for the probability of default of the counterparty. The main inputs for the counterparty default risk are the estimated loss-given default (LGD) of an exposureand the probability of default of the counterparty. The LGD of an exposure is the loss of basic own funds which the insurer incur if the counterparty defaulted. The LGD will represent the recoverables in reporting currency applied to a loss rate fixed in QIS5 specification (50% if the risk mitigating contract exists,100% otherwise). Considering these, for a reinsurance arrangement LGD, the loss-given default is calculated as follows:

$$LGD = \max(50\%(Recoverables_i - Collateral_i), 0), \tag{8}$$

where

- Recoverables$_i$ = Best estimaterecoverables from the reinsurance contract,
- Collateral$_i$ = Risk-adjusted value of collateral in relation to the reinsurance arrangement

Considering the corellation matrix between various probabilities of default we can calculate the aggregate risk and so we obtain the SCR$_{def,1}$(Capital requirement for counterparty default risk of type 1 exposures). SCR$_{def,2}$ (Capital requirement for counterparty default risk of type 2 exposures) should be calculated separately. Aggregating these two requirements we get the total SCR$_{def.}$ as follows:

$$SCR_{def} = \sqrt{SCR_{def,1}^2 + SCR_{def,2}^2 + 1.5 \times SCR_{def,1}^2 \times SCR_{def,2}^2} \tag{9}$$

Tabel 2 Requirement for counterparty default risk

	Type 1	Type 2
Type 1-σ	190,549	0
Type 1 -q	3	0
SCR def	571,648	0
Total SCR def	571,648	
%LGD (Type 1)	13.68%	

Source: *own calculations*

We note that the capital is dependent on the credit rating of the reinsurers; the higher the rating the lower the capital. Also we can say that the stability of the reinsurer's rating is very important. If the reinsurer is downgraded more capital will be put up at a large stage .Diversification of the reinsurance reduces the capital, but this effect is much smaller than the effect of the credit rating on capital.

4.4.Operational risk

Operational risk results from inappropriate or not successful processes, systems, people and also from foreign events including only legal risks and excludes reputation risks or provided by strategi decisions.

QIS5 suggests a calculation formula for this risk but it still needs to be developed. Thus the solvency operational capital requirement can be calculated as the minimum between 30% of the Basic SCR and Basic operational risk, as follows:

$$SCR_{Op} = \min(0.3 \times \mathrm{BSCR}, \mathrm{Op}) + 0.25 \times Exp_{ul} \quad (10)$$

where Op- basic operational risk charge for all business other than life insurance where the investment risk is borne by the policyholders and was determined as follows:

$$Op = \max\left(Op_{premiums}, Op_{provisions}\right) \quad (11)$$

Exp_{ul}- amount of annual expenses incurred during the previous 12 months in respect life insurance where the investment risk is borne by the policyholders. In our case, Exp_{ul}=0.

The inputs for operational risk are: earned premium during the previous 12 months for non-lifeinsurance obligations, without deducting premiums ceded to reinsurance (Gross written premium -Δ Unearned premium reserve). In our case: Earn non-life=39,196,842.41Ron (where GWP=34,318,253Ron and ΔUPR= 4,878,589.41Ron, technical provisions = 10,055,947.48 Ron (Reported But Not Settled at 31.12.2012 (9,296,017.76 Ron) , Incurred but not reported at 31.12.2012(759,929.72RON)). Starting from these assumptions and taking into consideration the amounts calculated for Var of SCR market (76,835.44), SCRunderwriting(7,015,391.51) and SCRcounterparty (571,648), we obtain the following results:

Tabel 3 Capital requirement for operational risk

Op provisions	301,678.42
Op premiums	883,189.91
Basic operational risk	883,189.91
BSCR	3,669,816.68
SCR operational	883,189.91

Source: *own calculations*

4.5. AgregatedVaR

As we mentioned before, the purpose of Solvency II is to estimate the aggregated Value-at-Risk, which is equivalent to the final Solvency Capital Requirement. Therefor, two stages have to be implemented. Firstly, based upon the risk matrix correlations between market, underwriting and counterparty risks, according to QIS5, we assumed the correlations of 0.25, 0.25 and 0.5 between the pairs: (market, counterparty), (market, underwriting) and (counterparty, underwriting). Thus, it is obtained the Basic Capital Requirement, to which adding the SCR Operational, results the final Solvency Capital Requirement.

For the case of the non-life insurer discusses in this paper, there were obtained the following results:

Table 4 Solvency capital requirements

SCR Market	76,835
SCR Underwriting	7,015,391
SCR Counterparty	571,648
Basic SCR	3,669,816
SCR Operational	883,190
SCR Final	*4,553,006*

The level of requirements previously obtained reveals a 40% higher level than the constraints specified within Solvency I through the Minimum Solvency Margin. Compared to QIS5 results on the Romanian insurance market, this value is lower than 107.74% (Marin, 2011) obtained for the aggregated SCR for 18 insurers whom participated to the survey.

The weights of Basic SCR and SCR Operational in SCR final amount to 80.61% and 19.39% are approximately close to the market average.

4.6. Backtesting

In the area of risk management, in order to be sure that the results of possible losses based on VaR models are not biased risk managers apply a backtesting method to diagnose problems and improve them. In essence, it is an extremely important way to test theaccuracy and identify theapproaches in which improvement is needed (Dowd, 2008).

Basically, for Value-at-Risk it is is important to evaluate theefficiency of the model by comparing its performances to other regressions, becauseeach time-serie proves different characteristics and needs a particularized type of analysis.

The standard way for implementing backtesting is the Kupiec method, which analyzes weather the observed violation frequency is close to the nominal violation frequency for theVaR model and specific confidence interval. The null hypothesis is that the model is correct, and the violations havea binomial distribution.

Consequently, in our model, since theestimated probability is above the desired null significance level, theGARCH family models implemented in theanalysis of market risk areaccepted.

5.Conclusions

Recently, the focus on risk management increased dramatically. The crisis determined theauthorities to pay moreattention to setting minimum capital levels for different kind of financial institutions because the insolvency might result in substantial losses that can affect different parts of theeconomy. For the insurance market, the European Commission has established the Solvency II Directive, with key points regarding the accurate valuation of capital requirement, increased transpareny and disclosure, all leading to a higher protection of the policyholder, an improved risk management and, hence, a more stable insurance market

This study evaluates the risks for a non-life insurer active within the Romanian market, proposing a different approach for the market risk evaluation(GJR-GARCH) than the proposals of QIS5 in order to assess possibleasymmetries between theeffects of positiveand negative shocks of the same magnitude on the conditional volatility. This is a very important aspect since these models have been proved capable to capture leptokurtosis, skewnessand volatility clustering, which are commonly observed in high frequency financial time series data.

Considering the fact that VaR is not a coherent risk measure, in order to provide data about the risk exposure that VaR can neglect, especially when theestimation models are based upon regular market risks rather than low frequency high valueevents that could generate losses, there can be implemented the stress testing technique. Basically, this method describes how a portfolio would have performed under extreme market conditions, which even though happen scarcely, are still possible.

This study evaluates the risks ofa non-life insurer active within the Romanian market, proposing a different approach for the market risk evaluation than the requirements of QIS5.

Hence, we can conclude that for a macoeconomic stabilty and for avoiding the financial crises, is of utmost importance to understand and properly evaluate the all types of potential risks, wether the case of an insurance company, bank, pension fund or other structure.

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APPENDIX

Table 1 Prestimation analysis

	Interest rate	Significance-5%
LB statistic	1,011,581	32.801
Heteroskedasticity test (prob.)	5%	5%
ADF test statistic	-5.874	-2.8527
JB statistic	8795	10.597
Skewness	-1.577	0
Kurtosis	12.4	3

Table 2 Preestimationanalysis – currency risk

	EUR	CHF	USD	Significance- 5%
Ljung-Box statistic	728,852,088	125,933,826	32,599,719	32.801
Heteroskedasticity test (prob.)	0	0	0	5%
ADF test statistic	-30.248	-29.7528	-42.9466	-2.8527
JB statistic	18589.56	14439.87	1078.055	10.597
Skewness	0.0111	-0.3472	0.299	0
Kurtosis	17.603	15.85	6.465	3

Table 3 Estimated results – currency risk

EUR				CHF				USD			
	Coef	*SE*	*Prob*		*Coef*	*SE*	*Prob.*		*Coef*	*SE*	*Prob.*
AR(1)	0.166	0.019	0	AR(3)	-0.059	0.024	0.016	AR(1)	0.047	0.023	0.040
MA(3)	-0.038	0.019	0.046								
VarianceEquation											
ω	0	0	0.002	ω	0	0	0	ω	0.	0	0.002
γ_1	0.279	0.070	0.000	α	0.071	0.010	0.000	A	0.064	0.008	0
γ_2	-0.147	0.069	0.033	γ_1	0.243	0.026	0.000	β	0.926	0.010	0
β	0.93	0.012	0	γ_2	-0.185	0.034	0				
					0.906	0.010	0				

Table 4 Premium-reserve correlation matrix

LoBs	2	3	4	5	6
2	1				
3	0.25	1			
4	0.25	0.25	1		
5	0.25	0.25	0.25	1	
6	0.25	0.25	0.25	0.5	1

Table 5 Underwriting risk

LoBs	Premium Risk		Reserve Risk		Underwriting Risk	
	PVM (lob)	σ pr (lob)	RVM (lob)	σ res lob	V (lob)	σ (lob)
2	20,374,142	274,508	3,032,700	559,663	23,406,842	282,272
3	88,718	149,599	16,754	5,036	105,472	126,238
4	3,771,892	126,491	1,216,049	276,556	4,987,941	141,932
5	192,228	30,117	72,964	104,561	265,192	43,957
6	47,362	8,157	-	-	47,362	8,157