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The Impact Made on Project Portfolio Optimisation by the Selection of Various Risk Measures

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This study addresses the effect of selecting an appropriate risk measure and the impact of this choice on the efficient frontier of the project portfolio of an organisation. The appropriate choice of a firm's project portfolio has a great impact on the organisational success. Each portfolio manager selects the best projects with different criteria and consistent with firm's strategic objectives. We used the Markowitz efficient frontier method to select the best projects of the organisation. The choice of proper measures impacts on this decision and can change the organisation's portfolio. The standard deviation was applied, and the relevant optimisation was made for this purpose. Then, the semi-standard deviation was used to differentiate between favourable and unfavourable opportunities. Afterwards, Value at Risk and Expected Shortfall were applied as appropriate risk measures to make a better estimate of the tail risks. All these risk measures were used to select the best possible projects. Managers should select the appropriate risk measures according to their objectives, estimation of their project distribution, and characteristics of the projects. This research studied the best measures consistent with construction projects and the effect of changes in these measures.

Keywords: *Portfolio Optimisation; Risk Measures; Monte Carlo Simulation; Downside Risk*; *Value at Risk; Expected Shortfall.*

Introduction

Portfolio optimisation is the selection of the best possible projects among a set of available candidates. The Markowitz mean–variance model uses the trade-off between risk and return to find the efficient frontier (Markowitz, 1952). The traditional portfolio theory uses unrealistic assumptions, which have become the object of some later studies. Chang *et al*. (2000) Liagkouras & Metaxiotis, (2014) and Saborido *et al*. (2016) considered the cardinality constraints for their optimisation. Sefair *et al*. (2016) optimised a portfolio of non-divisible projects with semi-variance as a risk measure. Portfolio managers must consider both maximising the expected return and minimising the risk (Woodside-Oriakhi *et al*., 2011). In the portfolio optimisation process, it is very important to use relevant measures, specifically in terms of risk, for selecting the best possible projects. Changes in risk measures can alter the selected projects and, therefore, the portfolio of projects. Measures are determined using different approaches. Risk can be defined as a threat. With this approach, the related measures are used to review the success criteria critical for the portfolio of projects. Reasons for unsuccessful attempts are considered as risks for that portfolio. Risk can be considered as the range of deviations from the expected outcomes of the project. These deviations in outcomes can be categorised as positive or negative, and various measures can be defined accordingly. The selected risk measure strongly depends on the definition and the approach used for the evaluation of project risks. The selection of the measures can also alter the optimal project portfolio and result in a completely different set of projects. This paper aims to examine the impact made on the optimisation process by the selection of various risk measures.

Risk Measurement

Risk is defined as the probability of future loss, which exists due to the uncertainty of the occurrence of an event in the future. According to Gilb (2002), risk is any phenomenon that can alter the results expected by an investor. The concept of risk plays a key role in project management and is one of the primary concerns of project managers. Therefore, the sources of risks must be identified first to enable its measurement and efficient management. Risk management can be identified as a process of identification, analysis, evaluation, response and control of risks in projects (Guide, 2001; Rodriguez *et al*., 2017; Rose, 2013). Over the past years, a variety of standards and models was proposed for risk management in different industries. Rodriguez *et al.* (2017) developed a method for the selection of appropriate IT risk management, Zare Naghadehi *et al.* (2016) focused on an urban tunnelling project, Wu *et al.* (2015) specialised in offshore pipeline projects, and

Rodriguez *et al*. (2016) investigated IT projects. Becker & Smidt (2015) studied workforce-related project risks and 9C. Wang *et al*. (2016) investigated the influence of risk propensity on the risk perception of construction project managers. The following stage is risk quantification. Yousefi *et al*. (2016) studied and quantified risks causing claims, and Pfeifer *et al*. (2015) investigated risks causing delays. Liu *et al*. (2017) proposed a risk assessment model and Cao & Song (2016), assessed the risks of co-creating value with customers under uncertainty. One common way for managers is evaluating the effect of uncertain factors on the Net Present Value (NPV) and Internal Rate of Return (IRR) (Hacura *et al*., 2001; Liu *et al*., 2017; Rezaie *et al*., 2007; Suslick *et al*., 2009; 2000; Ye & Tiong, 2000).

From the perspective of project managers, sometimes risk is merely presented as being qualitative. Having a view on risk is effective in its management, but numerous mental judgments and differences in opinions among the managers make it hardly helpful in optimisation. Therefore, after the identification of risks, it is appropriate to examine the risk measurement method. This quantitative approach can also be very helpful in examining the interdependencies and interrelation of risks. It should be noted that even with appropriate risk management systems, interdependencies and interrelation of risks can be ignored. Zhang (2016), investigated this risk dependence. Even with the intuition of the project risks, giving a quantitative estimate of the risks is quite difficult, unless a very specific application of the risk measure is clearly specified. Thus, to design and develop a proper risk measure, it is necessary to clarify its characteristics. Based on this concept, the theory of Coherent Risk Measures is presented by Artzner *et al.* (1999). In this study, the desired features of risk measures are defined as Monotonicity, Subadditivity, Positive Homogeneity, and Translational Invariance (Artzner *et al*., 1999; Jorion, 2010).

Monte Carlo Simulation

The Monte Carlo simulation method can be applicable for resolving problems with almost any degree of complexity. Also, such factors as path dependency, fat tails, non-linearity, multiple risk factors, interdependencies etc., which can cause problems with other approaches, can be examined easily. The Monte Carlo simulation can be used in dealing with dimensionality (Cong & Oosterlee, 2016). Simulation methods are suitable for solving multi-dimensional problems. These problems include situations, in which the results are dependent upon more than one risk factor. The Monte Carlo simulation has been used in lots of portfolio management researches during the past decades. Cong & Oosterlee (2016) applied this method to a multi-period mean–variance portfolio optimisation problem; Brandt *et al*. (2005) used it for a dynamic portfolio selection; Denault & Simonato (2017) and Cesari & Cremonini (2003) addressed different market situations and calculated the respective risk-adjusted performance. Denault & Simonato (2017) used the combination of least-squares regressions and Monte Carlo simulations for dynamic portfolio choices. Buchner (2015), applied the Monte Carlo approach for pricing of options, and Wang *et al.* (2016) used the Monte Carlo approach for finding the Value at Risk of a portfolio made of options and bonds. Pajares & Lopez-Paredes (2011) applied this method in finding the statistical distribution of a project (Acebes *et al*., 2015). Assuming the stochastic nature of projects returns, it is possible to use a statistical learning technique to refine the results (Acebes *et al*., 2015).

This method can also be used with the estimation of confidence levels, as an index for the accuracy of results. In this study, NPV and IRR have been examined using the Monte Carlo simulation method at the 90 % confidence level. Furthermore, this method can be applicable to portfolios with heterogeneous or complex projects. Generally, the Monte Carlo simulation is used when either there are no analytical methods at hand, or they are so complicated that this method would find an answer in a much easier way. Overall, it can be stated that with an increase in the complexity, this approach will look more appealing. In the figures below illustrate the NPV and IRR calculated for one of the projects at the 90 % confidence level.

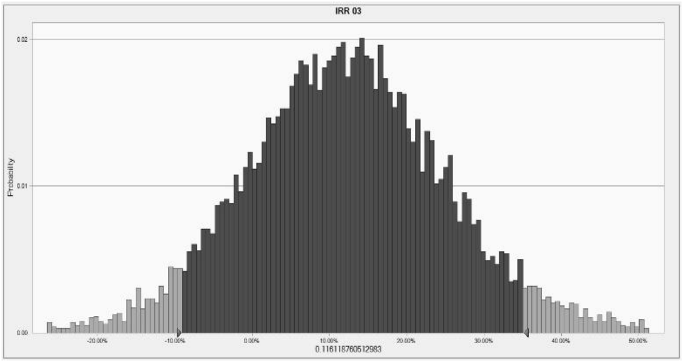

Figure 1. Simulated Distribution of a Project's IRR

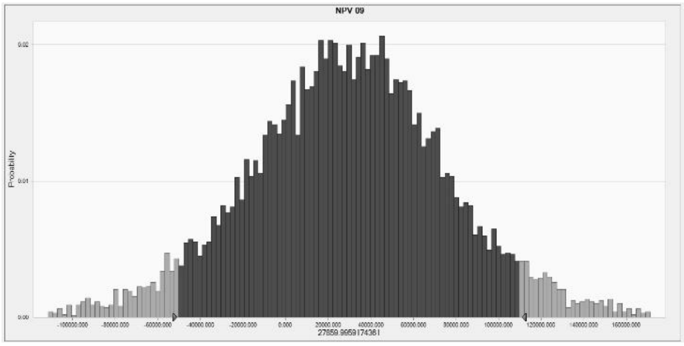

Figure 2. Simulated Distribution of a Project's NPV

Optimising the Project Portfolio of an Organisation

At the first step of this study, different cost and return data of construction projects were grouped according to the types of projects. Then, the relevant distribution for each type of project was determined. Once the distribution of each project was established, the simulation was made of uncertain factors, such as returns and costs of the projects. For any of the organisation's projects that may have needed a decision, the estimation of the return and cost data was assessed using the Monte Carlo simulation. Aiming to reach reliable and valid results, data were simulated 10000 times. The following figure illustrates the IRR distributions of possible projects.

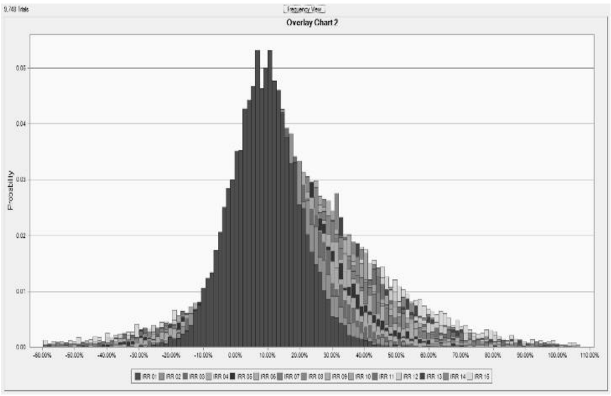

Figure 3. IRR Distributions of Possible Projects

Quantification of Risk

Risks can be examined in two ways: 1 — Uncertainty, which shows the change in the factors leading to the occurrence of risk and the uncertainty of the occurring event; 2 — Exposure, which indicates the amount of exposure due to changes in risk factors. Conditional distribution of risk is estimated using these two components, and then, the characteristics of this distribution are used to determine the value of the risk measure.

Standard Deviation

One practical way of evaluating project risks is considering its impact on the expected return. Risks make the project outcomes and expected returns less predictable. As a result, the risk increases with the expected return volatility. Therefore, risk can be defined as the standard deviation of the project returns (Markowitz, 1952). Projects valuable to the organisation were examined based on their categorisation. The estimated return and corresponding risks were assessed using the Monte Carlo simulation. Relationships and project interdependencies were examined next. The estimation of these relations was fairly important in reaching a credible optimisation in the selection of the projects.

Then, with the help of Markowitz mean-variance model, the amount of investment allocated to each project was determined. As it is evident from the figure, the output of this optimisation is to reach an efficient frontier. That is, only the projects and the investment weights relevant to this efficient frontier are optimal. This efficient frontier has higher return and/or lower risk, compared to any other possible choice.

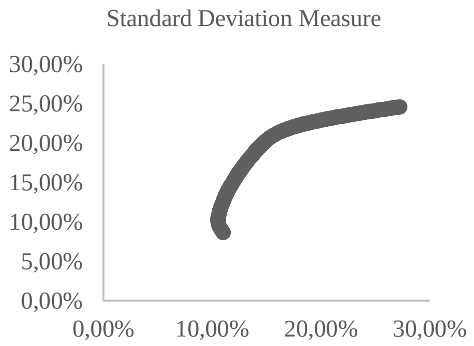

Figure 4. Portfolio Optimisation with Standard Deviation

Downside Risk

Another perspective allows for the right-side of the return distribution to be considered as project opportunities. This approach may look more accurate from the perspective of investors. Theoretically, it is much more realistic than the mean–variance approach, since the portfolio managers are in fact only concerned with the left-side of the return distribution. Paquin *et al*. (2016) investigated this downside risk, and its impact on the expected profitability of a firm, and Sefair *et al*. (2016) used semi-variance as a risk measure in their optimisation in the oil and gas industry.

Risks that arise from uncertainty can be defined in terms of upside and downside volatilities. Obviously, the upside volatilities are suitable opportunities which, based on the situation, can improve the project return. In fact, the downside volatilities are the main concern of portfolio managers. Therefore, it is inappropriate to use risk measures that consider the same weights to positive and negative returns, such as standard deviation. Most portfolio managers and project managers act asymmetrically towards upside and downside volatilities (loss and gain) due to loss aversion. Therefore, optimising the portfolio with the mean–variance method, which penalises both positive and negative volatilities, leads to a portfolio that minimises the total volatilities, which also include suitable opportunities. Therefore, using the mean–variance method, the output portfolio includes projects with the maximum return in any level of the total volatility the or minimum total volatility at any return level. To resolve this issue and to distinguish between the risks that lead to loss and project opportunities, the semi-standard deviation measure can be used as the risk measure. Next, this definition of risk was used in the optimisation of risk and return.

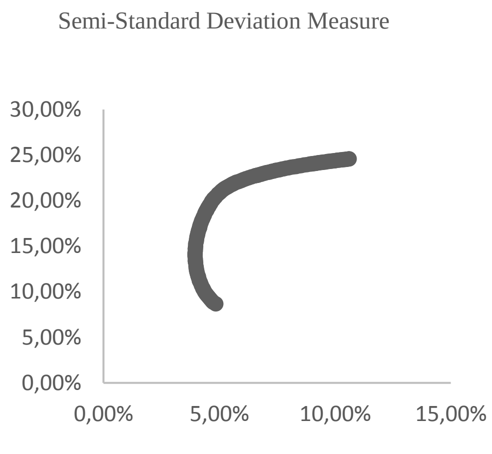

Figure 5. Portfolio Optimisation with the Semi-Standard Deviation

As it is evident from the figure, the efficient frontier derived from the semi-standard deviation method has different weightings. The interpretation of this efficient frontier in different risk and return levels is depicted in the first diagram with the exception that not all total volatilities are minimised. The selected projects on this efficient frontier may have higher total volatilities than the first model. Here, only the downside risks of the project were minimised.

Value at Risk

Normality is one of the first assumptions which is generally considered for distributions. However, most risks contain skewness and leptokurtosis. Most risk measures, such as the standard deviation and semi-variance, perform based on the normal distribution assumption and, therefore, if there is any deviation from this assumption, their application cannot be justified. Thus, it is practical to use a measure that can still be applied even if the distribution is abnormal. VaR is the percentage of portfolio value that is exposed to the risk of loss.

Value at Risk is more consistent with management comprehension of the risk management and the limitations it faces. At any time during the life of a project, a portfolio manager needs to have awareness about the chance of loss in the portfolio value to make proper decisions. Therefore, using Value at Risk as a measure of risk, which gives a clear interpretation of minimising the downside risks, is rather competent. This measure is commonly used in the finance literature. The VaR has been used and frequently investigated as a well-known risk measure (Allen, 2003; Chen *et al*., 2012; Dempster, 2002; Dowd, 1998; Duffie & Pan, 1997; Holton, 2003; Jorion, 2000). Value at Risk is a common risk measure for various risk factors. Value at Risk can be used for any portfolio and enables the comparison of the risks of different portfolios. VaR is the most outstanding among the risk measures. For instance, VaR is used as a risk measure by regulators of some industries, such as banking (Scaillet, 2003; Wang & Zhao, 2016). This risk measure has been employed as a standard tool for risk management during the past decades (Spierdijk, 2016). Value at Risk helps with the aggregation of risks of portfolio components, and thus with the calculation of portfolio risk. For this purpose, interactions and correlations of different risk factors should be considered. Balbas *et al*. (2017) proposed an approximation for optimising VaR.

One of the most important advantages of Value at Risk is that it provides quantitative benchmarks, which enables the estimation of interdependent fat tails and abnormal risks. Tsao (2010) incorporated VaR in mean-VaR efficient frontier and argued that this selection method was more accurate when distributions were abnormal. Basak & Shapiro (2001), Jang & Park (2016), Yiu (2004) and Zhao & Xiao (2016) considered VaR as a risk constraint, while Yiu (2004) found it would result in the reduction of risky asset investments (Zhu *et al*., 2016). Zhang & Gao (2017) applied dynamic value-at-risk constraints, and Zhu *et al*. (2016) used the maximum VaR solving the portfolio selection problem as a constraint. Lu *et al*. (2016) investigated the optimal reinsurance under the both VaR and Tail VaR risk measures. Value at Risk has a dynamic and futuristic approach which allows for a more accurate estimation of risk. Chan & Sit (2016) studied the random walk behaviour of VaR. He *et al*. (2016) proposed a Copula-based Portfolio Value at Risk (PVaR) model. Another reason, which can encourage portfolio and project managers to use Value at Risk, is the increase in project uncertainties. In addition, the complexity of project portfolios and the emergence of various types of projects in terms of cost, time, strategic goals etc., have challenged the portfolio managers in the risk measurement.

The following diagram uses the Markowitz model to optimise the risk and return. Here, the exception applies, namely, that the Value at Risk was put forward as the risk benchmark. As demonstrated, the efficient frontier has changed with the change in the risk measure. This model is more suitable for managers who seek for an estimate of possible losses of project portfolios.

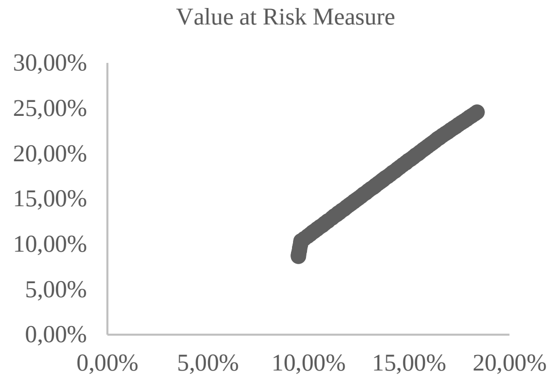

Figure 6. Portfolio Optimisation with Value at Risk

Expected Shortfall

Even though Value at Risk measure is practical, it should be noted that VaR does not provide any description of the left-hand tail of the distribution and only estimates the probability of occurrence of losses above a specific level. If the loss goes beyond VaR, the amount of this excess loss cannot be measured. A benchmark named Conditional VaR (CVaR) or Expected Shortfall (ES) is available to address the issue as it considers the loss that exceeds VaR. Also, since Value at Risk is measured together with some errors and using data with different time gaps or various statistical methods, it can lead to different results in the estimation of VaR (Jorion, 2010).

Considering VaR weaknesses, Artzner *et al*. (1999) proposed the expected shortfall measure. Banulescu & Dumitrescu (2015) used the expected shortfall as a risk measure to decompose the risk. Chen & Yang (2016) used stochastic programming with the conditional VaR for multi-period portfolios. Degiannakis & Potamia (2016) investigated the accuracy of predictions of Multiple-days-ahead value-at-risk and the expected shortfall forecasting. Chen *et al*. (2012) forecasted Bayesian VaR and the expected shortfall for a heteroscedastic return series. Wang & Zhao (2016) studied the semi-parametric CVaR estimation. Mbairadjim Moussa *et al*. (2014) calculated the linear portfolio VaR and the expected shortfall for heavy-tailed return distributions. Ortiz-Gracia & Oosterlee (2014) calculated the VaR and the expected shortfall for nonlinear portfolios with options. Kim & Lee (2016) considered nonlinear expectile regression models for estimation. Righi & Ceretta (2015) compared expected shortfall estimation models. Kellner & Rösch (2016) analysed the reaction of VaR and the expected shortfall in relation to sources of model risk. Brandtner & Kursten (2015) applied the expected shortfall to decision making.

The expected shortfall is a proper candidate for risk measurement. This measure is the average of the worst losses. Generally, VaR is used as the determining border of the worst loss. This measure has many applications. Of course, compared to VaR, ES is a more flawless measure of risk as it tells us what to expect in bad situations. In other words, it shows how bad the conditions can get, while VaR does not provide any information about the losses above a specified level.

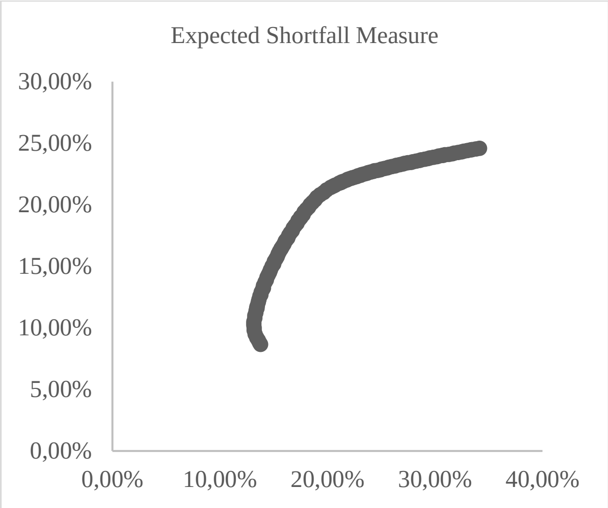

Figure 7. Portfolio optimisation with the expected shortfall

This diagram uses the expected shortfall as the measure of risk and shows a change in the efficient frontier. This definition is more suitable for managers who are after the minimisation of tail losses. Generally, decision-making regarding the expected risk and return is much more credible using ES compared to VaR.

Conclusion

This study used the Markowitz efficient frontier method to select the best projects of an organisation. First, all projects were grouped according to their type and based on the point of view of experts. For each project type, based on historical data and information, the relevant distribution for project cost, return and time was established. Projects that could receive investments were categorised into one of the established groups based on project characteristics. Then, using the Monte Carlo simulation, uncertain factors, such as return and cost data of each project, were estimated according to their relevant distribution. Their relevant NPV and IRR were calculated as well.

In the process of portfolio optimisation, it is very important to use relevant risk measures. The next step is to select the appropriate risk measure. First, based on the common definition, the standard deviation can be used, and the relevant optimisation should be made. Then, to discern good opportunities for investing in projects from possible losses, the semi-standard deviation can be applied. It should be noted that in both models, the assumption of a normal distribution is rather important and should the project returns be abnormal, the risk would be underestimated. Therefore, in the process of the research, VaR and the expected shortfall are applied as the appropriate risk measures to achieve a better estimate of tail risks. This research estimated different efficient frontiers according to chosen risk measures. It should be noted that project and portfolio managers should select the appropriate risk measure according to the estimates of their project's distribution and based on the characteristic of each project. This choice impacts on the change of the estimated efficient frontier and, as a result, the selected project portfolios of the organisation.

References

Acebes, F., Pereda, M., Poza, D., Pajares, J., & Galan, J. M. (2015). Stochastic earned value analysis using Monte Carlo simulation and statistical learning techniques. *International Journal of Project Management*, 33(7), 1597–1609. https://doi.org/10.1016/j.ijproman.2015.06.012

Allen, S. (2003). Financial risk management: a practitioner's guide to managing market and credit risk (with CD-ROM) (Vol. 119): John Wiley & Sons.

Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. *Mathematical finance*, 9(3), 203–228. https://doi.org/10.1111/1467-9965.00068

Balbas, A., Balbas, B., & Balbas, R. (2017). VaR as the CVaR sensitivity: Applications in risk optimization. *Journal of Computational and Applied Mathematics*, 309, 175–185. https://doi.org/10.1016/j.cam.2016.06.036

Banulescu, G. D., & Dumitrescu, E. I. (2015). Which are the SIFIs? A Component Expected Shortfall approach to systemic risk. *Journal of Banking & Finance*, 50, 575–588. https://doi.org/10.1016/j.jbankfin.2014.01.037

Basak, S., & Shapiro, A. (2001). Value-at-Risk-Based Risk Management: Optimal Policies and Asset Prices. *Review of Financial Studies*, 14(2), 371–405. https://doi.org/10.1093/rfs/14.2.371

Becker, K., & Smidt, M. (2015). Workforce-related risks in projects with a contingent workforce. *International Journal of Project Management*, 33(4), 889–900. https://doi.org/10.1016/j.ijproman.2014.10.014

Brandt, M. W., Goyal, A., Santa-Clara, P., & Stroud, J. R. (2005). A Simulation Approach to Dynamic Portfolio Choice with an Application to Learning About Return Predictability. *Review of Financial Studies*, 18(3), 831–873. https://doi.org/10.1093/rfs/hhi019

Brandtner, M., & Kursten, W. (2015). Decision making with Expected Shortfall and spectral risk measures: The problem of comparative risk aversion. *Journal of Banking & Finance*, 58, 268–280. https://doi.org/10.1016/j.jbankfin.2015.03.012

Buchner, A. (2015). Equilibrium option pricing: A Monte Carlo approach. Finance Research *Letters*, 15, 138–145. https://doi.org/10.1016/j.frl.2015.09.004

Cao, J., & Song, W. (2016). Risk assessment of co-creating value with customers: A rough group analytic network process approach. *Expert Systems with Applications*, 55, 145–156. https://doi.org/10.1016/j.eswa.2016.02.012

Cesari, R., & Cremonini, D. (2003). Benchmarking, portfolio insurance and technical analysis: a Monte Carlo comparison of dynamic strategies of asset allocation. *Journal of Economic Dynamics and Control*, 27(6), 987–1011. https://doi.org/10.1016/S0165-1889(02)00052-0

Chan, N. H., & Sit, T. (2016). Artifactual unit root behavior of Value at risk (VaR). Statistics & Probability Letters, 116, 88–93. https://doi.org/10.1016/j.spl.2016.04.006

Chang, T. J., Meade, N., Beasley, J. E., & Sharaiha, Y. M. (2000). Heuristics for cardinality constrained portfolio optimisation. *Computers & Operations Research*, 27(13), 1271–1302. https://doi.org/10.1016/S0305-0548(99)00074-X

Chen, H. H., & Yang, C. B. (2016). Multiperiod Portfolio Investment Using Stochastic Programming with Conditional Value at Risk. *Computers & Operations Research*. https://doi.org/10.1016/j.cor.2016.11.011

Chen, Q., Gerlach, R., & Lu, Z. (2012). Bayesian Value-at-Risk and expected shortfall forecasting via the asymmetric Laplace distribution. *Computational Statistics & Data Analysis*, 56(11), 3498–3516. https://doi.org/10.1016/j.csda.2010.06.018

Cong, F., & Oosterlee, C. W. (2016). Multi-period mean–variance portfolio optimization based on Monte-Carlo simulation. *Journal of Economic Dynamics and Control*, 64, 23–38. https://doi.org/10.1016/j.jedc.2016.01.001

Degiannakis, S., & Potamia, A. (2016). Multiple-days-ahead value-at-risk and expected shortfall forecasting for stock indices, commodities and exchange rates: Inter-day versus intra-day data. *International Review of Financial Analysis*. https://doi.org/10.1016/j.irfa.2016.10.008

Dempster, M. A. H. (2002). Risk management: value at risk and beyond: Cambridge University Press. https://doi.org/10.1017/CBO9780511615337

Denault, M., & Simonato, J.-G. (2017). Dynamic portfolio choices by simulation-and-regression: Revisiting the issue of value function vs portfolio weight recursions. *Computers & Operations Research*, 79, 174–189. https://doi.org/10.1016/j.cor.2016.09.022

Dowd, K. (1998). Beyond value at risk: the new science of risk management.

Duffie, D., & Pan, J. (1997). An overview of value at risk. *The Journal of derivatives*, 4(3), 7–49. https://doi.org/10.3905/jod.1997.407971

Gilb, T. (2002). Risk Management: A practical toolkit for identifying, analyzing and coping with project risks. Paper presented at the International Symposia of the International Council On Systems Engineering (INCOSE). https://doi.org/10.1002/j.2334-5837.2002.tb02482.x

Guide, A. (2001). Project Management Body of Knowledge (PMBOK® GUIDE). Paper presented at the Project Management Institute.

Hacura, A., Jadamus-Hacura, M., & Kocot, A. (2001). Risk analysis in investment appraisal based on the Monte Carlo simulation technique. *The European Physical Journal B - Condensed Matter and Complex Systems*, 20(4), 551–553. https://doi.org/10.1007/s100510170238

He, K., Liu, Y., Yu, L., & Lai, K. K. (2016). Multiscale dependence analysis and portfolio risk modeling for precious metal markets. *Resources Policy*, 50, 224–233. https://doi.org/10.1016/j.resourpol.2016.09.011

Holton, G. A. (2003). Value-at-risk: theory and practice (Vol. 2): Academic Press New York.

Jang, B. G., & Park, S. (2016). Ambiguity and optimal portfolio choice with Value-at-Risk constraint. *Finance Research Letters*, 18, 158–176. https://doi.org/10.1016/j.frl.2016.04.013

Jorion, P. (2000). Risk management lessons from long-term capital management. *European financial management*, 6(3), 277–300. https://doi.org/10.1111/1468-036X.00125

Jorion, P. (2010). Financial Risk Manager Handbook: FRM Part I (Vol. 625): John Wiley & Sons.

Kellner, R., & Rosch, D. (2016). Quantifying market risk with Value-at-Risk or Expected Shortfall? – Consequences for capital requirements and model risk. *Journal of Economic Dynamics and Control*, 68, 45–63. https://doi.org/10.1016/j.jedc.2016.05.002

Kim, M., & Lee, S. (2016). Nonlinear expectile regression with application to Value-at-Risk and expected shortfall estimation. *Computational Statistics & Data Analysis*, 94, 1–19. https://doi.org/10.1016/j.csda.2015.07.011

Liagkouras, K., & Metaxiotis, K. (2014). A new probe guided mutation operator and its application for solving the cardinality constrained portfolio optimization problem. *Expert Systems with Applications*, 41(14), 6274–6290. https://doi.org/10.1016/j.eswa.2014.03.051

Liu, J., Jin, F., Xie, Q., & Skitmore, M. (2017). Improving risk assessment in financial feasibility of international engineering projects: A risk driver perspective. *International Journal of Project Management*, 35(2), 204–211. https://doi.org/10.1016/j.ijproman.2016.11.004

Lu, Z. Y., Meng, L. L., Wang, Y., & Shen, Q. (2016). Optimal reinsurance under VaR and TVaR risk measures in the presence of reinsurer's risk limit. Insurance: *Mathematics and Economics,* 68, 92–100. https://doi.org/10.1016/j.insmatheco.2016.03.001

Markowitz, H. (1952). Portfolio selection. *The journal of finance*, 7(1), 77-91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Mbairadjim Moussa, A., Sadefo Kamdem, J., & Terraza, M. (2014). Fuzzy value-at-risk and expected shortfall for portfolios with heavy-tailed returns. *Economic Modelling*, 39, 247–256. https://doi.org/10.1016/j.econmod.2014.02.036

Ortiz-Gracia, L., & Oosterlee, C. W. (2014). Efficient VaR and Expected Shortfall computations for nonlinear portfolios within the delta-gamma approach. *Applied Mathematics and Computation*, 244, 16–31. https://doi.org/10.1016/j.amc.2014.06.110

Pajares, J., & Lopez-Paredes, A. (2011). An extension of the EVM analysis for project monitoring: The Cost Control Index and the Schedule Control Index. *International Journal of Project Management*, 29(5), 615–621. https://doi.org/10.1016/j.ijproman.2010.04.005

Paquin, J. P., Gauthier, C., & Morin, P. P. (2016). The downside risk of project portfolios: The impact of capital investment projects and the value of project efficiency and project risk management programmes. *International Journal of Project Management*, 34(8), 1460–1470. https://doi.org/10.1016/j.ijproman.2016.07.009

Pfeifer, J., Barker, K., Ramirez-Marquez, J. E., & Morshedlou, N. (2015). Quantifying the risk of project delays with a genetic algorithm. *International Journal of Production Economics*, 170, Part A, 34–44. doi: https://doi.org/10.1016/j.ijpe.2015.09.007

Rezaie, K., Amalnik, M. S., Gereie, A., Ostadi, B., & Shakhseniaee, M. (2007). Using extended Monte Carlo simulation method for the improvement of risk management: Consideration of relationships between uncertainties. *Applied Mathematics and Computation*, 190(2), 1492–1501. https://doi.org/10.1016/j.amc.2007.02.038

Righi, M. B., & Ceretta, P. S. (2015). A comparison of Expected Shortfall estimation models. *Journal of Economics and Business*, 78, 14–47. https://doi.org/10.1016/j.jeconbus.2014.11.002

Rodriguez, A., Ortega, F., & Concepcion, R. (2016). A method for the evaluation of risk in IT projects. *Expert Systems with Applications*, 45, 273–285. https://doi.org/10.1016/j.eswa.2015.09.056

Rodriguez, A., Ortega, F., & Concepcion, R. (2017). An intuitionistic method for the selection of a risk management approach to information technology projects. *Information Sciences*, 375, 202–218. https://doi.org/10.1016/j.ins.2016.09.053

Rose, K. H. (2013). A Guide to the Project Management Body of Knowledge (PMBOK® Guide)—Fifth Edition. *Project Management Journal*, 44(3), e1-e1. https://doi.org/10.1002/pmj.21345

Saborido, R., Ruiz, A. B., Bermudez, J. D., Vercher, E., & Luque, M. (2016). Evolutionary multi-objective optimization algorithms for fuzzy portfolio selection. *Applied Soft Computing,* 39, 48–63. https://doi.org/10.1016/j.asoc.2015.11.005

Scaillet, O. (2003). The origin and development of VaR. Modern Risk Management: A History, 15th Anniversary of Risk, 151–158.

Sefair, J. A., Mendez, C. Y., Babat, O., Medaglia, A. L., & Zuluaga, L. F. (2016). Linear solution schemes for Mean-SemiVariance Project portfolio selection problems: An application in the oil and gas industry. *Omega.* https://doi.org/10.1016/j.omega.2016.05.007

Spierdijk, L. (2016). Confidence intervals for ARMA–GARCH Value-at-Risk: The case of heavy tails and skewness. *Computational Statistics & Data Analysis*, 100, 545–559. https://doi.org/10.1016/j.csda.2014.08.011

Suslick, S. B, Schiozer, D., & Rodriguez, M. R. (2009). Uncertainty and risk analysis in petroleum exploration and production. Terræ, 6, 30–41.

Tsao, C. Y. (2010). Portfolio selection based on the mean–VaR efficient frontier. *Quantitative Finance*, 10(8), 931–945. https://doi.org/10.1080/14697681003652514

Wang, C. S., & Zhao, Z. (2016). Conditional Value-at-Risk: Semiparametric estimation and inference. *Journal of Econometrics*, 195(1), 86–103. https://doi.org/10.1016/j.jeconom.2016.07.002

Wang, C. M., Xu, B. B., Zhang, S. J., & Chen, Y. Q. (2016). Influence of personality and risk propensity on risk perception of Chinese construction project managers. *International Journal of Project Management*, 34(7), 1294–1304. https://doi.org/10.1016/j.ijproman.2016.07.004

Wang, X., Xie, D., Jiang, J., Wu, X., & He, J. (2016). Value-at-Risk estimation with stochastic interest rate models for option-bond portfolios. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2016.11.013

Woodside-Oriakhi, M., Lucas, C., & Beasley, J. E. (2011). Heuristic algorithms for the cardinality constrained efficient frontier. *European Journal of Operational Research*, 213(3), 538–550. https://doi.org/10.1016/j.ejor.2011.03.030

Wu, W. S., Yang, C. F., Chang, J. C., Chateau, P. A., & Chang, Y. C. (2015). Risk assessment by integrating interpretive structural modeling and Bayesian network, case of offshore pipeline project. Reliability Engineering & System Safety, 142, 515–524. https://doi.org/10.1016/j.ress.2015.06.013

Ye, S., & Tiong, R. L. K. (2000). NPV-at-Risk Method in Infrastructure Project Investment Evaluation. *Journal of Construction Engineering and Management*, 126(3). https://doi.org/10.1061/(ASCE)0733-9364(2000)126:3(227)

Ye, S., & Tiong, R. L. K. (2000). NPV-at-risk method in infrastructure project investment evaluation. *Journal of construction engineering and management*, 126(3), 227–233. https://doi.org/10.1061/(ASCE)0733-9364(2000)126:3(227)

Yiu, K. F. C. (2004). Optimal portfolios under a value-at-risk constraint. *Journal of Economic Dynamics and Control*, 28(7), 1317–1334. https://doi.org/10.1016/S0165-1889(03)00116-7

Yousefi, V., Yakhchali, S. H., Khanzadi, M., Mehrabanfar, E., & Saparauskas, J. (2016). Proposing a neural network model to predict time and cost claims in construction projects. *Journal of Civil Engineering and Management*, 22(7), 967–978. https://doi.org/10.3846/13923730.2016.1205510

Zare Naghadehi, M., Benardos, A., Javdan, R., Tavakoli, H., & Rojhani, M. (2016). The probabilistic time and cost risk analysis of a challenging part of an urban tunneling project. *Tunnelling and Underground Space Technology*, 58, 11–29. https://doi.org/10.1016/j.tust.2016.04.007

Zhang, Q., & Gao, Y. (2017). Portfolio selection based on a benchmark process with dynamic value-at-risk constraints. *Journal of Computational and Applied Mathematics*, 313, 440–447. https://doi.org/10.1016/j.cam.2016.10.001

Zhang, Y. (2016). Selecting risk response strategies considering project risk interdependence. *International Journal of Project Management*, 34(5), 819–830. https://doi.org/10.1016/j.ijproman.2016.03.001

Zhao, P., & Xiao, Q. (2016). Portfolio selection problem with Value-at-Risk constraints under non-extensive statistical mechanics. *Journal of Computational and Applied Mathematics*, 298, 64–71. https://doi.org/10.1016/j.cam.2015.12.008

Zhu, D. M., Xie, Y., Ching, W. K., & Siu, T. K. (2016). Optimal portfolios with maximum Value-at-Risk constraint under a hidden Markovian regime-switching model. *Automatica*, 74, 194–205. https://doi.org/10.1016/j.automatica.2016.07.032

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