CHAPTER 7

Risk Management in Emerging Markets in Post 2007–2009 Financial Crisis: Robust Algorithms and Optimization Techniques Under Extreme Events Market Scenarios

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Introduction

The 2007–2009 Global Financial Crisis (GFC) has emphasized the necessity of a proper identification and assessment of embedded liquidity risk in financial trading portfolios for emerging markets. In essence, liquidity trading risk arises due to the inability of financial entities to liquidate their holdings, at reasonable prices, as time elapses throughout the liquidation (closeout) period. Undeniably, certain collapses in some well-known financial entities and the consequential financial turmoil were caused, to some degree, by the impact of trading liquidity risk on structured portfolios. To that end, the main objective of this chapter is to develop and test a reasonable approach for the assessment, management, and control of market price risk exposure for financial trading portfolios that contain a

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number of illiquid equity assets under intricate market circumstances and to propose an approach for determining the upper limits of the risk-budgeting boundaries.

To evaluate the risks involved in their trading operations, major financial institutions are increasingly exploiting Value at Risk (VaR) models. Since financial institutions differ in their individual characteristics, a tailor-made internal risk model is more appropriate. Fortunately, and in accordance with Basel capital accords, financial institutions are permitted to develop their own internal risk models for the purposes of providing for adequate risk measures. Furthermore, internal risk models can be used in the determination of economic capital that financial entities must hold to endorse their trading of securities. The benefit of such an approach is that it takes into account the relationship between various assets classes and can accurately assess the overall risk for a whole combination of multiple trading assets (Al Janabi, 2012, 2013, 2014; Al Janabi, Arreola-Hernández, Berger, & Nguyen, 2017).

Nowadays, VaR has become an important and useful tool for monitoring market and liquidity risk, and its use is being encouraged by the Bank for International Settlements (BIS), Basel II and Basel III capital adequacy accords on banking supervision (Bank for International Settlements, 2009, 2013). In essence, VaR estimates the downside risk of a portfolio of market-priced assets at a particular confidence level over a chosen time horizon. In effect, VaR strives to assess adverse market events in the lower tail of a return distribution of a trading portfolio—events more likely to cause financial trouble to a firm if they arise.

Given that VaR focuses solely on downside risk (that is, the impact of bad outcomes) and is customarily expressed in monetary terms, it is viewed as an insightful and transparent market and liquidity risk assessment and forecasting tool for top-level management in both financial and non-financial entities. The recognition of VaR as a risk assessment and forecasting tool has triggered ample interest in its use among portfolio managers, risk-management practitioners, and academics alike. Notwithstanding the apparent benefits of VaR for financial risk disclosure and reporting purposes, VaR has also been backed for enterprise-wide risk management because of its ability to aggregate and forecast market and liquidity risk across different asset classes (Al Janabi, 2014). In essence, VaR could be valuable in making portfolio asset allocation and hedging decisions, managing cash-flows, setting upper limits risk-budgeting thresholds, and in the overall optimization procedure for selection and evaluation of structured portfolios.

A large body of literature have examined and empirically tested different VaR techniques for both financial and non-financial markets. For instance, Garcia, Renault, and Tsafack (2007) tackle a specific issue within the VaR and that is the subadditivity property required for the VaR to be a coherent measure of risk. In a similar vein, Campbell, Huisman, and Koedijk (2001) develop an optimum-portfolio selection model that maximizes expected returns subject to a downside risk constraint rather than standard deviation alone. The suggested model allocates financial assets by maximizing expected return conditional on the constraint that the expected maximum loss should be within the VaR limits set by the risk manager.

On the other hand, Alexander and Baptista (2004) analyze the portfolio selection implications arising from imposing a VaR constraint as a risk-management tool on the mean-variance (MV) model (Markowitz, 1952) and compare them with those arising from the imposition of a conditional VaR constraint (CVaR). Likewise, Alexander and Baptista (2008) look at the impact of adding a VaR constraint to the problem of an active manager who seeks to outperform a benchmark by a given percentage. In doing so, the authors minimize the tracking error variance (TEV) by using the model of Roll (1992). In a similar vein, Cain and Zurbruegg (2010) propose a technique that involves switching between risk measures in different market environments, to capture the well-documented dynamic nature of risk within a portfolio optimization setting. Thus, the in-sample results show categorically that switching between various measures, such as CVaR, time-varying (GARCH) variances and simple standard deviations, can lead to a better performance than using any single measure.

Another strand of theoretical and empirical research has been focused on using asymmetric copula models in the context of managing downside correlations. It is a well-known phenomenon that equity returns experience an increase in correlations (i.e., asymmetric or lower tail dependence) during downside markets (Ang & Chen, 2002; Longin & Solnik, 2001), which at the same time violates the assumption of elliptical dependence in mean-variance analysis. As a result, using more advanced flexible multivariate copulas (so-called vine copulas, and introduced first by Aas, Czado, Frigessi, & Bakken, 2009) offers a key prospect for tackling this kind of asymmetric behavior. In this line of research, Low, Alcock, Faff, and Brailsford (2013) examine the use of multidimensional elliptical and asymmetric copula models to forecast returns for portfolios with 3–12 constituents. In their analysis, they assumed that investors have no short-sales constraints and a utility function characterized by the minimization of CVaR is employed.

On another front, Al Janabi (Al Janabi, 2012, 2013, 2014) tackles the issue of adverse market price impact on liquidity trading risk and coherent portfolio optimization using a parametric liquidity-adjusted VaR (LVaR) methodology. The proposed adverse price unwinding approach comprises a liquidation multiplier (add-on) that can adjust the impact of unfavorable price movement throughout the closeout period along with an optimization algorithm that allocates assets subject to imposing meaningful financial and operational constraints.

Furthermore, in their research paper, Madoroba and Kruger (2014) introduce a new VaR model that incorporates intraday price movements on high–low spreads and adjusts for a trade impact measure, a novel sensitivity measure of price movements due to trading volumes. Furthermore, the authors compare and contrast 10 worldwide-recognized liquidity risk-management models including the "*Al Janabi model*," which is used in this chapter for liquidly risk modeling and for optimizing upper limits LVaR risk budgeting.[1]

In a different modeling technique, Al Janabi et al. (2017) propose a portfolio optimization methodology based on the integration of DCC (dynamic conditional correlation) t-copula and LVaR models to enhance asset allocation decisions under illiquid market conditions. Their empirical findings prove the superiority of the DCC-copula-LVaR modeling technique over the traditional Markowitz (1952) optimization procedure for a portfolio composed of international stock market indices, gold, and crude oil across various trading scenarios.

[1] For other relevant literature on liquidity, asset pricing and portfolio choice and diversification one can refer as well to Angelidis and Benos (2006); Berkowitz (2000); Madhavan, Richardson, and Roomans (1997); Hisata and Yamai (2000); Le Saout (2002); Amihud, Mendelson, and Pedersen (2005); Takahashi and Alexander (2002); Cochrane (2005); and Meucci (2009), among others. Furthermore, within the copula technique, and particularly the vine copula approach, there were indeed very few studies in this respect and most of published research is still focused on the issue of transaction costs (i.e., bid-ask spreads). In particular, Weiß and Supper (2013) investigate the issue of forecasting liquidity-adjusted intraday VaR with vine copulas. In their paper, they propose to model the joint distribution of bid-ask spreads and log returns of a stock portfolio by implementing Autoregressive Conditional Double Poisson and GARCH processes for the marginals and vine copulas for the dependence structure. By estimating the joint multivariate distribution of both returns and bid-ask spreads from intraday data, they incorporate the measurement of commonalities in liquidity and co-movements of stocks and bid-ask spreads into the forecasting of three types of liquidity-adjusted intraday VaR.

In this backdrop, the objective of this chapter is to provide practical and robust assessment of market risk for equity trading portfolios (frequently it can be called, trading, investment, or price risk). As such, the aim is to create a practical technique to assist in the establishment of sound risk-management practices (for equity portfolios that contain both long-only and long- and short-sales trading positions) and within a prudential regulatory framework of rules and policies. To that end, the optimization algorithms and parameters that are required for the construction of robust LVaR and stress-testing methods are reviewed from previous research studies and applied to equity trading portfolios of the six Gulf Cooperation Council (GCC) financial markets. Moreover, a robust technique for the incorporation of illiquid assets is defined and is appropriately integrated into LVaR and stress-testing models. Effectively, the developed methodology and risk-assessment algorithms can aid in evolving risk-management practices in emerging markets and predominantly in light of the aftermaths of the GFC, credit crunch and the resultant 2007–2009 financial turmoil.

This chapter intends to make the following key contributions to the academic literature in this specific liquidity risk and portfolio management fields. First, it represents one of the limited numbers of research studies that empirically examines liquidity risk management using actual daily data of emerging GCC zone stock markets. Second, a daily database of stock market indices of the GCC region is used whose behavior is presumably more diverse than if equity assets of any particular stock market had been employed, as other authors have done heretofore. Third, unlike most empirical studies in this field, this study employs a robust liquidity trading risk-management model that considers risk forecasting under intricate market circumstances. Fourth, this chapter implements a novel approach to the optimization of multiple-assets portfolios by implementing an LVaR framework along with a multivariate dependence modeling technique and GARCH-M (1,1) method for estimating expected returns and conditional volatilities. To that end, in this chapter, we implement a robust optimization algorithm based on Al Janabi model (Madoroba & Kruger, 2014) for optimizing and selecting upper limits risk budgeting with LVaR constraints using realistic operational and financial scenarios.

In this background, the implemented methodology and risk-assessment algorithms can aid in advancing risk-management practices in emerging markets, particularly in the wake of the sub-prime credit crunch and the resulting 2007–2009 financial turmoil. In addition, the proposed quantitative risk-management techniques and optimization algorithms can have important uses and applications in expert systems, machine learning, smart financial functions, and financial technology (FinTech) in big data environments. The balance of the chapter is organized as follows. The following section lays out all the quantitative risk-management foundation of LVaR method and includes full mathematical derivation of liquidity risk-management techniques and Al Janabi model (Madoroba & Kruger, 2014), which integrates the effects of illiquid assets in daily market risk management. The results of empirical tests and all case studies for the simulation and optimization of upper limits LVaR risk budgeting are discussed in Section "Evaluating and Controlling of Market Liquidity Risk Exposures: Optimization Case Study of Emerging GCC Financial Markets". Section "Concluding Remarks and Recommendations" provides concluding remarks and recommendations.

Derivation of Al Janabi Model

In this section, the derivation of Al Janabi Model for Market Liquidity Risk Evaluation with a Closed-Form Parametric Process has been discussed. For the computation of VaR, the volatility of each risk factor is extracted from a predefined historical observation period and can be estimated using GARCH-M (1,1) model under the assumptions of adverse market settings. The potential effect of each component of the multiple-assets portfolio on the overall portfolio value is then worked out. These effects are then aggregated across the whole portfolio using the dependence measure (correlations parameters) between the risk factors (which are, again, extracted from the historical observation period) to give the overall VaR value of the portfolio with a given confidence level. As such, for a single trading position, the absolute value of VaR can be defined in monetary terms as follows:

$$\text{VaR}_i = \left| \left(\mu_i - \alpha * \sigma_i \right) \left(\text{Asset}_i * Fx_i \right) \right| \tag{7.1}$$

where μ_i is the expected return of asset i, α is the confidence level (or in other words, the standard normal variant at confidence level α) and σ_i is the conditional volatility of the return of the security that constitutes the single position and can be estimated using a GARCH-M (1,1) model.[2] While the term Asset_i indicates the mark-to-market monetary value of asset i, Fx_i denotes the unit foreign exchange rate of asset i. If the expected return of the asset, μ_i, is very small or close to zero, then Eq. (7.1) can be reduced to[3]:

$$\text{VaR}_i = \left|\alpha * \sigma_i * \text{Asset}_i * Fx_i\right| \tag{7.2}$$

Indeed, Eq. (7.2) includes some simplifying assumptions, yet researchers and practitioners in the financial markets routinely use it for the estimation of VaR for a single trading asset.

Trading risk in the presence of multiple risk factors is determined by the combined effect of individual risks. The extent of the total risk is determined not only by the magnitudes of the individual risks but also by their dependence measures (i.e., correlations matrix). Portfolio effects are crucial in risk management not only for large diversified portfolios but also for individual instruments that depend on several risk factors. For multiple-assets portfolio, VaR is a function of each individual security's risk and the correlation parameters $\left[\rho_{i,j}\right]$, as follows:

$$\text{VaR}_P = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\text{VaR}_i\,\text{VaR}_j\,\rho_{i,j}} = \sqrt{\left[\text{VaR}\right]^T\left[\rho\right]\left[\text{VaR}\right]} \tag{7.3}$$

This formula is a general one for the computation of VaR for multiple-assets portfolios regardless of the number of trading securities. It should be noted that the second term of the above formula is rewritten in terms of matrix-algebra—a useful form to avoid mathematical complexity, as

[2] The time-varying pattern of assets volatility has been widely recognized and modeled as a conditional variance within the GARCH framework, as originally developed by Engle (1982, 1995). Engle (1982) introduced a likelihood ratio test to ARCH effects and a maximum likelihood method to estimate the parameters in the ARCH model. This approach was generalized by Bollerslev (1986) and Engle and Kroner (1995). In fact, the generalized autoregressive conditional heteroskedasticity in mean, GARCH-M (1,1) model, is used in our empirical analysis for the estimation of expected return and conditional volatility for each of the time series variables.

[3] If the purpose of the risk analysis is to investigate diverse stock market dependences and related risk management measure, then $Asset_i$ should be the mark-to-market prices of the individual stock market indices.

more and more multiple-assets classes are added to the portfolio. In addition, this tactic can streamline the programming and computational processes and allow for the incorporation of short-sales positions into the market risk-management algorithms.

On the other hand, liquidity is a key risk factor, which until lately, has not been appropriately dealt with by risk models. Illiquid trading positions can add considerably to losses and can give negative signals to traders due to the higher expected returns they entail. The concept of liquidity trading risk is immensely important for using VaR accurately and recent upheavals in financial markets confirm the need for laborious treatment and assimilation of liquidity trading risk into VaR models.

The choice of the time horizon or number of days to liquidate (unwind) a position is very important factor and has big impact on VaR numbers, and it depends upon the objectives of the portfolio and the liquidity of its multiple-assets holdings. For financial entities' trading portfolios invested in liquid currencies, a one-day closeout horizon may be acceptable. For an investment manager with a monthly re-balancing and reporting focus, a 30-day period may be more appropriate. Ideally, the holding period should correspond to the longest period for orderly portfolio liquidation (Al Janabi, 2008a).

The simplest way to account for liquidity trading risk is to extend the holding horizon of illiquid positions to reflect a suitable liquidation period. An adjustment can be made by adding a multiplier to the VaR measure for each class of trading assets, which at the end depends on the liquidity of each asset. Nonetheless, the weakness of this method is that it allows for subjective assessment of the liquidation horizon. Furthermore, the typical assumption of a one-day horizon (or any inflexible time horizon) within VaR framework neglects any calculation of trading risk related to liquidity effect (that is, when and whether a trading position can be sold out and at what price). A broad VaR model should incorporate a liquidity premium (or liquidity risk factor). This can be worked out by formulating a method by which one can unwind a position, not at some ad hoc rate but at the rate that market conditions is optimal, so that one can effectively set a risk value for the liquidity effects. In general, this will raise significantly the VaR, or the amount of economic capital to support the trading position.

In fact, if returns are independent and they can have any elliptical multivariate distribution, then it is possible to convert the VaR horizon parameter from daily to any t-day horizon. The variance of a t-day return should be t times the variance of a 1-day return or $\sigma^2 = f(t)$. Thus, in terms of standard deviation (or volatility), $\sigma = f(\sqrt{t})$ and the daily or overnight VaR number [VaR (1-day)], it is possible to determine the liquidity-adjusted VaR (LVaR) for any t-day horizon as:

$$\text{LVaR}(t-\text{day}) = \text{VaR}(1-\text{day})\sqrt{t} \tag{7.4}$$

The above formula was proposed and used by J.P. Morgan in their earlier *RiskMetrics*™ method (Morgan Guaranty Trust Company, 1994). This methodology implicitly assumes that liquidation occurs in one block sale at the end of the holding period and that there is one holding period for all assets, regardless of their inherent trading liquidity structure. Unfortunately, the latter approach does not consider real-life trading situations, where traders can liquidate (or re-balance) small portions of their trading portfolios on a daily basis. The assumption of a given holding horizon for orderly liquidation inevitably implies that assets' liquidation occurs during the holding period. Accordingly, scaling the holding horizon to account for orderly liquidation can be justified if one allows the assets to be liquidated throughout the holding period.

In what follows, we review a re-engineered approach for computing a closed-form LVaR with explicit treatment of liquidity trading risk and robust assessment of coherent (investable) portfolios.[4] The key methodological contribution is a different liquidity-scaling-factor than the traditional root-t multiplier. The proposed model and liquidity-scaling-factor is more realistic and less conservative than the conventional root-t multiplier. In essence, the suggested multiplier (add-on) is a function of a predetermined liquidity threshold(s) defined as the maximum position that can be unwound without disturbing market prices during one trading day. The essence of the model relies on the assumption of a stochastic stationary process and some rules of thumb, which can be of crucial value for more accurate overall trading risk assessment during market stress periods when liquidity dries up in consequence of a financial crisis. In addition, the re-engineered model is quite simple to implement even by very large

[4] The concept of coherent (investable) market portfolios refers to rational financial portfolios that are subject to meaningful financial and operational constraints. In this sense, coherent market portfolios lie-off the efficient frontiers as defined by Markowitz (1952), and instead have logical and well-structured long-only and long- and short-sales asset allocation.

financial institutions with multiple assets and risk factors. To that end, a practical framework of a methodology (within a simplified mathematical modeling technique) is proposed below for incorporating and calculating LVaR of illiquid assets with different closeout periods, detailed along these lines.[5]

The market risk of an illiquid asset is larger than the risk of an otherwise identical liquid position. This is because unwinding the illiquid position takes longer time than unwinding the liquid position, and, as a result, the illiquid position is more exposed to the volatility of the market for a longer period. In this approach, an asset trading position will be thought of illiquid if its size surpasses a certain liquidity threshold. The threshold (which is determined by traders for different assets and/or financial markets) and defined as the maximum position which can be unwound, without disrupting market prices, in normal market conditions and during one trading day. Consequently, the size of the asset trading position relative to the threshold plays an important role in determining the number of days that are required to closeout the entire position. This effect can be translated into a liquidity increment (or an additional liquidity risk factor) that can be incorporated into VaR analysis. If, for instance, the par value of an asset position is $200,000 and the liquidity threshold is $50,000, then it will take four days to sell out the entire trading position. Therefore, the initial position will be exposed to market variation for one day, and the rest of the position (that is $150,000) is subject to market variation for an additional three trading days. If it is assumed that daily changes of market values follow a stationary stochastic process, the risk exposure due to illiquidity effects is given as follows.

In order to take into account the full illiquidity of assets (that is, the required unwinding period to liquidate an asset) we define the following:

t = number of liquidation days (t-days to liquidate the entire asset fully)

σ_{adj}^2 = variance of the illiquid asset trading position; and

σ_{adj} = liquidity risk factor or standard deviation of the illiquid asset trading position.

The proposed approach assumes that the trading position is closed out linearly over t-days and hence it uses the logical assumption that the losses due to illiquid trading positions over t-days are the sum of losses over the individual trading days. In addition, we can assume with reasonable accu-

[5] The mathematical approach presented herein is largely drawn from Al Janabi, 2012, 2013, Al Janabi, 2014, and Al Janabi et al., 2017 research papers.

racy that asset returns and losses due to illiquid trading positions are independent and identically distributed (*iid*) and serially uncorrelated day-to-day along the liquidation horizon and that the variance of losses due to liquidity risk over t-days is the sum of the variance (σ_i^2, $\forall i$, $i = 1,2\ldots,t$) of losses on the individual days, thus:

$$\sigma_{\text{adj}}^2 = \left(\sigma_1^{\ 2} + \sigma_2^{\ 2} + \sigma_3^{\ 2} + \cdots + \sigma_{t-2}^{\ \ 2} + \sigma_{t-1}^{\ \ 2} + \sigma_t^{\ 2}\right) \tag{7.5}$$

In fact, the square root-t approach (i.e., Eq. [7.4]) is a simplified special case of Eq. (7.5) under the assumption that the daily variances of losses throughout the holding period are all the same as first day variance, $\sigma_1^{\ 2}$, thus $\sigma_{\text{adj}}^{\ \ 2} = \left(\sigma_1^{\ 2} + \sigma_1^{\ 2} + \sigma_1^{\ 2} + \cdots + \sigma_1^{\ 2}\right) = t\sigma_1^{\ 2}$.

As discussed above, the square root-t equation overestimates asset liquidity risk since it does not consider that traders can liquidate small portions of their trading portfolios on a daily basis; and then it implicitly denotes that the whole trading position can be sold completely on the last trading day. However, this would be an overstatement of VaR; and the true VaR has to be between the 1-day VaR and 1-day VaR$\sqrt{t}$.

Indeed, in real financial markets operations, liquidation occurs during the holding period and thus scaling the holding horizon to account for orderly liquidation can be justified if one allows the assets to be liquidated throughout the holding period. As such, for this special linear liquidation case and under the assumption that the variance of losses of the first trading day decreases linearly each day (as a function of t), we can derive from Eq. (7.5) the following:

$$\sigma_{\text{adj}}^{\ \ 2} = \left(\left(\frac{t}{t}\right)^2 \sigma_1^{\ 2} + \left(\frac{t-1}{t}\right)^2 \sigma_1^{\ 2} + \left(\frac{t-2}{t}\right)^2 \sigma_1^{\ 2} + \cdots + \left(\frac{3}{t}\right)^2 \sigma_1^{\ 2} + \left(\frac{2}{t}\right)^2 \sigma_1^{\ 2} + \left(\frac{1}{t}\right)^2 \sigma_1^{\ 2}\right) \tag{7.6}$$

In this manner, if the asset position is liquidated in equal parts at the end of each trading day, the trader faces a 1-day holding period on the entire position, a 2-day holding period on a fraction $(t\text{-}1)/t$ of the position, a 3-day holding period on a fraction $(t\text{-}2)/t$ of the position and so forth. Evidently, the additional liquidity risk factor depends only on the number of days needed to sell an illiquid trading position linearly. Thus, for the general case of t-days, the following algorithm of t gives the variance of the liquidity risk factor:

$$\sigma_{\text{adj}}{}^{2} = \sigma_{1}{}^{2}\left(\left(\frac{t}{t}\right)^{2} + \left(\frac{t-1}{t}\right)^{2} + \left(\frac{t-2}{t}\right)^{2} + \cdots + \left(\frac{3}{t}\right)^{2} + \left(\frac{2}{t}\right)^{2} + \left(\frac{1}{t}\right)^{2}\right) \quad (7.7)$$

To calculate the sum of the squares, it is convenient to use a short-cut approach. From mathematical finite series, the following relationship can be deduced:

$$(t)^{2} + (t-1)^{2} + (t-2)^{2} + \cdots + (3)^{2} + (2)^{2} + (1)^{2} = \frac{t(t+1)(2t+1)}{6} \quad (7.8)$$

Hence, after substituting Eq. (7.8) into Eq. (7.7), the following can be achieved:

$$\sigma_{\text{adj}}{}^{2} = \sigma_{1}{}^{2}\left[\frac{1}{t^{2}}\{(t)^{2} + (t-1)^{2} + (t-2)^{2} + \cdots + (3)^{2} + (2)^{2} + (1)^{2}\}\right] \text{ or}$$

$$\sigma_{\text{adj}}{}^{2} = \sigma_{1}{}^{2}\left(\frac{(2t+1)(t+1)}{6t}\right) \quad (7.9)$$

Accordingly, from Eq. (7.9) the liquidity risk factor can be expressed in terms of volatility (or standard deviation) as:

$$\sigma_{\text{adj}} = \sigma_{1}\left\{\sqrt{\frac{1}{t^{2}}[(t)^{2} + (t-1)^{2} + (t-2)^{2} + \cdots + (3)^{2} + (2)^{2} + (1)^{2}]}\right\} \text{ or}$$

$$\sigma_{\text{adj}} = \sigma_{1}\left\{\sqrt{\frac{(2t+1)(t+1)}{6t}}\right\} \quad (7.10)$$

The result of Eq. (7.10) is of course an algorithm of time and not the square root of time as employed by some financial market's participants based on the *RiskMetrics*™ methodologies (Morgan Guaranty Trust Company, 1994).

The above model can also be used to compute LVaR for any time horizon. Likewise, in order to perform the calculation of LVaR under illiquid market conditions, it is possible to use the liquidity factor of Eq. (7.10) and define the following[6]:

$$\mathrm{LVaR}_{\mathrm{adj}} = \mathrm{VaR}\sqrt{\frac{(2t+1)(t+1)}{6t}} \tag{7.11}$$

where, VaR = Value at Risk under continuous liquid market outlooks and; $\mathrm{LVaR}_{\mathrm{adj}}$ = Value at Risk under illiquid market scenarios. The latter equation indicates that $\mathrm{LVaR}_{\mathrm{adj}} > \mathrm{VaR}$, and for the special case when the number of days to liquidate the entire multiple-assets is one trading day, then $\mathrm{LVaR}_{\mathrm{adj}} = \mathrm{VaR}$. Consequently, the difference between $\mathrm{LVaR}_{\mathrm{adj}}$ and VaR should be equal to the residual market risk due to the illiquidity of any particular asset class under illiquid markets outlooks. In fact, the closeout periods (t) necessary to liquidate the entire multiple-assets portfolios is related to the choice of the liquidity threshold; however, the size of this threshold is likely to change under adverse market perspectives. Indeed, the choice of the closeout horizon can be estimated from the total trading position size and the daily trading volume that can be unwound into the market without significantly disrupting asset market prices; and in actual practices, it is generally estimated as:

$$t = \frac{\text{Total Trading Position Size of Asset}_i}{\text{Daily Trading Volume of Asset}_i} \tag{7.12}$$

In practice, the daily trading volume of any trading asset is estimated as the average volume over some period of time, generally a month of trading activities. In effect, the daily trading volume of assets can be regarded as the average daily volume or the volume that can be unwound in a severe crisis period. The trading volume in a crisis period can be roughly approximated as the average daily trading volume less a number of standard deviations. Albeit this alternative approach is quite simple, it is still relatively objective. Moreover, it is reasonably easy to gather the required data to perform the necessary liquidation scenarios; and thereafter the closeout periods.

[6] It is important to note that Eq. (7.11) can be used to calculate LVaR for any time horizon subject to the constraint that the overall LVaR figure should not exceed at any setting the nominal exposure, in other words the total trading volume.

In essence, the above liquidity-scaling factor (or multiplier) is more robust and less conservative than the conventional root-t multiplier and can aid financial entities in allocating reasonable and liquidity market-driven regulatory and economic capital requirements. Furthermore, the above algorithm can be applied for the computation of LVaR for every asset and for the entire portfolio of multiple-assets. In order to calculate the LVaR for the entire portfolio under illiquid market circumstances $\left(\text{LVaR}_{P_{\text{adj}}}\right)$, the above algorithm can be extended, with the aid of Eq. (7.3), into a matrix-algebra arrangement to yield the following:

$$\text{LVaR}_{P_{\text{adj}}} = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\text{LVaR}_{i_{adj}}\,\text{LVaR}_{j_{\text{adj}}}\,\rho_{i,j}} = \sqrt{\left[\text{LVaR}_{\text{adj}}\right]^{T}\left[\rho\right]\left[\text{LVaR}_{\text{adj}}\right]} \quad (7.13)$$

The elements of the vectors of Eq. (7.13), that is, the absolute value of $\text{LVaR}_{i\text{adj}}$, for each trading asset can now be calculated with the aid of Eqs. (7.1), (7.2), and (7.11), in this manner:

$$\text{LVaR}_{i\text{adj}} = \left|\left(\mu_i - \alpha * \sigma_i\right)\ \text{Asset}_i * Fx_i\sqrt{\frac{(2t_i+1)(t_i+1)}{6t_i}}\right| \quad (7.14)$$

On the other hand, for the special case when μ_i is small or close to zero, we can have:

$$\text{LVaR}_{i\text{adj}} = \left|\alpha * \sigma_i * \text{Asset}_i * Fx_i\sqrt{\frac{(2t_i+1)(t_i+1)}{6t_i}}\right| \quad (7.14a)$$

Now, we can define the ultimate two vectors $\left[\text{LVaR}_{\text{adj}}\right]^{T}$ and $\left[\text{LVaR}_{\text{adj}}\right]$ as follows:

$$\left[\text{LVaR}_{\text{adj}}\right]^{T} = \left[\text{LVaR}_{1_{\text{adj}}}\quad \text{LVaR}_{2_{\text{adj}}}\ \cdots \text{LVaR}_{n_{\text{adj}}}\right] \quad (7.15)$$

$$\left[\text{LVaR}_{\text{adj}}\right] = \begin{bmatrix}\text{LVaR}_{1_{\text{adj}}}\\ \text{LVaR}_{2_{\text{adj}}}\\ \cdots\text{LVaR}_{n_{\text{adj}}}\end{bmatrix} \quad (7.16)$$

The above algorithms (in the form of two vectors and a matrix, $\left[\mathrm{LVaR}_{\mathrm{adj}}\right]^{T}$, $\left[\mathrm{LVaR}_{\mathrm{adj}}\right]$ and $\left[\rho\right]$) can facilitate the programming and computational processes of the optimization engine so that the risk/portfolio manager can specify different closeout horizons for the whole portfolio and/or for each single asset according to the required number of days to unwind the entire multiple-assets completely. The latter can be achieved by specifying an overall benchmark closeout horizon to liquidate the entire constituents of the multiple-assets portfolio. The closeout horizons required to liquidate trading assets holdings (of course, depending on the type of each asset) may be obtained from the various publications in financial markets and can be compared with the assessments of individual traders of each trading unit. As a result, it is possible to construct simple statistics of the asset volume that can be liquidated and the necessary time horizon to unwind the whole volume.[7]

Evaluating and Controlling of Market Liquidity Risk Exposures: Optimization Case Study of Emerging GCC Financial Markets[8]

In this research study, databases of daily price returns of the six GCC stock markets' main indicators (indices) are assembled and appropriately matched for the actual days of operation of each country. The total numbers of indices that are considered in this research study are nine indices;

[7] In fact, the concept of liquidity risk in financial markets and institutions can imply either the added transaction costs related to trading large quantities of a certain financial security, or it can deal with the ability to trade this financial asset without triggering significant changes in its market prices (see Roch & Soner, 2013, for further details and empirical analysis).

[8] A number of Middle-Eastern countries have joined the implementation of modified versions of Basel II and Basel III capital accords. In fact, the GCC financial markets, in general, are in progressive stages of implementing advanced risk management regulations and techniques. Moreover, in recent years outstanding progress has been done in cultivating the culture of risk management among local financial entities and regulatory institutions. In the Middle East, the majority of banking assets is expected to be covered by Basel II and Basel III regulations by 2020. Generally speaking, capital ratios are fairly strong in the GCC, though they have fallen lately as banks have expanded their products and operations. Within the GCC, there have been negotiations for common application of Basel II and Basel III rules, though with different timeframes. This is due to the fact that some GCC countries are more diverse, for instance, in terms of the presence of foreign banks than others.

seven local indices for the six GCC stock markets (including two indices for the UAE markets) and two benchmark indices, detailed as follows:

DFM General Index (United Arab Emirates, Dubai Financial Market General Index)
ADX Index (United Arab Emirates, Abu Dhabi Stock Market Index)
BA All Share Index (Bahrain, All Share Stock Market Index)
KSE General Index (Kuwait, Stock Exchange General Index)
MSM30 Index (Oman, Muscat Stock Market Index)
DSM20 Index (Qatar, Doha Stock Market General Index)
SE All Share Index (Saudi Arabia, All Share Stock Market Index)
Shuaa GCC Index (Shuaa Capital, GCC Stock Markets Benchmark Index)
Shuaa Arab Index (Shuaa Capital, Arab Stock Markets Benchmark Index)

For this particular study, we have chosen a confidence interval of 95% (or 97.5% with "one-tailed" loss side) and quite a few closeout horizons to compute LVaR. Historical database (of more than six years) of daily closing index levels, for the period 17/10/2004–22/05/2009, are assembled for the purpose of carrying out this research and further for the construction of market risk-management parameters and risk limits (or risk budgeting). In fact, the selected time-series datasets fall within the period of the most critical part of the 2007–2009 global financial turmoil and are drawn from Reuters 3000 Xtra Hosted Terminal Platform and Thomson's Datastream database. The examination and analysis of data and discussions of relevant empirical findings are organized and explained as follows.

Stochastic Properties of the Returns Series

In the process of estimating and analyzing the stochastic properties of data, first, the daily continuous compounded returns of the nine stock market indices are calculated. These daily returns are key inputs for the computation of conditional volatilities, correlation matrices, systematic risk, skewness, kurtosis, and to apply Jarque-Bera (*JB*) non-normality test. Next, based on Al Janabi model (Madoroba & Kruger, 2014), robust financial modeling, optimizing algorithm, and a software package are designed for constructing structured multiple-assets portfolios and consequently for the implementation LVaR and scenario analysis under extreme illiquid market outlooks. This is followed by integrating the dependence measures (correlation factors) of Table 7.3 into the risk-engine simulation algorithms.

To that end, Table 7.1 illustrates the daily conditional volatility of each of the sample indices under regular (normal) market and intricate (stressed) market outlooks that was estimated via the means of a GARCH-M (1,1) technique. Intricate market volatilities are computed by fitting an empirical distribution of past daily returns for all stock market indices. Thus, the maximum negative returns (losses), which are witnessed in the historical time series, are selected for this purpose (refer to Table 7.2) for the maximum daily gains and losses and the dates of occurrence. This approach can aid in overcoming some of the limitations of normality assumption and can provide a better analysis of LVaR, especially under stressed and illiquid market perspectives.

Next, statistical analysis and testing of non-normality (i.e., asymmetrical behavior in returns distribution) are performed on the sample indices. To take into account the distributional anomalies of asset returns, test of non-normality is conducted on the sample equity indices using the Jarque-Bera (*JB*) test. In the first study, the measurements of skewness and kurtosis are realized on the sample equity indices, and the empirical results are depicted in Table 7.1. It is seen that all indices show asymmetric behavior (between both positive and negative values). Moreover, kurtosis studies show similar patterns of abnormality (i.e. peaked distributions). Nonetheless, the Jarque-Bera (JB) test shows an obvious general deviation from normality and, thus, rejects the hypothesis that GCC stock markets' time-series returns are normally distributed.

Upper Limit LVaR Risk Budgeting for Mainstream Financial Trading Units

Maximum risk limits (or risk-budgeting thresholds) are an important concern for any corporate trading-asset risk-management unit and it should be defined clearly and used wisely to ensure complete control on the trading/investment unit's exposure to risk. All LVaR limit-setting and control, monitoring and reporting should be performed by the risk-management unit, independently from the front office's traders.

How should we set upper LVaR risk limits to safeguard against maximum loss amounts? These are some of the central questions that risk managers need to address in designing their risk management systems. In this chapter a simplified—however, a robust—methodology is presented for the setting

Table 7.1 Conditional volatility, expected returns, systematic risk, and Jarque-Berra Test (JB) for non-normality

Stock market indices	*Daily volatility (regular market)*[a]	*Daily volatility (intricate market)*[a]	*Arithmetic mean*	*Expected return*[a]	*Systematic risk (beta factor)*	*Skewness*	*Kurtosis*	*Jarque-Bera (JB) Test*
DFM General Index	1.81%	12.16%	0.12%	0.14%	0.58	0.01	7.86	955[b]
ADX Index	1.32%	7.08%	0.07%	0.07%	0.40	0.12	7.26	734[b]
BA All Share Index	0.58%	3.77%	0.05%	0.04%	0.06	0.43	10.24	2142[b]
KSE General Index	0.71%	3.74%	0.09%	0.08%	0.14	–0.18	8.38	1173[b]
MSM30 Index	0.79%	8.70%	0.12%	0.10%	0.10	–0.57	18.40	9617[b]
DSM20 Index	1.48%	8.07%	0.06%	0.07%	0.31	–0.11	5.59	273[b]
SE All Share Index	1.86%	11.03%	0.03%	0.01%	0.98	–0.97	8.47	1361[b]
Shuaa GCC Index	1.30%	8.10%	0.06%	0.08%	1.05	–0.66	14.00	4949[b]
Shuaa Arab Index	1.15%	7.57%	0.07%	0.10%	1.00	–0.61	13.79	4758[b]

Source: Designed by the author using in-house built software

[a]Denotes estimation of conditional volatility and expected return using GARCH (1,1)-M model
[b]Denotes statistical significance at the 0.01 level

Table 7.2 Maximum daily positive returns (gain) and negative returns (loss) and the dates of occurrence

Stock market indices	*Maximum daily positive return (gain)*	*Dates of occurrence*	*Maximum daily negative return (loss)*	*Dates of occurrence*
DFM General Index	9.94%	1/23/2008	−12.16%	3/14/2006
ADX Index	6.57%	5/9/2005	−7.08%	1/22/2008
BA All Share Index	3.61%	1/24/2006	−3.77%	8/13/2007
KSE General Index	5.05%	3/16/2006	−3.74%	3/14/2006
MSM30 Index	5.22%	10/16/2007	−8.70%	1/22/2008
DSM20 Index	6.22%	2/4/2008	−8.07%	1/22/2008
SE All Share Index	9.39%	5/13/2006	−11.03%	1/21/2008
Shuaa GCC Index	11.14%	5/13/2006	−8.10%	1/21/2008
Shuaa Arab Index	9.43%	5/13/2006	−7.57%	1/21/2008

Source: Designed by the author using in-house built software

Table 7.3 Dependence measures (correlation factors) of stock market indices

	DFM general index	*ADX index*	*BA all share index*	*KSE general index*	*MSM30 index*	*DSM20 index*	*SE all share index*	*Shuaa GCC index*	*Shuaa Arab index*
DFM general index	100%								
ADX index	56%	100%							
BA all share index	12%	8%	100%						
KSE general index	17%	16%	12%	100%					
MSM30 index	12%	17%	11%	11%	100%				
DSM20 index	18%	23%	12%	12%	20%	100%			
SE all share index	20%	20%	7%	16%	11%	10%	100%		
Shuaa GCC index	37%	35%	13%	19%	13%	26%	62%	100%	
Shuaa Arab index	39%	36%	12%	24%	15%	26%	60%	93%	100%

Source: Designed by the author using in-house built software of upper limits LVaR risk budgeting. To that end, a variety of optimization case studies are examined in order to setup techniques for the computation of maximum LVaR risk-budgeting limits and to establish adequate procedures for handling certain situations in which trading/investment units are above the authorized LVaR upper limits. In fact, these upper limits LVaR methodology and computational procedure must be examined and approved by the senior management of the financial entity because it is crucial that all trading/investment units use these authorized LVaR limits as strict guidelines and policies for their risk takings. In addition, any excessive risk taking beyond the ratified LVaR limits must be reported to top management by the risk-management unit. Likewise, traders/asset managers need to provide full and justified clarifications of why their reported LVaRs are beyond the approved limits (Al Janabi, 2013, 2008a).

To that end, Tables 7.4, 7.5, 7.6, 7.8, and 7.9 represent different optimization case studies for establishing of realistic upper limits LVaR risk budget-

Table 7.4 Risk-budgeting upper limits in AED with 10 days closeout period, different correlation factors (ρ), and under regular (normal) market outlook

Upper limits risk budgeting	ρ = *Empirical*	ρ = *+1*	ρ = *0*
LVaR first case study of optimization	3,494,906	5,883,546	2,679,576
LVaR second case study of optimization	8,249,941	8,249,941	8,249,941
LVaR third case study of optimization	**11,767,031**	4,276,034	**12,432,381**
LVaR fourth case study of optimization	8,415,267	**10,609,262**	6,974,587

Source: Designed by the author using in-house built software

Notes: This table demonstrates risk-budgeting upper limits with four optimization case studies, and with 10 days closeout period, different correlation factors, and under regular (normal) market outlooks

Table 7.5 Risk-budgeting upper limits in AED with 10 days closeout period, different correlation factors (ρ), and under stressed (intricate) market outlook

Upper limits risk budgeting	ρ = *Empirical*	ρ = *+1*	ρ = *0*
LVaR first case study of optimization	20,449,118	34,921,874	15,683,656
LVaR second case study of optimization	52,091,452	**52,091,452**	52,091,452
LVaR third case study of optimization	**68,535,481**	33,290,131	**71,970,610**
LVaR fourth case study of optimization	47,690,472	50,763,385	41,653,465

Sources: Designed by the author using in-house built software

Notes: This table demonstrates risk-budgeting upper limits with four optimization case studies, and with 10 days closeout period, different correlation factors, and under stressed (intricate) market outlooks

Table 7.6 Risk-budgeting upper limits in AED with 5 days closeout period, different correlation factors (ρ), and under regular (normal) market outlook

Upper limits risk budgeting	*ρ = Empirical*	*ρ = +1*	*ρ = 0*
LVaR first case study of optimization	2,641,900	4,447,542	2,025,569
LVaR second case study of optimization	6,236,369	6,236,369	6,236,369
LVaR third case study of optimization	**8,895,040**	3,232,378	**9,397,997**
LVaR fourth case study of optimization	6,361,344	**8,019,848**	5,272,293

Source: Designed by the author using in-house built software

Notes: This table demonstrates risk-budgeting upper limits with four optimization case studies, and with 5 days closeout period, different correlation factors, and under regular (normal) market outlooks

Table 7.7 Risk-budgeting upper limits in AED with 5 days closeout period, different correlation factors (ρ), and under stressed (intricate) market outlook

Upper limits risk budgeting	*ρ = Empirical*	*ρ = +1*	*ρ = 0*
LVaR first case study of optimization	15,458,080	26,398,456	11,855,729
LVaR second case study of optimization	39,377,437	**39,377,437**	39,377,437
LVaR third case study of optimization	**51,807,954**	25,164,974	**54,404,668**
LVaR fourth case study of optimization	36,050,608	38,373,512	31,487,060

Source: Designed by the author using in-house built software

Notes: This table demonstrates risk-budgeting upper limits with four optimization case studies, and with 5 days closeout period, different correlation factors, and under stressed (intricate) market outlooks

Table 7.8 Risk-budgeting upper limits in AED with 15 days closeout period, different correlation factors (ρ), and under regular (normal) market outlook

Upper limits risk budgeting	*ρ = Empirical*	*ρ = +1*	*ρ = 0*
LVaR first case study of optimization	4,181,429	7,039,282	3,205,939
LVaR second case study of optimization	9,870,521	9,870,521	9,870,521
LVaR third case study of optimization	**14,078,492**	5,115,998	**14,874,540**
LVaR fourth case study of optimization	10,068,322	**12,693,296**	8,344,643

Source: Designed by the author using in-house built software

Notes: This table demonstrates risk-budgeting upper limits with four optimization case studies, and with 15 days closeout period, different correlation factors, and under regular (normal) market outlooks

Table 7.9 Risk-budgeting upper limits in AED with 15 days closeout period, different correlation factors (ρ), and under stressed (intricate) market outlook

Upper limits risk budgeting	*ρ = Empirical*	*ρ = +1*	*ρ = 0*
LVaR first case study of optimization	24,466,047	41,781,763	18,764,479
LVaR second case study of optimization	62,324,052	**62,324,052**	62,324,052
LVaR third case study of optimization	**81,998,269**	39,829,488	**86,108,179**
LVaR fourth case study of optimization	57,058,564	60,735,106	49,835,676

Source: Designed by the author using in-house built software

Notes: This table demonstrates risk-budgeting upper limits with four optimization case studies, and with 15 days closeout period, different correlation factors, and under stressed (intricate) market outlooks

ing. In all optimization case studies, the effects of various asset allocations (with or without short selling) are investigated for the purpose of setting of adequate LVaR risk-budgeting limits. Thus, in all case studies, the optimization is based on the definition of LVaR as the maximum downside loss over a specified time horizon and within a given confidence level. The optimization technique solves the problem by finding the market positions that maximize the downside losses, subject to the fact that all optimization constraints are satisfied within their boundary values. Furthermore, in all case studies for the optimization of the upper boundaries of risk budgeting, different liquidation horizons (closeout periods) of 5, 10, and 15 trading days are assumed. In fact, the case of 10 days closeout period represents the agreed-upon regulatory parameter as specified by Basel committee on banking supervision and capital adequacy requirements. In addition, for the sake of simplification of the optimization process and thereafter its examination, a volume trading limit of AED 200,000,000 is assumed as a constraint for the whole multiple-assets portfolio—that is the financial entity (or trading unit) must keep a maximum overall market value of stocks of no more than AED 200,000,000 (between long-only and long- and short-sales positions).

While in the first LVaR optimization case study distinct asset allocations are assumed, in the second case study all trading positions are concentrated in one market index that has, under intricate market circumstances, the highest daily conditional volatility, that is, the Dubai Financial Market (DFM) General Index. Finally, in the third and fourth case studies the effect of short selling of the sample stocks (or indices) is also contemplated by randomly short selling some of the sample stocks.

The principal effect of diversification on LVaR upper limits risk-budgeting setting seems to be through the first LVaR optimization case study; that is, with unequal asset allocation percentages. By and large, the highest LVaR upper limits risk budgeting (with empirical correlations parameters) are for the third optimization case study, when the trading budget is allocated between long- and short-sales equity trading positions (refer to Tables 7.4 and 7.5 for the optimization case studies under regular and stressed markets outlooks). As such, optimization case study three dominates all the other case studies with the exception when correlation factors tend to move strongly in the same direction (that is, when $\rho = +1$).[9] These phenomena can be explained by the nature of dependence measures (correlation factors) and the impact of short selling that are implemented in this optimization research study. In fact, in accordance with our previous research studies on other emerging financial markets, such as Morocco and Mexico (Al Janabi, 2007, 2008b), we have found by and large that short selling tends to decrease LVaR figures and, hence, the upper limits of LVaR risk budgeting. Thus, for the case of emerging GCC stock markets the above phenomena of high LVaR risk budgeting under $\rho = +1$ can be explained by the nature of the diminutive correlation factors that we have witnessed for the entire GCC stock markets (refer to Table 7.3 for further details). These tiny correlation factors have led to grand diversification benefits for long-only equity trading holdings and visa-versa for long- and short-sales positions.

While Tables 7.4 and 7.5 represent the typical regulatory case of 10 days closeout period, we decided to expand our empirical testing and provide evidences of the recommended techniques and algorithms by presenting two more optimization simulations with 5 and 15 days of liquidation horizons respectively. To that end, Tables 7.6, 7.7, 7.8, and 7.9 illustrate the upper limit of LVaR risk budgeting with 5 and 15 days of closeout periods, under both regular and intricate markets outlooks. Similar to the above case studies with 10 days liquidation horizon, the third LVaR case study for optimizing and determining upper limits risk budgeting indicates in general the highest risk-budgeting allocation under both regular and stressed markets perspectives. As expected, the case with 5 days closeout period produces less risk budgeting than the case with 10 days liquidation horizon and vice-versa for the optimization case with 15 days unwinding period.

As a conclusion of these structured optimization case studies, senior management of the financial institution can set the upper limits of daily

[9] Optimization results of the upper limits of risk-budgeting with different correlation parameters are highlighted in bold throughout Tables 7.4, 7.5, 7.6, 7.7, 7.8, and 7.9.

LVaR risk budgeting for their equity trading multiple-assets portfolios as follows.

Risk-Budgeting Parameters Under 10 Days Closeout Period (Basel Regulatory Case)

- Top limit amount of approved daily LVaR risk budgeting under regular market outlooks, with empirical correlations = AED 11,767,031.
- Top limit amount of approved daily LVaR risk budgeting under intricate market outlooks, with empirical correlations = AED 68,535,481.
- Top limit amount of approved daily volume limit for the whole multiple-assets trading portfolio = AED 200,000,000 (between long-only and long- and short-sales trading positions).
- Maximum closeout periods for all multiple-assets in the trading portfolio = 10 days

Risk-Budgeting Parameters Under 5 Days Closeout Period

- Top limit amount of approved daily LVaR risk budgeting under regular market outlooks, with empirical correlations = AED 8,895,040.
- Top limit amount of approved daily LVaR risk budgeting under intricate market outlooks, with empirical correlations = AED 51,807,954.
- Top limit amount of approved daily volume limit for the whole multiple-assets trading portfolio = AED 200,000,000 (between long-only and long- and short-sales trading positions).
- Maximum closeout periods for all multiple-assets in the trading portfolio = 5 days

Risk-Budgeting Parameters Under 15 Days Closeout Period

- Top limit amount of approved daily LVaR risk budgeting under regular market outlooks, with empirical correlations = AED 14,078,492.
- Top limit amount of approved daily LVaR risk budgeting under intricate market outlooks, with empirical correlations = AED 81,998,269.
- Top limit amount of approved daily volume limit for the whole multiple-assets trading portfolio = AED 200,000,000 (between long-only and long- and short-sales trading positions).
- Maximum closeout periods for all multiple-assets in the trading portfolio = 15 days

It should be mentioned that the above optimized top limits of LVaR risk budgeting are in their converted (or equivalent) UAE dirham (AED) values at the current or prevailing foreign exchange rates for all other emerging GCC countries versus the UAE dirham.

Concluding Remarks and Recommendations

There are many methods and ways to identify, measure, and control liquidity trading risk, and risk managers have the task to ascertain the identity of those algorithms that suit their requirements. In fact, there is no right or wrong way to assess and manage liquidity trading risk; it all depends on each financial entity's objectives, lines of business, risk appetite and the availability of funds for investment in trading risk-management projects. Regardless of the methodology chosen, the most important factors to consider are the establishment of sound risk practices, policies, and standards and the consistency in the implementation process across all lines of businesses and risks.

Under special conditions when changes in market risk factors are normally distributed, Liquidity-Adjusted Value at Risk (LVaR) can be computed using a closed-form parametric methodology, along with the application of GARCH-M (1,1) modeling technique for the estimation of conditional volatilities and expected returns. For upper limits LVaR risk budgeting and daily trading risk-assessment purposes, these assumptions are made for the sake of simplifying the computational process. However, for emerging markets environments, it is crucial to extend the closed-form parametric methodology with other quantitative algorithms, such as stress-testing and simulation analysis under intricate markets outlooks. This is done with the objective of estimating the impact of the assumptions that are made under the LVaR methodology. Likewise, the effects of illiquidity of trading assets and closeout horizons in emerging markets must be dealt with wisely and should be brought into existence within the LVaR framework of optimization algorithms.

Our empirical results suggest that in almost all tests, there are clear asymmetric behaviors in the distribution of returns of the Gulf Cooperation Council (GCC) stock market indices. The appealing outcome of this empirical research study suggests the inevitability of combining LVaR optimization algorithms with other quantitative risk-management techniques, such as, stress-testing and scenario analysis to grasp a better view of the other remaining risks (such as, the presence of fat-tails in the probability distribution of returns) that cannot be revealed with the plain assumption of normality.

In fact, the implications of the findings of this empirical research study on the GCC stock markets suggest that although there is a clear departure from normality in the distribution of assets' returns, this issue can be tackled without the need of complex mathematical and computational processes. In effect, it is possible to handle these issues, for equity cash assets, with the simple use of a closed-form parametric algorithm along with the incorporation of a credible stress-testing approach (under intricate market outlooks), as well as by enhancing the risk optimization engine with a rational illiquidity risk factor that takes into account real-world trading circumstances. In this research study, a robust model for the assessment of illiquidity of both long-only and long- and short-selling trading positions is integrated into the optimization algorithms. In contrast to other liquidity models, the liquidity methodology that is applied in this work is more appropriate for real-world trading practices since it considers selling small fractions of the long/short trading securities on a daily basis. This liquidity model can be implemented for the entire multiple-assets portfolio or for each asset within the structured equity trading portfolio. Indeed, the developed methodology and risk-assessment algorithms, which is based on Al Janabi model (Madoroba & Kruger, 2014), can aid in progressing quantitative risk-management practices in emerging markets and above all in the wake of the 2007–2009 credit crunch and the ensuing financial turmoil.

In conclusion, optimizing LVaR risk-budgeting upper limits is an important concern as part of daily quantitative risk-management process for strategic decision-making within trading financial entities. To that end, a robust risk-engine and optimization algorithms are presented to demonstrate a novel technique for the setting of upper limits LVaR risk budgeting. The robust optimization algorithm and mathematical modeling techniques are based on Al Janabi model (Madoroba & Kruger, 2014). Thus, in all optimization case studies, the volume limit in UAE dirham (AED200,000,000) is assumed constant and is used as a constraint, on the complex quantitative algorithms, for the computation of LVaR upper limits risk budgeting. For this particular research study, risk-budgeting parameters are computed for regular and stressed market circumstances and under the notion of different dependence measures (correlation factors) and with different closeout periods of 5, 10, and 15 days respectively. As such, quite a few structured optimization case studies are performed with different asset allocations (with or without short selling) and with the objectives of providing of upper limits LVaR risk-budgeting structures for equity trading risk-management units, under regular and intricate market outlooks.

Finally, the implemented methodology and risk-assessment algorithms can aid in advancing quantitative risk-management practices in emerging markets, particularly in the wake of the sub-prime credit crunch and the ensuing 2007–2009 financial turmoil. In addition, the proposed quantitative risk-management techniques and optimization algorithms can have important uses and applications in expert systems, machine learning, smart financial functions, and financial technology (FinTech) in big data environments.

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