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Spectral Risk Measures in RAROC: A Risk-Sensitive Framework for Risk-Adjusted Financial and Accounting Information — Evidence from the DAX 40

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Research Article

Keywords: Financial Statement Analysis, Spectral Risk Measures, Coherent Measures, RAROC, economic capital

Posted Date: October 29th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11259429/v1

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Additional Declarations: No competing interests reported.

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Abstract

This research is devoted to the incorporation of Spectral Risk Measures (SRMs) into the Risk-Adjusted Return on Capital (RAROC) framework. In doing so we contribute to Accounting and Finance information for auditing, management accounting and investment purposes. We argue that this is particularly useful in times of crises, for instance due to systemic risk. Bearing in mind that traditional RAROC relies usually on Value-at-Risk (VaR) which is not coherent in general and can fail subadditivity when tails are very heavy (Danielsson et al., 2013), SRMs offer the desired properties of coherence when the included risk spectrum is admissible (see Acerbi, 2002). It also offers a tail-sensitive alternative that incorporates a user-specified degree of risk aversion.

Considering the above we propose a methodology building on (Zachos, 2023 and Zachos, 2026). Moreover, we calculate SRM-based RAROC, VaR-based RAROC and we complement our work by calculating Expected Shortfall-based RAROC. For those calculations a twofold approach is suggested: one that is predominantly market-linked and one that is firm specific. To do so we utilize historical data of DAX 40 and the companies that constitute the index. Furthermore, we suggest certain occasions where the proposed RAROC version could be employed by accounting practitioners, financial analysts or investors. Finally, we examine the significance of the values that RAROC takes, depending on the risk measure that is used.

Keywords: *Financial Statement Analysis; Spectral Risk Measures; Coherent Measures; RAROC; economic capital.*

JEL Classification Numbers: M41; G32; G22

1. Introduction and Motivation

The research at hand examines the inclusion of Spectral Risk Measures (SRMs) into the Risk-Adjusted Return on Capital (RAROC), in order to contribute to Accounting and Finance practices. We consider that this work has particular relevance in auditing, management accounting, and investment decision-making. Motivation for this study stems from the growing need of robust risk-

adjusted performance metrics, particularly during periods of financial instability where phenomena like systemic risk are prominent. In such environments, traditional performance evaluation tools may fail to capture extreme losses and interconnected risks adequately.

Conventional RAROC methodologies predominantly rely on Value-at-Risk (VaR) as the underlying risk measure. However, VaR has been widely criticized for its coherence issues as it fails to satisfy subadditivity under fat-tailed return distributions (Danielsson et al., 2013). This limitation becomes particularly problematic in times of market stress, where tail risks and contagion effects are more pronounced. In contrast, Spectral Risk Measures, originally introduced by (Acerbi, 2002), belongs to the class of coherent risk measures and incorporate user-defined risk aversion through a weighting (spectral) function applied to the distribution of losses.

More recent literature further highlights the advantages of SRMs. For instance, (Tsang et al., 2022) demonstrate their flexibility in portfolio optimization under uncertainty, while (Jin and Gao, 2025) emphasize their ability to dynamically capture time-varying risk preferences in multi-period settings. Additionally, recent actuarial and financial studies underline the relevance of incorporating systematic (Assa, 2025) and systemic (Zachos, 2026) components of risk into coherent risk measurement frameworks, particularly in applications such as reinsurance and capital allocation. These developments reinforce the argument that SRMs provide a more comprehensive and economically meaningful representation of risk, especially in the tails of the loss distribution.

Building on this theoretical foundation, the present study proposes a methodology inspired by (Zachos, 2026), in which a basic quantification of systemic risk is explicitly incorporated into the risk spectrum of the selected SRM. Such an approach enables the adjustment of risk weights in order to reflect both individual risk tolerance and market risk conditions. The proposed framework allows for greater flexibility in representing investor preferences and market dynamics.

Empirically, the study computes SRM-based RAROC and compares it with both VaR-based and Expected Shortfall (ES)-based RAROC measures. Expected Shortfall, itself a coherent alternative to VaR (Acerbi and Tasche, 2002), serves as a useful benchmark, given its regulatory prominence and sensitivity to extreme losses. The analysis utilizes historical data from the DAX 40 index and its constituent firms, enabling a detailed examination of how different risk measures influence capital allocation and performance evaluation.

Furthermore, the study explores practical applications of the proposed SRM-RAROC framework for accounting professionals, financial analysts, and institutional investors. Such applications could be used in capital budgeting, performance benchmarking, and risk-sensitive investment analysis.

Summing up, the research evaluates the extent to which RAROC estimates vary depending on the selected risk measure and consequently highlights the importance of risk measure selection in financial decision-making. At a glance, findings suggest that SRM-based RAROC provides a coherent, flexible, and tail-sensitive alternative that is suited to environments characterized by crisis and extreme risk events. Finally, we consider Expected Shortfall's coherence properties and its wide acceptance in practice (Emmer, 2015). To that end we complement our work by examining it also with the same data.

Accordingly, we attempt to tackle the following three questions. To which extent does the choice of risk measure affect RAROC estimates? Does the proposed SRM-based RAROC generate materially different risk-adjusted performance measures compared with VaR- and ES-based RAROC? And third does incorporation risk aversion through the spectral weighting function adds flexibility to risk-sensitive financial and accounting performance assessment?

The rest of the paper includes research contributions, as an extension of section 1. Section 2 discuses basic concepts are discussed. In section 3 data analysis follows. In section 4, we analyze the methodology we propose. Section 5 discusses key findings and section 6 addresses conclusions and future research that is based on this methodological effort.

1.1 Research Contribution

The study makes three contributions.

First, it makes a methodological contribution by integrating a Spectral Risk Measure into the RAROC framework. Such an approach extends conventional RAROC as it allows the risk component underlying economic capital to reflect a specified degree of risk aversion.

Second, we provide an empirical comparison of three risk-measure specifications within the RAROC framework: Spectral Risk Measures, Value at Risk and Expected Shortfall. Using DAX 40 and all of its constituent, over 2015–2024 period, we examine whether alternative representations of risk lead to materially different assessments of risk-adjusted performance.

Third, we contribute to the use of accounting and financial information in risk-adjusted performance analysis. By combining accounting-based measures, specifically an accounting flow (revenue less operating expenses less asset impairments) with market-based risk information, the proposed framework provides a risk-sensitive interpretation of accounting outcomes. In this way, the study

argues that accounting and financial information can be further refined when financial performance is considered jointly with the economic capital required to support it.

The contribution of the study should be understood in terms of the importance of risk-measure selection within RAROC. The empirical results do not imply that one risk measure is universally superior to all alternatives. Rather, they demonstrate that the specification of the underlying risk measure can affect RAROC outcomes. The use of an SRM additionally allows the analyst to make the degree of risk aversion an explicit component of the measurement framework. Therefore, this feature provides a potentially useful basis for developing more risk-sensitive approaches to financial performance assessment, particularly in environments characterized by elevated uncertainty or adverse market conditions.

Overall, the study attempts to establish that risk measurement and financial performance measurement should not be treated as separate analytical exercises. The information conveyed by accounting performance measures can be substantially influenced by the way in which the associated risk is specified and quantified. Integrating Spectral Risk Measures into RAROC consequently offers a framework through which financial performance can be evaluated not only according to the return, but also according to nature, severity and risk preferences associated with the potential losses underlying the required capital.

2. Basic Concepts

2.1 Risk Adjusted Return on Capital (RAROC)

Risk-Adjusted Return on Capital (RAROC) emerged in the late 1970s at Bankers Trust as a pioneering framework for evaluating the profitability of an economic entity while considering the risks they undertake (Zaik et al. 1996). Such a concept suggested an important shift from traditional, risk-oblivious performance metrics, laying the groundwork for contemporary, capital-at-risk methodologies (Matten, 2000).

The key feature of RAROC is that it measures return of an economic entity relative to the economic capital required to cover unexpected losses which is calculated predominantly by a risk measure. It enables institutions to compare performance across many sectors in order to make decisions on pricing, capital allocation, and strategic planning (Crouhy et al., 2014). In essence it ensures that capital is used for its most efficient, risk-adjusted use.

As aforementioned above, RAROC originated in the banking sector for practical reasons. Yet, RAROC can be used for other purposes, for instance investing or insurance. It is fundamental for performance measurement at the desk, division, or portfolio level, for optimizing loan pricing, and in strategic capital budgeting decisions (Gregory, 2020). Also, research interest for RAROC can be found in (Loebnitz, 2011), (Loebnitz and Roorda, 2011), (Bandyopadhyay, 2016), (Saha et al., 2016), and more recently in (Misra, 2023).

Prokopczuk et al. (2007) provide a useful review; their equation (3.2) gives a basic formula:

$$RAROC = \frac{Expected\ Return}{Economic\ Capital}. \tag{2.1}$$

The denominator in (2.1) is the amount of money that is needed to secure the financial institution's survival in a worst-case scenario and can be straightforwardly expressed by a risk measure. Prokopczuk et al. (2007, eq. 3.5) also give a VaR-based version:

$$RAROC = \frac{Expected\ Return}{VaR}. \tag{2.2}$$

2.2 Risk Measures

Let Ω be a sample space. In addition, we assume that there is an investment over a single time period, specifically from 0 to T and $X: \Omega \to \mathbb{R}$ is the monetary outcome of this investment. Also, consider the probability space $(\Omega, F, \mathbb{P})$ and $\mathcal{G}$ which is the set of real valued functions on Ω.

Definition 2.1 *A risk measure is a function from the set $\mathcal{G}$ of risks X to the real numbers $\rho: \mathcal{G} \to \mathbb{R}$.*

Also, we have the accepted future wealth of an investor, namely the acceptance set $\mathcal{A}$. In accordance with (Artzner et al., 1999, Definition.2.3) an acceptance set $\mathcal{A}$ associated to a risk measure ρ can be denoted by $\mathcal{A}\rho$ and its definition is

$$\mathcal{A}\rho = \{X \in \mathcal{G} |\ \rho(X)\ \leq 0\ \}. \tag{2.3}$$

In addition, (Artzner et al., 1999, Definition 2.2) suggests that the total rate of return *r* of a reference instrument (for instance the total return of an investment), the risk measure associated with an acceptance set as defined in (2.3) is the mapping from $\mathcal{G}$ to the real numbers (denoted by $\rho_{\mathcal{A},r}$) and is defined by the following (2.4):

(2.4) $$\rho_{\mathcal{A},r}(X) = \inf\{m \in \mathbb{R} | mr + X \in \mathcal{A}\}.$$

The importance of risk measures as defined in (2.4) for regulatory purposes is very well documented and can be witnessed for instance in [BCBS, 2012), p.20]. Alternatively, they can also be utilized for accounting compliance or even investment purposes [see for instance (Konstantinides and Zachos, 2019) or (Balbas et al., 2016)].

2.3 Properties of Risk Measures

The fundamental properties are listed below:

(1) Sub-additivity: $\rho(Z) + \rho(Y) \geq \rho(Z + Y)$ for any $Z, Y \in \mathcal{G}$.
(2) Positive homogeneity: $\rho(\lambda Y) = \lambda\rho(Y)$ for any $\lambda \geq 0$.
(3) Monotonicity: for any $Z, Y \in \mathcal{G}$ such that $Z \geq Y$ at all scenarios, then $\rho(Z) \leq \rho(Y)$.
(4) Cash or translation invariance: for any $Z \in \mathcal{G}$ and let M be an investment with guaranteed risk-free returns m, then $\rho(Z + M) = \rho(Z) - m$.
(5) Convexity: $\rho[\lambda Y + (1 - \lambda)Z] \leq \lambda\rho(Y) + (1 - \lambda)\rho(Z)$ for any $Z, Y \in \mathcal{G}$ and any $\lambda \in [0,1]$.
(6) Law Invariance: If Z, Y have the same distribution under $\mathbb{P}$, then $\rho(Z) = \rho(Y)$.
(7) Comonotonic Additivity: If Z, Y are comonotonic, then $\rho(Z) + \rho(Y) = \rho(Z + Y)$.
Properties from (1) to (6) are analyzed in (Artzner et al., 1999), (Föllmer and Shied, 2023), (Kusuoka, 2001), (Wang et al., 2015) and (Föllmer and Shied, 2008), while analysis of Comonotonic Additivity is in (Dhaene et al., 2002).

Definition 2.2 *A monetary risk measure is a risk measure satisfying monotonicity and translation invariance.*

Definition 2.3 *A coherent risk measure is a risk measure satisfying monotonicity, translation invariance, homogeneity and sub-additivity.*

A coherent measure is desirable in the sense that the acceptance set associated with it is closed and thus satisfies the 4 axioms suggested by (Artzner et al., 1999, from Axiom 2.1 up to 2.4). For a rigorous analysis we refer the reader to (Artzner et al., 1999), Proposition 2.1), (Artzner et al., 1999, Proposition 2.2), (Artzner et al., 1999, Proposition 2.3) and their proofs.

2.4 Important Risk Measures

A definition of Value at Risk VaR_α is the following:

Definition 2.4 $VaR_\alpha(X) = sup\{x \in R | P(X \geq x) > 1 - \alpha\}$.

In simple terms, VaR is a threshold loss value of an investment, which exhibits $1 - \alpha$ probability of exceeding this threshold in a certain time horizon and there is no additional trading involved. The main advantages of VaR_α are easy computation and its wide use while an important disadvantage is its lack of coherence since its sub-additivity fails in cases of fat tailed distributions (see (Danielsson et al., 2013)). A coherent alternative is the Expected Shortfall:

Definition 2.5 *The expected shortfall is the risk measure given by* $ES_\alpha = \frac{1}{\alpha}\int_0^\alpha VaR_p(Y)dp$ *for any random variable* Y *and any real number* $0 < \alpha < 1$.

In practical terms it can be perceived as the expected value of an investment, on condition that the value is less than the quantile p of the worst outcomes. (Acerbi and Tasche, 2002) denotes that ES can be expressed in terms of the distribution of the investment's returns $F_X = \mathbb{P}(X \leq \mathrm{x})$:

(2.5) $$ES_\alpha = -\frac{1}{\alpha}\int_0^\alpha F_X^{\leftarrow}(p)dp.$$

ES, as given in (2.5), is a coherent risk measure, tail sensitive and its regulatory relevance is very well documented (see for instance BCBS (2012)). Also, it is more conservative than VaR, since $ES_\alpha(Y) \geq VaR_\alpha(Y)$ for any given risk Y.

2.5 Spectral Risk Measures

Spectral Risk Measures (SRMs) are useful and relatively tractable tools, in the sense that they offer an easy computable means of risk estimation. In contrast to the most popular risk measures, namely VaR and ES, SRMs include a weighting function, namely the risk spectrum, that incorporates the risk aversion of investors.

The concept of Spectral Risk Measures was introduced by (Acerbi, 2002) as a class of risk measures extending Expected Shortfall. A risk measure (ρ) is called spectral if it can be written as

(2.6) $$\rho(X) = \int_0^1 \varphi(p)F_X^{\leftarrow}(p)dp,$$

where: (X) is a random variable representing losses, $F_X^{\leftarrow}(p)$ is the quantile function of (X), $\varphi(p)$ is a weighting function (or risk spectrum) to reflect the risk aversion of the decision-maker.

The risk spectrum $\varphi(p)$, in order to give a Coherent risk measure must be admissible as (Acerbi, 2002) suggests, in the sense that it must fulfill the following properties:

1. Non-negativity: $\varphi(p) \geq 0$,
2. Normalization: $\int_0^1 \varphi(p)dp = 1$,
3. Monotonicity: $\varphi(p_1) \geq \varphi(p_2)$ for $p_1 \geq p_2$.

These properties ensure that SRMs satisfy subadditivity, monotonicity, positive homogeneity, and translation invariance properties of coherence (Artzner et al., 1999). This subset of SRMs exhibits a resemblance with the distortion risk measures as they have the same properties. Yet, with construction and reparameterization differences: In distortion Risk Measures for quantifying risk, concave distortion risk measures modify the probability distribution (Balbas et al., 2009), while in (Acerbi, 2002) Spectral Risk Measures modify returns according to the expected utility function (Zachos, 2023).

As stated in (Zachos, 2026) there are some subclasses of spectral risk measures developed in recent literature that may exhibit coherence under certain conditions:

(1) Power: Suggested in (Dowd et al., 2008), where the risk spectrum of (2.6) in this case is the following:

$$\varphi(d,p) = dp^{d-1}. \tag{2.7}$$

(2) Exponential: Suggested by [(Acerbi, 2002), p.178] and represented by (Cotter and Dowd, 2006) and (Dowd and Blake 2006) with the following risk spectrum:

$$\varphi(p) = \frac{Ae^{-Ap}}{1-e^{-A}}, \tag{2.8}$$

where $A \geq 0$ in (2.8) stands as the Arrow- Pratt coefficient of absolute risk aversion.

(3) The Wang transform (Wang, 2000) also belongs in this list. Although it predates SRMs, nevertheless it also satisfies its requirements. It is also interesting that it fulfills the requirements of (Balbas et al., 2009) with regard to a well-defined risk measure.

Although this paper focuses on one application of SRM, some other applications could be with regard to Portfolio Optimization, Regulatory Frameworks or even in Insurance and Actuarial Science. Some key benefits in the use of SRMs are presented below:

(1) Tailor-made Risk Aversion: One of the biggest advantages of SRMs is their ability to adapt according to the risk profile of the user. VaR and ES treat all users' risk preferences in the same way, while SRMs modify the preferences to be specified in the risk estimate for the decisionmaker.

(2) Tailor made conservatism according to potential systemic risk: As highlighted in (Zachos, 2026) SRM can be built to capture systemic risk once emerged which denotes that it could be a useful tool for regulators in order to mitigate risk.

(3) Utilization of the Full Distribution: VaR and ES are only focused on the tail of the loss distribution while SRMs utilize the whole distribution and consequently no information is omitted.

(4) Coherence: By using an admissible risk spectrum SRMs satisfy the four axioms of coherence as presented in (Artzner et al., 1999) which are subadditivity, monotonicity, positive homogeneity, and translation invariance. We refer the reader to (Artzner et al., 1999) for a thorough analysis of the apparent benefits of coherence.

(5) Customization: A potential practitioner can construct tailor-made risk measures depending on the occasion (see (Acerbi, 2002), (Dowd and Blake, 2006) or (Zachos, 2026) for subtleties).

Therefore, it is clear that SRM provides additional flexibility that may be valuable for risk-sensitive RAROC applications and thus, which is why we use them here.

Concerning criticism, we should mention the apparent subjectivity in the use of SRMs and the computational complexity especially for high-dimensional analysis. Moreover, the empirical estimation of $\varphi(p)$ remains an area of active research (Bellini and Bignozzi, 2015). In our case the Power Spectral Risk Measure (2.7) is utilized.

3. Data

For our analysis we choose returns from DAX 40 index and the companies that constitute it. In table 1 (see appendix) it provides a list of all the companies and their coding. By selecting data from a mature market, we aim to establish a sound basis for this type of research, and we can proceed with data from an emerging market in the near future. Some other features of DAX 40 favoring our choice

are the following: it includes heterogeneous sectors, its constituents are economically significant firms, the relatively liquid securities, availability of data and suitability for testing risk sensitive performance measures. Moreover, we use daily observations over a 10-year period, from 02/01/2015 to 30/12/2024. In addition, for all the companies that constitute DAX 40 we have utilized data from their balance sheets and income statements for extracting revenue, operating expenses and asset impairments. All data are taken from Bloomberg.

4. Methodology

If we consider a practitioner's perspective (an Accountant or a Financial analyst) we know that instead of the expected returns is more interested in the accounting flow, as extracted from the financial statements. Moreover, we believe that VaR might be limited in the sense that it might exhibit coherence issues in certain cases. To that end we propose an alternative equation based on (2.2):

$$RAROC = \frac{Revenue - Expenses - Impairment\ Assets}{coherent\ risk\ measure}. \tag{4.1}$$

The inclusion of asset impairments is a straightforward attempt to capture the risk as depicted in a Balance Sheet and a Profit and Loss statement (see Petersen and Plenborg (2010) work on IAS36). Its importance stems from IFRS9 Financial Instrument (European Banking Authority, 2017), which is a topic for academic scrutiny (see for instance (Rompotis and Balios, 2024). Overall, the numerator provides a risk-adjusted extension of accounting-based performance information, allowing financial statement outcomes to be interpreted jointly with the economic capital required to absorb adverse outcomes.

With regard to a coherent risk measure we utilize SRM for the apparent advantages it exhibits (see relevant subsection). Specifically, the power SRM as presented in (2.7) and we set the parameter of d of the weighting function to 1.2. Elaborating on this default choice we mention that by looking at Dowd (2008), we justify that it responds to a somewhat mildly risk-averse profile. As we consider that this is the predominant characteristic of the vast majority of an analyst or an investor, we chose to be equal to 1.2 as it refers to the most common profile. Also, at equation 14.11 of Zachos (2026), we notice that variable Y attempts to capture systemic risk. Since we are working with data from a mature, well-established market we consider that there is no need to depict systemic risk and thus this variable is neutralized, or in other words Y=1.

Regarding the results, we get on subsection 5.1 (see below) at first, we attempt a market linked approach in the following sense: For capturing risk we consider beta, as extracted from CAPM of (Sharpe, 1964) and (Lintner, 1965). Recalling that beta represents sensitivity of each company's returns compared to the index, it indicates how much risk the company bears relative to the market. Also, since we are interested in risk analysis, we use beta as we are aware that it captures and quantifies systematic risk (Sharpe, 1964). To that end, we calculate the beta of every company's return, and we multiply by the index's SRM. The result is and index-based SRM_β that reflects each company's β.

Therefore, the final version of (4.1) that we use is:

(4.2) $$RAROC_{srm} = \frac{R-E-IA}{1-SRM_\beta}$$

Where R is the Revenue of 2024, as extracted from Profit and Loss statement of each company, E denotes operating expenses of 2024, again as extracted from Profit and Loss statement of each company and IA denotes asset impairments of 2024 as depicted in each company's Profit and Loss statement. Having a closer look at the denominator we need to clarify that the risk measure is expressed in percentage in percentage. We do that on purpose as we are interested in expressing the RAROC in EUR, in order to straightforwardly compare figures extracted from the accounting statements. Specifically, the quantity $(R - E - IA)$. In case we expressed each risk measure in capital we would get a ratio that would not be comparable to the aforementioned figures. For comparison we also calculate the Expected Shortfall version, or

(4.3) $$RAROC_{ES} = \frac{R-E-IA}{1-ES_\beta},$$

and the VaR version, which is

(4.4) $$RAROC_{VaR} = \frac{R-E-IA}{1-VaR_\beta}.$$

With regard to the results we get on subsection 5.2 (see below), instead of deriving firm-level risk from betas, we attempt a firm-specific approach in the sense that we use each company's data to calculate risk measures and work accordingly. Recall that previously the index's risk measure was combined with each company's beta in order to get RAROC's denominator. Also, regarding the numerator of (4.5), (4.6) and (4.7) we have calculated a ten-year average (2015-2024) for Revenue, Expenses and asset impairments respectively. All the figures are extracted from Balance Sheets and Profit and Loss statements of each company.

Therefore, the final version of (4.1) that we utilize is:

(4.5) $$RAROC_{srm} = \frac{\overline{R-E-IA_{15-24}}}{1-SRM}$$

For comparison we also calculate the Expected Shortfall version, or

(4.6) $$RAROC_{ES} = \frac{\overline{R-E-IA_{15-24}}}{1-ES},$$

And the VaR, which is

(4.7) $$RAROC_{VaR} = \frac{\overline{R-E-IA_{15-24}}}{1-VaR}.$$

The confidence level we chose for risk measures are 95% and 99%. Having a closer look at denominators of (4.2), (4.3), (4.4), (4.5), (4.6) and (4.7) we have to consider the following: The results we are getting for risk measures are the worst outcomes which are habitually negative. Also, the numerator gives a glance at the accounting performance of an economic entity. What we get from (4.2), (4.3), (4.4), (4.5), (4.6) and (4.7) is a risk-sensitive conservatism in performance assessment, which could be perceived as complementary with the notion of accounting conservatism (see (Agarwal et al., 2025) or (Zadeh et al., 2022)). Recalling the accounting conservatism holds that

revenues are recognized only when they are realized or assured of being received. Complementary to that it is natural to analyze revenue under the scope of stochastic risk that is quantified by a risk measure.

5. Key Findings

5.1 Market-linked approach: results based on company's betas

In the table below we have the outcomes of the Power Spectral Risk Measure ($d = 1.2$) with regard to the index returns. Moreover, we have the results when we use the Expected Shortfall and the Value at Risk. In the same table we have the results both for 99% and 95% confidence level. The results are in accordance with what is expected, as the most conservative result occurs when Power SRM for 99% is calculated, the least when VaR is employed for 95% confidence level and all other results are in between.

Table 2. Risk Measures outcomes- Historical method

Power Spectral Risk Measure outcome 99%	-5,61%
VaR - 99%	-3,53%
Expected Shortfall - 99%	-4,68%
Power Spectral Risk Measure outcome 95%	-3,46%
VaR - 95%	-1,83%
Expected Shortfall - 95%	-2,89%
Risk Measures outcomes - Historical method	

Table 3 includes in second column all the betas of each company. The third column has the RAROC denominator when we use Power SRM for 99% confidence level (see equation 4.2). Moreover, the fourth column has RAROC denominator with VaR and 99% (see equation 4.4) confidence level and last column includes the results with Expected Shortfall and 99% confidence level (equation 4.3).

Table 3. Betas- RAROC Denominator 99%

Ticket	betas	RAROC Denominator - Power Spectral Risk Measure 99%	RAROC Denominator - VaR - 99%	RAROC Denominator - ES - 99%
ADS GY	0,955	-5,36%	-3,37%	-4,47%

Ticket	betas	RAROC Denominator - Power Spectral Risk Measure 99%	RAROC Denominator - VaR - 99%	RAROC Denominator - ES - 99%
AIR GY	1,230	-6,90%	-4,34%	-5,76%
ALV GY	0,894	-5,01%	-3,16%	-4,18%
BAS GY	1,064	-5,97%	-3,76%	-4,98%
BAYN GY	0,971	-5,45%	-3,43%	-4,55%
BEI GY	0,410	-2,30%	-1,45%	-1,92%
BMW GY	0,933	-5,23%	-3,29%	-4,37%
BNR GY	0,878	-4,93%	-3,10%	-4,11%
CBK GY	1,088	-6,10%	-3,84%	-5,09%
CON GY	1,031	-5,78%	-3,64%	-4,83%
DB1 GY	0,602	-3,38%	-2,13%	-2,82%
DBK GY	1,511	-8,47%	-5,33%	-7,07%
DHL GY	1,065	-5,98%	-3,76%	-4,98%
DTE GY	0,423	-2,37%	-1,49%	-1,98%
DTG GY	1,183	-6,63%	-4,17%	-5,53%
ENR GY	1,606	-9,01%	-5,67%	-7,52%
EOAN GY	0,160	-0,90%	-0,57%	-0,75%
FME GY	0,778	-4,37%	-2,75%	-3,64%
FRE GY	0,669	-3,75%	-2,36%	-3,13%
G1A GY	0,789	-4,42%	-2,78%	-3,69%
G24 GY	0,610	-3,42%	-2,15%	-2,85%
HEI GY	1,389	-7,80%	-4,90%	-6,50%
HEN3 GY	0,362	-2,03%	-1,28%	-1,69%
HNR1 GY	0,680	-3,82%	-2,40%	-3,18%
IFX GY	1,296	-7,27%	-4,57%	-6,06%
MBG GY	0,878	-4,93%	-3,10%	-4,11%
MRK GY	0,665	-3,73%	-2,35%	-3,11%
MTX GY	1,157	-6,49%	-4,08%	-5,41%
MUV2 GY	0,817	-4,58%	-2,88%	-3,82%
PAH3 GY	0,635	-3,57%	-2,24%	-2,97%
QIA GY	0,370	-2,08%	-1,31%	-1,73%
RHM GY	1,061	-5,95%	-3,75%	-4,97%

Ticket	betas	RAROC Denominator - Power Spectral Risk Measure 99%	RAROC Denominator - VaR - 99%	RAROC Denominator - ES - 99%
RWE GY	0,392	-2,20%	-1,38%	-1,83%
SAP GY	1,192	-6,68%	-4,21%	-5,58%
SHL GY	0,758	-4,25%	-2,68%	-3,55%
SIE GY	1,517	-8,51%	-5,35%	-7,10%
SY1 GY	0,308	-1,73%	-1,09%	-1,44%
VNA GY	0,109	-0,61%	-0,39%	-0,51%
VOW3 GY	0,874	-4,90%	-3,09%	-4,09%
ZAL GY	1,059	-5,94%	-3,74%	-4,95%
Betas - RAROC Denominator 99%				

Table 4 includes in second column all the betas of each company. In column three there is the RAROC denominator where we use Power SRM for 95% confidence level (equation 4.2). Moreover, in column 4 we have RAROC denominator with VaR and 95% confidence level (equation 4.4) and last column includes the results with Expected Shortfall and 95% confidence level (equation 4.3).

Table 4. Betas- RAROC Denominator 95%

Ticket	betas	RAROC Denominator - Power Spectral Risk Measure 95%	RAROC Denominator - VaR - 95%	RAROC Denominator - ES - 95%
ADS GY	0,95	-3,30%	-1,75%	-2,76%
AIR GY	1,23	-4,26%	-2,25%	-3,55%
ALV GY	0,89	-3,09%	-1,64%	-2,58%
BAS GY	1,06	-3,68%	-1,95%	-3,08%
BAYN GY	0,97	-3,36%	-1,78%	-2,81%
BEI GY	0,41	-1,42%	-0,75%	-1,18%
BMW GY	0,93	-3,23%	-1,71%	-2,70%
BNR GY	0,88	-3,04%	-1,61%	-2,54%
CBK GY	1,09	-3,76%	-1,99%	-3,14%
CON GY	1,03	-3,57%	-1,89%	-2,98%
DB1 GY	0,60	-2,08%	-1,10%	-1,74%
DBK GY	1,51	-5,23%	-2,76%	-4,37%

Ticket	betas	RAROC Denominator - Power Spectral Risk Measure 95%	RAROC Denominator - VaR - 95%	RAROC Denominator - ES - 95%
DHL GY	1,07	-3,69%	-1,95%	-3,08%
DTE GY	0,42	-1,46%	-0,77%	-1,22%
DTG GY	1,18	-4,09%	-2,16%	-3,42%
ENR GY	1,61	-5,56%	-2,94%	-4,64%
EOAN GY	0,16	-0,55%	-0,29%	-0,46%
FME GY	0,78	-2,69%	-1,42%	-2,25%
FRE GY	0,67	-2,31%	-1,22%	-1,93%
G1A GY	0,79	-2,73%	-1,44%	-2,28%
G24 GY	0,61	-2,11%	-1,12%	-1,76%
HEI GY	1,39	-4,81%	-2,54%	-4,02%
HEN3 GY	0,36	-1,25%	-0,66%	-1,04%
HNR1 GY	0,68	-2,35%	-1,25%	-1,97%
IFX GY	1,30	-4,48%	-2,37%	-3,74%
MBG GY	0,88	-3,04%	-1,61%	-2,54%
MRK GY	0,67	-2,30%	-1,22%	-1,92%
MTX GY	1,16	-4,00%	-2,12%	-3,34%
MUV2 GY	0,82	-2,83%	-1,49%	-2,36%
PAH3 GY	0,64	-2,20%	-1,16%	-1,84%
QIA GY	0,37	-1,28%	-0,68%	-1,07%
RHM GY	1,06	-3,67%	-1,94%	-3,07%
RWE GY	0,39	-1,36%	-0,72%	-1,13%
SAP GY	1,19	-4,12%	-2,18%	-3,44%
SHL GY	0,76	-2,62%	-1,39%	-2,19%
SIE GY	1,52	-5,25%	-2,78%	-4,38%
SY1 GY	0,31	-1,06%	-0,56%	-0,89%
VNA GY	0,11	-0,38%	-0,20%	-0,32%
VOW3 GY	0,87	-3,02%	-1,60%	-2,53%
ZAL GY	1,06	-3,66%	-1,94%	-3,06%
Betas - RAROC Denominator 95%				

Table 5 includes in second column the RAROC numerator, in third column the RAROC of equation (4.2) for 99% confidence level, which uses Power SRM. In fourth column we have VaR based RAROC of equation (4.4) for 99% confidence level. Finally, in fifth column we have ES based RAROC of equation (4.3) for 99% confidence level. All figures presented hereafter in tables are in thousands.

Table 5. RAROC Numerator- RAROC Outcomes 99% confidence level with betas

Ticket	RAROC Numerator	RAROC - PSRM 99%	RAROC - VaR - 99%	RAROC - ES - 99%
ADS GY	12.682.000 €	12.037.392 €	12.268.600 €	12.139.683 €
AIR GY	63.162.000 €	59.085.304 €	60.533.914 €	59.724.338 €
ALV GY	13.998.000 €	13.329.638 €	13.569.865 €	13.435.987 €
BAS GY	48.309.000 €	45.587.749 €	46.560.173 €	46.017.467 €
BAYN GY	19.420.000 €	18.416.533 €	18.776.251 €	18.575.650 €
BEI GY	5.235.000 €	5.117.313 €	5.160.325 €	5.136.455 €
BMW GY	130.187.000 €	123.711.066 €	126.035.559 €	124.739.697 €
BNR GY	13.052.500 €	12.439.690 €	12.660.068 €	12.537.269 €
CBK GY	18.286.000 €	17.234.121 €	17.609.698 €	17.400.048 €
CON GY	31.651.000 €	29.920.329 €	30.539.469 €	30.194.025 €
DB1 GY	2.851.100 €	2.757.899 €	2.791.735 €	2.772.926 €
DBK GY	46.154.000 €	42.548.159 €	43.817.401 €	43.106.449 €
DHL GY	46.788.000 €	44.149.839 €	45.092.536 €	44.566.416 €
DTE GY	20.919.000 €	20.434.573 €	20.611.542 €	20.513.322 €
DTG GY	45.775.000 €	42.927.126 €	43.940.710 €	43.374.475 €
ENR GY	29.785.000 €	27.322.911 €	28.186.789 €	27.702.528 €
EOAN GY	-3.653.000 €	-3.620.431 €	-3.632.439 €	-3.625.790 €
FME GY	15.701.910 €	15.045.141 €	15.282.139 €	15.150.192 €
FRE GY	17.944.000 €	17.295.175 €	17.530.189 €	17.399.470 €
G1A GY	3.738.892 €	3.580.491 €	3.637.630 €	3.605.815 €
G24 GY	252.986 €	244.615 €	247.653 €	245.964 €
HEI GY	1.870.100 €	1.734.865 €	1.782.661 €	1.755.915 €
HEN3 GY	13.407.000 €	13.140.502 €	13.238.066 €	13.183.946 €
HNR1 GY	3.252.700 €	3.133.097 €	3.176.402 €	3.152.312 €
IFX GY	10.937.000 €	10.195.815 €	10.458.601 €	10.311.660 €

Ticket	RAROC Numerator	RAROC - PSRM 99%	RAROC - VaR - 99%	RAROC - ES - 99%
MBG GY	127.009.000 €	121.044.251 €	123.189.270 €	121.994.017 €
MRK GY	11.970.000 €	11.539.357 €	11.695.361 €	11.608.591 €
MTX GY	6.948.000 €	6.524.568 €	6.675.403 €	6.591.157 €
MUV2 GY	59.423.000 €	56.819.560 €	57.757.778 €	57.235.257 €
PAH3 GY	-66.000 €	-63.728 €	-64.551 €	-64.093 €
QIA GY	1.108.575 €	1.086.012 €	1.094.269 €	1.089.689 €
RHM GY	1.205.000 €	1.137.280 €	1.161.481 €	1.147.975 €
RWE GY	314.000 €	307.247 €	309.716 €	308.346 €
SAP GY	13.908.000 €	13.036.563 €	13.346.621 €	13.173.395 €
SHL GY	16.685.000 €	16.004.062 €	16.249.948 €	16.113.075 €
SIE GY	55.121.000 €	50.798.865 €	52.319.934 €	51.467.883 €
SY1 GY	3.704.923 €	3.642.075 €	3.665.126 €	3.652.346 €
VNA GY	4.820.500 €	4.791.175 €	4.802.006 €	4.796.012 €
VOW3 GY	272.135.000 €	259.414.424 €	263.989.619 €	261.440.310 €
ZAL GY	6.641.500 €	6.269.215 €	6.402.274 €	6.328.017 €
RAROC Numerator - RAROC Outcomes 99% confidence level				

Table 6 includes in third column the RAROC of equation (4.2) for 95% confidence level, which uses Power SRM. In fourth column we have VaR based RAROC of equation (4.4) for 95% confidence level. Finally, in fifth column we have ES based RAROC of equation (4.3) for 95% confidence level.

Table 6. RAROC Numerator- RAROC Outcomes 95% confidence level with betas

Ticket	RAROC Numerator	RAROC - PSRM 95%	RAROC - VaR - 95%	RAROC - ES - 95%
ADS GY	12.682.000 €	12.276.536 €	12.464.270 €	12.341.539 €
AIR GY	63.162.000 €	60.583.902 €	61.771.706 €	60.994.040 €
ALV GY	13.998.000 €	13.578.100 €	13.772.730 €	13.645.532 €
BAS GY	48.309.000 €	46.593.621 €	47.386.298 €	46.867.781 €
BAYN GY	19.420.000 €	18.788.602 €	19.080.858 €	18.889.778 €
BEI GY	5.235.000 €	5.161.785 €	5.196.019 €	5.173.705 €
BMW GY	130.187.000 €	126.115.308 €	128.001.270 €	126.768.464 €
BNR GY	13.052.500 €	12.667.621 €	12.846.069 €	12.729.456 €

Ticket	RAROC Numerator	RAROC - PSRM 95%	RAROC - VaR - 95%	RAROC - ES - 95%
CBK GY	18.286.000 €	17.622.623 €	17.929.038 €	17.728.576 €
CON GY	31.651.000 €	30.560.752 €	31.064.854 €	30.735.162 €
DB1 GY	2.851.100 €	2.792.888 €	2.820.012 €	2.802.314 €
DBK GY	46.154.000 €	43.861.434 €	44.912.404 €	44.223.312 €
DHL GY	46.788.000 €	45.124.962 €	45.893.437 €	45.390.749 €
DTE GY	20.919.000 €	20.617.551 €	20.758.473 €	20.666.613 €
DTG GY	45.775.000 €	43.975.654 €	44.805.367 €	44.262.282 €
ENR GY	29.785.000 €	28.216.813 €	28.934.487 €	28.463.695 €
EOAN GY	-3.653.000 €	-3.632.844 €	-3.642.311 €	-3.636.149 €
FME GY	15.701.910 €	15.290.245 €	15.481.457 €	15.356.571 €
FRE GY	17.944.000 €	17.538.210 €	17.727.065 €	17.603.792 €
G1A GY	3.738.892 €	3.639.585 €	3.685.702 €	3.655.580 €
G24 GY	252.986 €	247.757 €	250.193 €	248.603 €
HEI GY	1.870.100 €	1.784.316 €	1.823.726 €	1.797.902 €
HEN3 GY	13.407.000 €	13.241.374 €	13.318.887 €	13.268.377 €
HNR1 GY	3.252.700 €	3.177.880 €	3.212.694 €	3.189.968 €
IFX GY	10.937.000 €	10.467.680 €	10.683.654 €	10.542.205 €
MBG GY	127.009.000 €	123.262.781 €	124.999.698 €	123.864.654 €
MRK GY	11.970.000 €	11.700.685 €	11.826.033 €	11.744.215 €
MTX GY	6.948.000 €	6.680.600 €	6.803.960 €	6.723.227 €
MUV2 GY	59.423.000 €	57.789.892 €	58.547.916 €	58.052.726 €
PAH3 GY	-66.000 €	-64.580 €	-65.241 €	-64.809 €
QIA GY	1.108.575 €	1.094.550 €	1.101.112 €	1.096.836 €
RHM GY	1.205.000 €	1.162.314 €	1.182.040 €	1.169.136 €
RWE GY	314.000 €	309.800 €	311.764 €	310.484 €
SAP GY	13.908.000 €	13.357.312 €	13.611.204 €	13.445.013 €
SHL GY	16.685.000 €	16.258.354 €	16.456.595 €	16.327.132 €
SIE GY	55.121.000 €	52.372.710 €	53.632.461 €	52.806.451 €
SY1 GY	3.704.923 €	3.665.907 €	3.684.184 €	3.672.278 €
VNA GY	4.820.500 €	4.802.371 €	4.810.894 €	4.805.348 €
VOW3 GY	272.135.000 €	264.146.401 €	267.850.566 €	265.430.017 €
ZAL GY	6.641.500 €	6.406.850 €	6.515.292 €	6.444.359 €

Ticket	RAROC Numerator	RAROC - PSRM 95%	RAROC - VaR - 95%	RAROC - ES - 95%
RAROC Numerator - RAROC Outcomes 95% confidence level				

Across the DAX 40 firms, increasing conservatism in the underlying risk measure systematically reduces the resulting RAROC. This indicates that the selection of the risk measure materially affects the interpretation of accounting-based performance and, consequently, the capital required to support that performance. This suggests that a conservative risk measure is appropriate in a severe recession or any other occasion (choose a conservative risk measure). Also, in terms of Performance management a manager might choose different cases for his forecasting. For instance an optimistic, a neutral or a pessimistic one and then her/his analysis could proceed accordingly. As (Drury, 2018) suggests, individuals within the economic entity should get the necessary help in order to make the best decisions possible and improve the efficiency of operations withing the entity.

Table 7 reports paired t-tests. There, we perform paired t-tests. Specifically, with regard to the first column we calculate the p-value of a paired Student's T-test with a two-tailed distribution between two groups of data. The p-value determines if there is a statistically significant difference between the means of the two groups. A result below 0.05 typically indicates that the difference is significant. Also, in second column we have calculations of the p-value of a paired Student's t-test with a one-tailed distribution. It determines whether the two related data sets have a statistically significant difference between their means. Again, a result below 0.05 typically indicates that the difference is significant.

Table 7. t-tests between numerator and risk measures (market-linked)

RAROC N.- PSRM 99%	
0,000253627	0,000126814
RAROC N. - VaR - 99%	
0,000248809	0,000124405
RAROC N. - ES - 99%	
0,000251487	0,000125744
RAROC N. - PSRM 95%	
0,000248645	0,000124323
RAROC N. - VaR - 95%	

0,000244787	0,000122394
RAROC N. - ES - 95%	
0,000247304	0,000123652
t-tests	

We compare RAROC's numerator, as extracted from the accounting statements, with all the results after using risk measures. In all cases we observe from table seven that the differences are statistically significant, even more than 99% confidence level. The above results give significantly different results once an accountant or a financial analyst considers the quantified risk that is stochastically evaluated.

Table 8. t-tests between PSRM – ES & VaR (market-linked)

PSRM vs VaR 99%	
0,000262654	0,000131327
PSRM vs ES 99%	
0,000265516	0,000132758
Var vs ES 99%	
0,00026042	0,00013021
PSRM vs VaR 95%	
0,000253255	0,000126627
PSRM vs ES 95%	
0,000255882	0,000127941
VaR vs ES 95%	
0,000251882	0,000125941
t-tests	

In table 8 we examine if the differences between the different risk measures we employ are statistically significant. The methodology is identical to that used for table 7. Once again, all differences are statistically significant, even at 99% confidence level.

5.2 Firm specific approach

Table 9 includes in second column the RAROC denominator when we use Power SRM for 99% confidence level (see equation 4.5). Moreover, in third column we have RAROC denominator with VaR and 99% (see equation 4.7) confidence level and last column includes the results with Expected Shortfall and 99% confidence level (equation 4.6).

Table 9. RAROC Denominator 99%

Ticket	RAROC Denominator - Power Spectral Risk Measure 99%	RAROC Denominator - VaR - 99%	RAROC Denominator - ES - 99%
ADS GY	-8,05%	-5,19%	-6,71%
AIR GY	-10,95%	-5,49%	-9,13%
ALV GY	-7,32%	-3,82%	-6,10%
BAS GY	-7,63%	-4,87%	-6,37%
BAYN GY	-9,76%	-4,94%	-8,14%
BEI GY	-5,62%	-3,32%	-4,69%
BMW GY	-8,35%	-5,16%	-6,96%
BNR GY	-8,17%	-4,83%	-6,81%
CBK GY	-11,75%	-6,94%	-9,80%
CON GY	-9,80%	-5,90%	-8,17%
DB1 GY	-6,11%	-3,61%	-5,09%
DBK GY	-11,27%	-6,97%	-9,40%
DHL GY	-7,43%	-4,39%	-6,20%
DTE GY	-6,28%	-3,86%	-5,24%
DTG GY	-6,83%	-4,27%	-5,69%
ENR GY	-11,72%	-5,47%	-9,77%
EOAN GY	-7,64%	-4,65%	-6,37%
FME GY	-8,85%	-4,63%	-7,38%
FRE GY	-7,86%	-4,66%	-6,56%
G1A GY	-9,39%	-4,55%	-7,83%
G24 GY	-7,39%	-4,32%	-6,17%
HEI GY	-8,12%	-4,64%	-6,77%
HEN3 GY	-6,47%	-3,41%	-5,39%
HNR1 GY	-7,08%	-4,17%	-5,91%
IFX GY	-9,22%	-5,80%	-7,69%
MBG GY	-9,40%	-6,00%	-7,84%
MRK GY	-7,00%	-4,26%	-5,84%
MTX GY	-10,37%	-5,69%	-8,65%
MUV2 GY	-7,54%	-4,29%	-6,29%

Ticket	RAROC Denominator - Power Spectral Risk Measure 99%	RAROC Denominator - VaR - 99%	RAROC Denominator - ES - 99%
PAH3 GY	-10,52%	-5,56%	-8,77%
QIA GY	-7,47%	-3,97%	-6,23%
RHM GY	-9,49%	-5,91%	-7,92%
RWE GY	-9,69%	-5,60%	-8,08%
SAP GY	-6,90%	-3,71%	-5,76%
SHL GY	-6,67%	-3,93%	-5,57%
SIE GY	-7,24%	-4,63%	-6,04%
SY1 GY	-6,15%	-3,82%	-5,13%
VNA GY	-7,54%	-5,10%	-6,29%
VOW3 GY	-10,76%	-5,58%	-8,98%
ZAL GY	-10,91%	-7,28%	-9,10%
RAROC Denominator 99%			

Table 10 includes in second column the RAROC denominator when we use Power SRM for 95% confidence level (equation 4.5). Moreover, in column 4 we have RAROC denominator with VaR and 95% confidence level (equation 4.7) and last column includes the results with Expected Shortfall and 95% confidence level (equation 4.6).

Table 10. RAROC Denominator 95%

Ticket	RAROC Denominator - Power Spectral Risk Measure 95%	RAROC Denominator - VaR - 95%	RAROC Denominator - ES - 95%
ADS GY	-4,99%	-2,78%	-4,17%
AIR GY	-5,83%	-3,01%	-4,88%
ALV GY	-4,19%	-2,22%	-3,50%
BAS GY	-4,85%	-2,58%	-4,05%
BAYN GY	-5,42%	-2,86%	-4,53%
BEI GY	-3,41%	-1,89%	-2,85%

Ticket	RAROC Denominator - Power Spectral Risk Measure 95%	RAROC Denominator - VaR - 95%	RAROC Denominator - ES - 95%
BMW GY	-5,07%	-2,81%	-4,24%
BNR GY	-4,71%	-2,40%	-3,94%
CBK GY	-7,11%	-3,96%	-5,95%
CON GY	-6,00%	-3,33%	-5,02%
DB1 GY	-3,76%	-2,11%	-3,15%
DBK GY	-6,98%	-3,82%	-5,84%
DHL GY	-4,61%	-2,57%	-3,85%
DTE GY	-3,73%	-2,03%	-3,12%
DTG GY	-4,41%	-2,37%	-3,69%
ENR GY	-5,90%	-2,95%	-4,94%
EOAN GY	-4,75%	-2,67%	-3,98%
FME GY	-5,01%	-2,77%	-4,19%
FRE GY	-4,79%	-2,71%	-4,01%
G1A GY	-5,01%	-2,54%	-4,19%
G24 GY	-4,48%	-2,47%	-3,75%
HEI GY	-4,94%	-2,74%	-4,14%
HEN3 GY	-3,69%	-1,99%	-3,09%
HNR1 GY	-4,24%	-2,19%	-3,55%
IFX GY	-6,09%	-3,55%	-5,10%
MBG GY	-5,53%	-2,88%	-4,63%
MRK GY	-4,37%	-2,49%	-3,66%
MTX GY	-5,74%	-2,94%	-4,80%
MUV2 GY	-4,19%	-2,15%	-3,51%
PAH3 GY	-5,84%	-3,06%	-4,88%
QIA GY	-4,20%	-2,26%	-3,52%

Ticket	RAROC Denominator - Power Spectral Risk Measure 95%	RAROC Denominator - VaR - 95%	RAROC Denominator - ES - 95%
RHM GY	-5,86%	-3,27%	-4,90%
RWE GY	-5,80%	-3,18%	-4,85%
SAP GY	-4,14%	-2,34%	-3,47%
SHL GY	-4,13%	-2,36%	-3,45%
SIE GY	-4,62%	-2,57%	-3,86%
SY1 GY	-3,88%	-2,05%	-3,25%
VNA GY	-4,98%	-2,68%	-4,17%
VOW3 GY	-5,95%	-3,12%	-4,98%
ZAL GY	-7,17%	-4,14%	-6,00%
RAROC Denominator 95%			

Table 11 includes in second column the RAROC numerator, in third column the RAROC of equation (4.5) for 99% confidence level, which uses Power SRM. In fourth column we have VaR based RAROC of equation (4.7) for 99% confidence level. Finally, in fifth column we have ES based RAROC of equation (4.6) for 99% confidence level.

Table 11. RAROC numerator - RAROC Outcomes 99% confidence level

Ticket	RAROC Numerator	RAROC - PSRM 99%	RAROC - VaR - 99%	RAROC - ES - 99%
ADS GY	11.690.900 €	10.819.842 €	11.113.772 €	10.955.324 €
AIR GY	55.678.400 €	50.184.822 €	52.782.743 €	51.020.687 €
ALV GY	77.074.000 €	71.818.803 €	74.239.750 €	72.641.224 €
BAS GY	51.422.700 €	47.775.281 €	49.034.004 €	48.344.409 €
BAYN GY	17.659.900 €	16.089.110 €	16.828.980 €	16.330.302 €
BEI GY	4.200.600 €	3.977.160 €	4.065.728 €	4.012.588 €
BMW GY	103.321.200 €	95.359.042 €	98.254.963 €	96.594.739 €
BNR GY	11.324.450 €	10.469.065 €	10.802.674 €	10.601.983 €
CBK GY	7.991.100 €	7.150.834 €	7.472.711 €	7.277.877 €
CON GY	31.343.240 €	28.545.332 €	29.596.804 €	28.974.693 €

Ticket	RAROC Numerator	RAROC - PSRM 99%	RAROC - VaR - 99%	RAROC - ES - 99%
DB1 GY	1.629.070 €	1.535.286 €	1.572.289 €	1.550.102 €
DBK GY	19.614.700 €	17.627.320 €	18.337.337 €	17.928.852 €
DHL GY	27.958.700 €	26.024.503 €	26.783.823 €	26.326.819 €
DTE GY	9.893.200 €	9.308.656 €	9.525.567 €	9.400.855 €
DTG GY	39.953.857 €	37.400.659 €	38.319.479 €	37.801.634 €
ENR GY	25.592.250 €	22.907.744 €	24.264.095 €	23.314.032 €
EOAN GY	-17.879.000 €	-16.610.376 €	-17.085.010 €	-16.808.334 €
FME GY	14.399.501 €	13.229.137 €	13.762.295 €	13.410.137 €
FRE GY	24.530.100 €	22.742.092 €	23.438.044 €	23.020.674 €
G1A GY	3.242.254 €	2.963.845 €	3.101.206 €	3.006.727 €
G24 GY	157.843 €	146.976 €	151.311 €	148.675 €
HEI GY	1.166.980 €	1.079.316 €	1.115.239 €	1.092.945 €
HEN3 GY	13.197.300 €	12.395.534 €	12.761.809 €	12.521.845 €
HNR1 GY	17.719.691 €	16.547.872 €	17.010.716 €	16.731.555 €
IFX GY	7.546.400 €	6.909.579 €	7.132.601 €	7.007.742 €
MBG GY	129.701.600 €	118.561.922 €	122.360.483 €	120.276.732 €
MRK GY	8.848.550 €	8.269.535 €	8.487.283 €	8.360.346 €
MTX GY	4.493.940 €	4.071.726 €	4.251.895 €	4.136.241 €
MUV2 GY	56.300.300 €	52.351.520 €	53.986.278 €	52.968.277 €
PAH3 GY	-75.500 €	-68.316 €	-71.523 €	-69.413 €
QIA GY	898.387 €	835.952 €	864.099 €	845.714 €
RHM GY	410.800 €	375.184 €	387.874 €	380.661 €
RWE GY	-4.043.500 €	-3.686.301 €	-3.829.239 €	-3.741.166 €
SAP GY	12.974.500 €	12.136.505 €	12.510.341 €	12.268.084 €
SHL GY	12.472.700 €	11.692.254 €	12.000.675 €	11.814.962 €
SIE GY	53.985.800 €	50.340.093 €	51.596.092 €	50.910.761 €
SY1 GY	2.680.823 €	2.525.395 €	2.582.177 €	2.549.935 €
VNA GY	5.345.500 €	4.970.601 €	5.086.348 €	5.029.136 €
VOW3 GY	210.530.30 €	190.069.607 €	199.394.333 €	193.187.255 €
ZAL GY	4.442.260 €	4.005.196 €	4.140.911 €	4.071.674 €
RAROC Numerator - RAROC Outcomes 99% confidence level				

Table 12 includes in second column the RAROC numerator, in third column the RAROC of equation (4.5) for 95% confidence level, which uses Power SRM. In fourth column we have VaR based RAROC of equation (4.7) for 95% confidence level. Finally, in fifth column we have ES based RAROC of equation (4.6) for 95% confidence level.

Table 12. RAROC numerator - RAROC Outcomes 95% confidence level

Ticket	RAROC Numerator	RAROC - PSRM 95%	RAROC - VaR - 95%	RAROC - ES - 95%
ADS GY	11.690.900 €	11.135.374 €	11.374.907 €	11.222.413 €
AIR GY	55.678.400 €	52.610.489 €	54.052.312 €	53.088.617 €
ALV GY	77.074.000 €	73.977.800 €	75.398.351 €	74.466.459 €
BAS GY	51.422.700 €	49.046.015 €	50.127.505 €	49.418.795 €
BAYN GY	17.659.900 €	16.752.063 €	17.169.014 €	16.893.962 €
BEI GY	4.200.600 €	4.062.075 €	4.122.500 €	4.084.059 €
BMW GY	103.321.200 €	98.335.713 €	100.501.007 €	99.116.469 €
BNR GY	11.324.450 €	10.815.420 €	11.059.428 €	10.895.417 €
CBK GY	7.991.100 €	7.460.614 €	7.686.413 €	7.542.358 €
CON GY	31.343.240 €	29.569.380 €	30.332.869 €	29.845.085 €
DB1 GY	1.629.070 €	1.570.046 €	1.595.345 €	1.579.386 €
DBK GY	19.614.700 €	18.334.961 €	18.893.687 €	18.532.332 €
DHL GY	27.958.700 €	26.727.819 €	27.257.696 €	26.921.252 €
DTE GY	9.893.200 €	9.537.541 €	9.695.892 €	9.593.858 €
DTG GY	39.953.857 €	38.267.366 €	39.027.409 €	38.532.779 €
ENR GY	25.592.250 €	24.166.396 €	24.860.050 €	24.388.658 €
EOAN GY	-17.879.000 €	-17.067.740 €	-17.414.454 €	-17.195.076 €
FME GY	14.399.501 €	13.712.912 €	14.011.460 €	13.820.546 €
FRE GY	24.530.100 €	23.407.718 €	23.881.971 €	23.583.863 €
G1A GY	3.242.254 €	3.087.442 €	3.161.913 €	3.111.728 €
G24 GY	157.843 €	151.078 €	154.040 €	152.142 €
HEI GY	1.166.980 €	1.112.001 €	1.135.874 €	1.120.619 €
HEN3 GY	13.197.300 €	12.727.503 €	12.939.909 €	12.801.937 €
HNR1 GY	17.719.691 €	16.998.470 €	17.339.755 €	17.112.212 €
IFX GY	7.546.400 €	7.113.270 €	7.287.417 €	7.180.489 €

Ticket	RAROC Numerator	RAROC - PSRM 95%	RAROC - VaR - 95%	RAROC - ES - 95%
MBG GY	129.701.600 €	122.902.385 €	126.073.651 €	123.963.858 €
MRK GY	8.848.550 €	8.477.906 €	8.633.194 €	8.536.262 €
MTX GY	4.493.940 €	4.250.131 €	4.365.677 €	4.288.151 €
MUV2 GY	56.300.300 €	54.033.968 €	55.116.499 €	54.391.762 €
PAH3 GY	-75.500 €	-71.336 €	-73.255 €	-71.984 €
QIA GY	898.387 €	862.141 €	878.495 €	867.862 €
RHM GY	410.800 €	388.068 €	397.794 €	391.605 €
RWE GY	-4.043.500 €	-3.821.902 €	-3.918.749 €	-3.856.406 €
SAP GY	12.974.500 €	12.458.366 €	12.677.775 €	12.539.794 €
SHL GY	12.472.700 €	11.978.262 €	12.185.521 €	12.056.264 €
SIE GY	53.985.800 €	51.602.763 €	52.635.296 €	51.977.198 €
SY1 GY	2.680.823 €	2.580.734 €	2.626.906 €	2.596.556 €
VNA GY	5.345.500 €	5.092.042 €	5.206.133 €	5.131.744 €
VOW3 GY	210.530.300 €	198.709.510 €	204.166.221 €	200.549.477 €
ZAL GY	4.442.260 €	4.144.955 €	4.265.683 €	4.190.707 €
RAROC Numerator - RAROC Outcomes 95% confidence level				

As in tables five and six, tables ten and eleven show that the more conservative the risk measure we use, the less the outcome becomes. This gives a rather intuitive explanation of how we should function in cases of extreme recession or any other occasion (choose a conservative risk measure). Also, in terms of Performance management a manager might choose different cases for his forecasting (for instance an optimistic, a neutral or a pessimistic one).

A key finding lies in table 13 where we perform several paired t-tests. By choosing paired two tails test, we examine if the different values we are getting a statistically significant difference. For instance, a result less than 0.05 suggests statistical important difference at 95% confidence level.

Table 13. t-tests between numerator and risk measures (firm specific)

RAROC N. - PSRM 99%	
0,000891844	0,000446

RAROC N. - VaR - 99%	
0,000664929	0,000332
RAROC N. - ES - 99%	
0,000904847	0,000452
RAROC N. - PSRM 95%	
0,000689888	0,000345
RAROC N. - VaR - 95%	
0,000611649	0,000306
RAROC N. - ES - 95%	
0,000693965	0,000347
t-tests	

In tandem with table 7, we compare RAROC's numerator, as extracted from the accounting statements, with all the results after utilizing risk measures. In all cases we observe from table 13 that the differences are statistically significant, even more than 99% confidence level. Like in table 7 the above results clearly give significantly different results once an accountant or a financial analyst considers the risk that is quantified by means of risk measures.

Table 14. t-tests between PSRM – ES & VaR (firm specific)

PSRM vs VaR 99%	
0,00154223	0,00077
PSRM vs ES 99%	
0,00082362	0,00041
Var vs ES 99%	
0,00233526	0,00117
PSRM vs VaR 95%	
0,00080069	0,0004
PSRM vs ES 95%	
0,00066831	0,00033
Var vs ES 95%	
0,00088122	0,00044
t-tests	

In table 14, and in tandem with table 8 we examine if the differences between the different risk measures we employ are statistically significant. Similar to the results we get in table 8, again in table 14 all differences are statistically significant, even at 99% confidence level. It should also be noted that in both approaches, market linked or firm specific, the conclusions are not deviating. A possible

explanation could be that in a mature market we wouldn't expect significant differences in risk sensitivity analysis depending on whether the emphasis is placed on the index itself or its constituents.

6. Conclusion and Future Research

This paper examined the incorporation of SRMs into the RAROC. The main reason for that is the contribution to Accounting and Finance information by quantifying risk stochastically. Such contribution may be useful for Auditing, Management Accounting and also for investing reasons. Similar efforts with regard to accounting can be found in (Mitroulia et. Al., 2025), who examine primarily the causality between ESG policies and tax avoidance.

Also, we suggested a methodology based on (Zachos, 2023 and Zachos, 2026) where quantification of risk is suggested and is incorporated in the risk spectrum of the used risk measure. In addition, we calculated SRM-based RAROC, VaR-based RAROC and we supplemented our work by calculating Expected Shortfall-based RAROC. In terms of data, we decided to work with a mature market and so we used historical data of DAX 40 and the companies that constitute the index.

Key findings are depicted in table 7 and 8 where we get statistical significance for the different values we get in RAROC, depending on the risk measure we employ. Specifically, in table 7 we compare RAROC's numerator, as extracted from the accounting statements, with all the results after using risk measures. It is clear that once a financial analyst, an accountant or even an investor decides to consider the risk that is quantified stochastically, it gets statistically significant results and thus it should most definitely be included in her/his analysis. Also, the findings in table 8 suggest that the results are sensitive to the risk measure employed. More importantly the results vary and more important they are statistically significant, even at 99% confidence level. One possible explanation could be the coherence issues that certain risk measures exhibit, in our case VaR.

Equally important to the above results are the ones we are getting from the firm specific approach in tables 13 and 14. Also, with regard to the numerator we have calculated a ten-year average (2015-2024) for Revenue, Expenses and asset impairment respectively. Like in table 7 and 8 we get statistical significance for the different values we get even at 99% confidence level. Also, by comparing market linked (see 5.1) or firm specific (see 5.2), the results are similar. This may be because we choose a mature market and thus, we consider that there are no significant differences between the index and its constituents when we attempt risk sensitivity analysis.

With regard to addressing the three main questions stated in introduction and therefore the aforementioned outcomes we may conclude that 1) the choice of risk measure does affect RAROC

estimates, as demonstrated at the tables. Also, the proposed SRM-based RAROC does generate materially different risk-adjusted performance measures compared with VaR- and ES-based RAROC, as presented in t-test we performed. Moreover, the incorporation of risk aversion through the spectral weighting function contributes to additional flexibility for risk-sensitive financial and accounting performance assessment.

In terms of data limitations, we should mention what remains unresolved. First, such findings need to be backed up with complementary research on a different data set. To that end regarding future research, we should consider an emerging market. We believe that in tandem with our findings from DAX 40, which is a mature one, we will get a rather robust result. Also, a different approach like sector analysis would be of great interest. In terms of model limitations, we should consider d values other than 1.2, in order to complement our analysis. In a nutshell we mention that 1.2 is mostly risk averse approach, reflecting a rather conservative analyst. We believe that it would be extremely useful to complement our research with different risk tolerance profiles. A further limitation is that betas were estimated by OLS regression analysis for extracting betas. In the near future we should also consider the Heteroskedasticity that is apparent in such time series data and select models that consider that characteristic (for instance Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models). Summing up, EOAN (E.ON SE), PAH3 (PORSCHE AUTOMOBIL HLDG-PRF) and RWE (RWE AG) in firm specific approach, demonstrated losses. By employing our methodology, we are getting counter intuitive results in the sense that while we use a more conservative approach, we end up with less pessimistic results. This is an indication that the proposed methodology is not suitable, at least not without modifications when we are analyzing performance of an entity which exhibits losses.

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Appendix

Table 1. DAX Coding

GICS Sector Code	GICS Sector	Ticker	Company Name	Sub-sector/Industry Group
2010	Aerospace & Defense	AIR GY	AIRBUS SE	Aerospace & Defense
2010	Aerospace & Defense	RHM GY	RHEINMETALL AG	Aerospace & Defense
2010	Aerospace & Defense	MTX GY	MTU AERO ENGINES AG	Aerospace & Defense
2510	Automobiles & Components	BMW GY	BAYERISCHE MOTOREN WERKE AG	Automobiles
2510	Automobiles & Components	MBG GY	MERCEDES-BENZ GROUP AG	Automobiles
2510	Automobiles & Components	VOW3 GY	VOLKSWAGEN AG-PREF	Automobiles
2510	Automobiles & Components	PAH3 GY	PORSCHE AUTOMOBIL HLDG-PRF	Automobiles
4010	Banks	DBK GY	DEUTSCHE BANK AG-REGISTERED	Banks
4010	Banks	CBK GY	COMMERZBANK AG	Banks
1510	Materials	BAS GY	BASF SE	Chemicals
3030	Consumer Staples	BEI GY	BEIERSDORF AG	Personal Care Products
3030	Consumer Staples	HEN3 GY	HENKEL AG & CO KGAA VOR-PREF	Household Products
1510	Materials	SY1 GY	SYMRISE AG	Specialty Chemicals
2530	Consumer Discretionary	ZAL GY	ZALANDO SE	Internet & Direct Marketing Retail
5510	Utilities	EOAN GY	E.ON SE	Electric Utilities
5510	Utilities	RWE GY	RWE AG	Electric Utilities
5510	Utilities	ENR GY	SIEMENS ENERGY AG	Renewable Energy/Utilities
4020	Financial Services	DB1 GY	DEUTSCHE BOERSE AG	Capital Markets
3510	Health Care	BAYN GY	BAYER AG-REG	Pharmaceuticals
3510	Health Care	MRK GY	MERCK KGAA	Life Sciences Tools & Services

GICS Sector Code	GICS Sector	Ticker	Company Name	Sub-sector/Industry Group
3510	Health Care	FME GY	FRESENIUS MEDICAL CARE AG	Health Care Equipment & Supplies
3510	Health Care	FRE GY	FRESENIUS SE & CO KGAA	Health Care Providers & Services
3510	Health Care	SHL GY	SIEMENS HEALTHINEERS AG	Health Care Equipment
3510	Health Care	QIA GY	QIAGEN N.V.	Biotechnology
2010	Industrials	SIE GY	SIEMENS AG-REG	Industrial Conglomerates
2010	Industrials	G1A GY	GEA GROUP AG	Industrial Machinery
1510	Materials	HEI GY	HEIDELBERG MATERIALS AG	Construction Materials
2510	Automobiles & Components	CON GY	CONTINENTAL AG	Auto Components
2010	Industrials	DTG GY	DAIMLER TRUCK HOLDING AG	Commercial Vehicles & Trucks
4030	Insurance	ALV GY	ALLIANZ SE-REG	Insurance
4030	Insurance	MUV2 GY	MUENCHENER RUECKVER AG-REG	Insurance
4030	Insurance	HNR1 GY	HANNOVER RUECK SE	Insurance
2010	Industrials	DHL GY	DHL GROUP	Air Freight & Logistics
2010	Industrials	BNR GY	BRENNTAG SE	Trading Companies & Distributors
6010	Real Estate	VNA GY	VONOVIA SE	Real Estate Management & Development
2520	Consumer Discretionary	ADS GY	ADIDAS AG	Textiles, Apparel & Luxury Goods
4510	Information Technology	SAP GY	SAP SE	Software
4510	Information Technology	IFX GY	INFINEON TECHNOLOGIES AG	Semiconductors
4510	Information Technology	G24 GY	SCOUT24 SE	Internet Services & Digital Classifieds
5010	Communication Services	DTE GY	DEUTSCHE TELEKOM AG-REG	Telecommunication Services

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- dataRQFA.xlsx