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Quantifying Financial Contagion: ΔCoVaR and Systemic Risk Across German and Italian Financial Institutions

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Abstract

This thesis examines systemic risk in the German and Italian financial systems by estimating the contribution of individual institutions to system distress. Thourgh annual accounting-based returns instead of market data, the analysis extends the applicability of ΔCoVaR to non-listed banks and insurers.. Moreover, equity participations are incorporated to capture structural interconnectedness and potential contagion channels.The results show that different institutions do not contribute to systemic risk in the same way: some have a stronger impact, while others play a much smaller role on the financial system. In the conclusion, the study shows the importance of careful supervision and strong stability measures to limit the spread of crises within the financial system.

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Finally, I thank myself for the determination and commitment that brought me to this point where i am.

Summary

This thesis investigates systemic risk and financial contagion in the German and Italian financial sector by applying the ΔCoVaR methodology proposed by Adrian and Brunnermeier (2016). The analysis combines accounting-based annual returns (2007–2024) with market-based data, and further adds cross-partecipations between banks and insurance companies to give a graphical representation of the systemic network.

The methodology employs the Cornish–Fisher expansion to estimate Value at Risk with limited annual observations, and a set of univariate regressions to quantify systemic effect of each institution to the whole financial system. Both robustness checks (Historical Simulation vs. Cornish–Fisher) and methodological comparisons (Quantile Regression vs. Cornish–Fisher) are performed.

The results highlight that large players such as Deutsche Bank, DZ Bank, and Munich Re emerge as systemically significant, while at the same time smaller institutions show almost stabilizing or insignificant effects. Differences between employing accounting and market based returns show that it is useful to look at both past and current market data.

The aim of this thesis is not to provide concrete policy implications but rather an illustrative framework showing how ΔCoVaR and network analysis can be applied to capture interdependencies in the German financial system. While the exercise remains constrained by limited data, the methodology could prove more robust and parsimonious if applied to deeper and broader datasets, thereby offering a more accurate representation of systemic vulnerabilities.

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Table 1: Glossary of key terms and notation

Term	Meaning
AR	Annual Return
CF	Cornish–Fisher expansion
CoVaR	Conditional Value at Risk
ΔCoVaR	Marginal change in system VaR
CSR	Corporate Social Responsibility
DF	Degrees of Freedom
ECB	European Central Bank
ETF	Exchange-Traded Fund
GFC	Global Financial Crisis (2007–2009)
HS	Historical Simulation
MES	Marginal Expected Shortfall
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
QR	Quantile Regression
ROE	Return on Equity
SE	Standard Error
UCITS	EU Directive for Undertakings for Collective Investment in Transferable Securities
VaR	Value at Risk

1 Introduction

The goal of this work is to give a picture of the German financial system by mapping German banks and insurers, more or less relevant. To do so, we assign each financial institution a risk level that measures its contribution to the whole financial system when it is under stress. As for Germany, the financial system is bank-based and highly decentralized, and the banking sector has the classic three-pillar structure: private banks (e.g., Deutsche Bank, Commerzbank), public banks (Sparkassen and Landesbanken), and cooperatives (Volks-/Raiffeisen), strongly rooted at the regional level. Precisely because it is bank-based and very interconnected, most intermediation runs through banks, so shocks to liquidity, funding, or credit propagate quickly through interbank links and regional chains (Sparkassen–Landesbanken). The three-pillar structure, together with networks and (at times) implicit guarantees, can create moral hazard and contagion.

Outline. —The remainder of the work is organized in five sections. In Section 3 presents the literature review, why we need financial intermediations and their dangers. Section 4 defines the key concepts and measurements and explains the methodology adopted. Section 5 reports the results and compares them with the quantile-regression approach used by Adrian and Brunnermeier, while Section 6 offers the discussion, limitations, and conclusions.

2 Background

2.1 Financial Intermediation and Liquidity Needs

In Diamond and Dybvig (1983), ex-ante identical agents have stochastic liquidity needs: liquidity is not always required, only when someone must make a payment. However, it is costly: keeping liquidity buffers for emergencies prevents investing that liquidity, and in the worst cases liquidating long-term investments to obtain cash leads to large value destruction. The authors conclude that the loss of efficiency is small in case of investment pooling: depositors can bring their money to the bank, and the bank maximizes the utility of all depositors with respect to the expected utility of an average depositor—so the task shifts from investors to the bank. The existence of the bank allows the long-term production technology to be used efficiently. Depositors can realize their consumption preferences: *type1* can invest in short-term storage, and *type2* can invest in long-term technology. Equally fundamental reasons why we need financial intermediaries are the functions of delegated monitors and delegated contractors, as shown by Diamond Diamond (1984).

Banks, in particular, reduce monitoring/verification costs when many small investors finance entrepreneurs. Without a bank, each investor is in direct contact with entrepreneurs and verification is very costly because it must be done across many projects. With a bank, instead, investors monitor a single subject (the bank), so the cost is spread over the total number of projects thanks to economies of scale. Moreover, the bank acts as a delegated contractor, managing on behalf of investors the relationship with the firm, reducing costs and inefficiencies. In a world where markets are incomplete, in the sense that a desired payoff cannot be replicated with existing securities, and even if markets were perfect we cannot write contracts that specify all rights and duties for every possible state of the world Arrow and Debreu (1954), we get ex post inefficiency (renegotiation can destroy value via inefficient liquidation) and ex ante inefficiency (renegotiation creates wrong incentives). Banks step in: in some cases with a soft claim we can avoid liquidation; in other situations it is better to have a hard claim instead of a soft one and force payment. So, in any case, it is better and more efficient to have bank financing.

2.2 Bank Fragility and Run Dynamics

If it is true that financial intermediation makes the interaction between investors and entrepreneurs more efficient, it is also true that the interconnectedness that characterizes the financial system can become a problem in situations of stress and danger. The classic literature on banking fragility shows how maturity transformation makes banks intrinsically exposed to bank runs and to propagation effects across the system.

Risk is defined in the literature and in practice in different ways, but a general definition is “the chance of (negative) deviation of the variable of interest from the reference value.” It is therefore a negative event that worsens the situation we expect to realize. There are different types, but all must be identified, measured, and well managed.

Historically, a catastrophic threat has been bank run risk: the risk that many individuals withdraw their money from a bank at the same time for fear it will become insolvent, triggering panic and pushing the bank toward potential failure. It is a self-fulfilling equilibrium; investor behavior is studied with the tools of Game Theory. Diamond and Dybvig (1983) frame a bank run as a (non-cooperative) Nash equilibrium: your strategy is the best response to your counterparty's strategy and vice versa, so nobody wants to deviate.[1]

Bank runs are often based on little information yet have the power to destroy even solid banks. In run scenarios, the equilibrium of the entire financial system is at risk, because runs are contagious: starting from one bank, they can spill over to others via direct propagation and indirect (psychological, self-fulfilling) channels. For this reason, since once they start they are extremely hard to stop, we should consider instruments that could prevent these situations. There are two types of run equilibria: bad news; and panic/negative sentiment.

Among the main tools: limit destabilizing news, central banks acting as lender of last resort, moratorium (temporarily freezing withdrawals), and requiring more equity capital from banks. But these are a double-edged sword: theoretical models show that a bank with guarantees (that it will be helped in problematic situations) has an incentive to take more risk. In particular, bailout guarantees/lender of last resort (LOLR)/too-big-to-fail lower the critical value p_c at which the bank prefers a riskier project over a risk-free one, leading to inefficiently high risk incentives versus the case of potential liquidation and without bailout. In short, state guarantees influence banks' risk behaviour.

[1] Thus, if a *type2* investor is not confident about receiving c2 in t2, they will withdraw funds as quickly as possible. If all *type2* investors act simultaneously, the bank is forced to liquidate long-term investments and is pushed toward bankruptcy.

3 Literature Review

3.1 Contagion in Interbank Networks

Classical models such as those by Diamond and Dybvig, however, consider the bank as an isolated entity in which the fragility of the banking system derives mainly from individual liquidity shocks due to bank runs. But this is not the case, and Allen and Gale (2000) show this in their paper, identifying different types of interbank network structures and showing that local shocks become global.

In a scenario in which the economy is made up of a number of regions and in which early and late consumers are uncertain but the overall demand for liquidity is constant, we can think of liquidity preference shocks as being imperfectly correlated across regions, so that banks hold interregional claims on other banks from other regions as a form of protection against liquidity preference shocks.

The cross holdings of deposits between regions works well as long as there is enough liquidity within the banking system; in case of excess demand for liquidity, the links created by these claims can prove to be dangerous. But in the case in which the overall demand for liquidity is greater than the stock of short assets, the only way to meet the request is the costly liquidation of long assets. Therefore, banks, in order to avoid using this extreme solution, first liquidate their claims on other regions. This is how a financial crisis propagates, but this depends on the pattern of interconnection that characterizes the interbank market. The author distinguishes the interbank market into complete and incomplete depending on whether each region is connected to all other regions or not. In the first case, each bank can absorb its liquidity shocks by drawing directly from the regions where the demand for liquidity is lower. In this way contagion does not occur. The scenario changes completely in the case of an incomplete interbank market. In case of a need for liquidity by a bank, the latter can obtain funds only from the few banks to which it is connected, which if in turn are connected to a limited number of other banks, the shock is absorbed in a more rigid and slow way.

The conclusion can be resumed as: the transmission of contagion heavily depends on the structure of interbank relationships: widespread and well-connected structures offer a greater capacity to absorb shocks, while structures which appear to be more separated favor the transmission of financial crises in the whole system.

3.2 Measures of Systemic Risk: MES and ΔCoVaR

When runs or shocks hit multiple banks, network externalities emerge: this is systemic risk, i.e., the probability that shocks propagate through financial connections and expectations, compromising the functioning of the whole system. According to Adrian and Brunnermeier (2016), systemic risk is the risk that institutional distress spreads widely and distorts the supply of credit and capital to the real economy.

Previous literature has aimed to define measures of systemic risk. A popular one is the Marginal Expected Shortfall (MES), defined as “the expected equity loss per dollar invested in this firm if the overall market declines by a certain substantial tail event.” Proposed by Acharya et al. (2017),MES is estimated with high-frequency market data (e.g., daily) and indicates how a single institution’s returns tend to worsen specifically in the worst periods of the market. Adrian and Brunnermeier also contributed with

ΔCoVaR; unlike MES as a measure of exposure (how vulnerable i is when the system goes bad), their measure captures contribution—how much the system worsens if i is under stress.

3.3 Endogenous Liquidity Crises and Hoarding

Illiquidity, however, can also be generated by liquidity hoarding behavior by the banks themselves. Gale and Yorulmazer (2013), in their paper, explain how a crisis can also be endogenous, meaning that it is the system itself that creates it: banks strategically withhold liquidity in order to cope with moments of uncertainty. Banks under stress must face liquidity shocks through two instruments: immediate liquidity (cash) and long-term assets (illiquid assets). The first is safe but costly because it does not yield interest, while the second is more profitable but expensive to liquidate in case of emergency. Banks therefore face a key choice of how much liquidity to hoard in advance before the shock occurs. Also in this model two situations are proposed. The first is characterized by a planner who distributes liquidity to those who actually need it, that is, to those facing the shock. In this case, each unit of liquidity held in advance prevents asset sales and thus value destruction. Opposed to this stable financial system, we have the real market situation, that is, without coordination. Here, banks decide individually, shaping their expectations and keeping liquidity today rather than lending it, in order to use it in case other banks sell assets later on, with consequent price collapses. This is the idea underlying liquidity hoarding.

The contagion mechanism arises from the fact that banks, fearing future fire sales, consider liquidity more valuable today and for this reason, at the moment of the shock, liquidity is not available and long-term assets must be liquidated at even lower prices. This self-propagating spiral is the result of individually rational behavior by each bank and has an inefficient overall outcome. In this way, systemic risk can arise from inside the financial network itself, even without any outside shock.

This has direct implications for empirical analysis: in moments of stress, the fact that a single bank is under pressure affects the fragility of the system as a whole. This relationship is precisely what is captured by ΔCoVaR proposed in this thesis, which measures the effect on systemic risk of a single financial institution facing a state of financial stress.

3.4 Research Gap and Contribution of This Thesis

The literature presented above provides a theoretical foundation for understanding how the banking system can be fragile, how contagion dynamics occur, and how systemic risk can be measured. However, most of the systemic risk indicators commonly used, such as MES or ΔCoVaR, rely on high-frequency market data and focus mainly on large listed financial institutions. This approach presents a limitation in countries characterized by the presence of regional, cooperative, and non-listed banks. Moreover, structural contagion channels represented by equity participations between institutions play a fundamental role. This thesis extends the applicability of ΔCoVaR to institutions for which market data are limited or unavailable by using returns calculated from accounting data. In addition, this work captures structural interdependencies that may amplify or mitigate systemic risk through equity cross-shareholdings.

Finally, the comparison between the German and Italian financial systems makes it possible to understand how institutional structures influence the transmission of financial shocks throughout the system.

4 Methodology

The objective of the following analysis is to quantify the contribution of each major German financial institution to systemic risk, as well as to map the structural interconnections between them through cross-shareholdings. The core of this work is the estimation of the ΔCoVaR (Delta Conditional Value at Risk) measure, proposed by Adrian and Brunnermeier (2016). This risk metric captures the marginal effect that the distress of a single institution may exert on the left tail of the distribution of system-wide returns. In practice, ΔCoVaR measures the shift in the conditional Value-at-Risk of the system when moving from the median state of a specific institution to its distressed state, defined at the 5% quantile.

While traditional measures of risk, such as Value-at-Risk, are institution-specific and static, ΔCoVaR explicitly incorporates the idea of conditional dependence, emphasizing the fact that systemic fragility emerges from the co-movement of financial institutions. In this sense, it represents a more appropriate tool for capturing systemic externalities.

To support this statistical perspective, the analysis also seeks to represent the structural dimension of the financial system. Specifically, an undirected network of cross-shareholdings among German financial institutions and insurance companies is constructed. Cross-shareholdings, in which one institution owns an equity stake in another, create potential channels for the transmission of shocks. By combining ΔCoVaR estimates with the network representation, it is possible to integrate the statistical dimension of systemic risk with its topological dimension, thus providing a more comprehensive understanding of financial stability of the system.

4.1 Data Collection

Thanks to the creation of a temporary Refinitiv Workspace (Eikon)[2] Student account, data collection was facilitated through the combined use of Datastream and Eikon, accessed via the DALAHO – Hohenheim Datalab platform, which provides university members and students with free access to several commercial databases.

For each institution, the balance sheet and income statement were exported into Excel, with all figures reported in millions of euros. From the income statement, the annual series (2007–2024) of Income before Taxes was extracted, while from the balance sheet the item Shareholders' Equity – Attributable to Parent Shareholders – Total was selected and adjusted by subtracting Minority Interest – Equity. The resulting time series were then ordered chronologically and organized into a dataset with "Year" as the index and, for each institution, two dedicated columns representing equity (eigenkapital) and results (ergebnis). Finally, returns were computed following the formula described in the methodology section, and a logarithmic transformation was applied.

These values were likewise transformed into logarithmic form. After an initial screening and selection of the main banks and insurance companies operating in Germany, the sample was restricted due to the lack of precise and up-to-date data, as well as

[2]Refinitiv Workspace is the current platform name, formerly known as Eikon. Refinitiv is a global provider of financial market data and infrastructure, formerly part of Thomson Reuters and since 2021 integrated into the London Stock Exchange Group (LSEG).

the limited availability of published financial statements for many smaller institutions. Consequently, only those institutions offering the most comprehensive historical coverage (2007–2024) were included. For delisted banks, or those not available in Refinitiv for various reasons, data collection was carried out manually using the official online archives of the respective institutions.

As for the systemic returns, annual percentage returns were collected from the "Price History" section under "Price & Charts" for the ETF iShares STOXX Europe 600 Banks UCITS ETF (ticker: SX7PEX.DE). The resulting dataset, combining the returns of all institutions and the system, consists of 17 observations across 16 variables.

A summary of the selected institutions is provided in Appendix **??**, indicating their respective stock tickers where available. For delisted institutions, references to the official online archives are collected separately in the section List of Sources in Appendix A.

4.1.1 Equity Holdings Data Collection and Processing

Data on inter-institutional equity holdings were collected from the Shareholders Report in the Ownership section of Refinitiv. For each institutions considered, the fields *Investor Name*, *% Outstanding*, *Investor Sub-Type*, *City*, and *Country/Region* were exported, filtering to institutions based in Germany. During the cleaning process, only investors classified as *Holding Company* or *Bank and Trust* were retained, and *% Outstanding* was converted to a percentage value. To construct the network of holdings, each dataset was filtered to keep only those observations where *Investor Name* corresponded to one of the institutions within the defined group, ensuring that the resulting dataset captured exclusively cross-holdings among the selected institutions. Finally, the filtered datasets were consolidated into a single file, comprehensive of a dedicated source column indicating the original source, so that every data point can still be traced back to its issuer.

4.2 Definition of Accounting-Based Returns

The analysis is based on annual financial statement data for a selected sample of banks and insurance companies over the period 2007–2024, thus covering a recession (2007–2009) and several significant financial crises, such as the global financial crisis of 2008, the European sovereign debt crisis (2010–2012), the financial shock caused by the Covid-19 pandemic in 2020, and the soaring inflation linked to energy shocks and geopolitical tensions, particularly the war in Ukraine that started in 2022.

The approach used in the paper by Adrian and Brunnermeier involves the estimation of VaR, Conditional VaR, and consequently ΔCoVaR through quantile regressions on the weekly equity returns of all publicly traded financial institutions, as they aimed to capture all forms of risk, including the risk of adverse asset price movements and funding liquidity risk. However, the ΔCoVaR can also be estimated using other valid approaches. The two authors computed ΔCoVaR using weekly data from 1917:Q1 to 2013:Q2 for all publicly traded US commercial banks, broker-dealers, insurance companies, and real estate companies.

In the following analysis, the intent is to apply the ΔCoVaR approach proposed by these economists to the German financial system. To this end, a list of German banks operating in Germany was collected, along with a list of the most important German insurance and reinsurance companies operating domestically, and their return data gathered.

For all publicly listed financial institutions, the objective was to collect market prices for each and compute daily returns using the formula

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

as proposed by Cerchiello and Giudici (2016).

The two authors focused on the Italian Banking System, characterised by a large number of important banks. They focused on large listed banks for which daily financial market data are available. For each bank, they considered the daily return obtained from the closing price on financial markets over a period of 148 consecutive days in 2013.

Unlike previous studies based on high-frequency market data (such as daily or weekly stock prices), the analysis conducted in this thesis adopts an alternative approach motivated by the specificity of the German context. In particular, the German financial market includes numerous medium- and small-sized institutions (such as Sparkassen, Landesbanken, and regional insurers) that, although playing a relevant role in the credit ecosystem and systemic risk transmission, are not publicly listed and do not have reliable market data time series. Consequently, an approach is needed to quantify systemic risk even for non-listed entities without resorting to questionable or inconsistent proxies.

For this reason, the present analysis relies on accounting data extracted from consolidated annual financial statements (*Geschäftsbericht*), available for a broad time span (2007–2024) and for a wide set of institutions regardless of their listing status. The return for each institution i is calculated using the following formula:

$$R_{i,t} = \frac{\text{Operatives Ergebnis}_{i,t}}{\text{Eigenkapital}_{i,t-1}} \tag{2}$$

The numerator *Operatives Ergebnis* was chosen as the annual economic performance measure of the institution. This financial statement item represents the operating result before taxes, equity interests, and extraordinary components, and succinctly reflects the bank's or insurance company's ability to generate income from its core business. This indicator has two main advantages. First, it ensures stability and intertemporal comparability, as it is less affected than net income by extraordinary items, tax adjustments, or one-off events. This makes it more suitable for the long-term analysis of systemic risk. Second, it provides homogeneity across institutions, since it is a common item reported by all German banks and insurers. This enhances the comparability of the indicator even among institutions with different operational structures.

The denominator considers the value of *Eigenkapital* at time $t-1$, i.e., the equity attributable to the parent company shareholders (excluding minority interests). The use of this item reflects the capital actually at risk borne by the bank's owners and is consistent with the economic concept of return on equity.

Temporal consistency and avoiding simultaneity are the two reasons why previous year's value was decided to be used. First, it allows the return to be interpreted as a yield on the capital initially available at the beginning of the period; then, using the final capital (same year) could introduce endogeneity, since the operating result directly contributes to changes in capital.

The exclusion of Minority Interests is justified by the fact that these shares do not represent fully controlled capital by the analyzed bank/insurer and therefore do not correctly reflect the risk assumed by main shareholders nor the capital exposed to operating activities generating the result.

Log-Transformation of Accounting Returns The institution i's annual accounting return in year t is therefore defined by Equation (2).

The calculation is performed iteratively for each bank present in the dataset. For every positive accounting return, the log-return for institution i at time t is calculated as:

$$r_{i,t} = \log\left(1 + R_{i,t}\right) \tag{3}$$

This logarithmic transformation serves two main purposes:

1. To stabilize variance and make the distribution more symmetric, rendering returns suitable for quantitative analyses and statistical models (e.g., quantile regressions);

2. To allow percentage comparisons between institutions with different capital levels, transforming returns into a scale interpretable as exponential growth.

In parallel, the *iShares STOXX Europe 600 Banks UCITS ETF (DE)*[3] index has been

[3]The iShares STOXX Europe 600 Banks UCITS ETF (DE) index includes the main publicly traded banks in European countries and is widely used as a benchmark for the European banking sector.

used as a proxy for the German financial system, assuming that, given the high integration of the German banking sector with the European one, the index realistically reflects the overall state of the system. The iShares STOXX Europe 600 Banks UCITS ETF (DE) can be considered as a proxy for systemic returns. While this ETF predominantly captures the performance of the European banking sector, it serves as a practical proxy for the broader financial system due to the strong interconnectedness between banks and insurers. We have used market prices because this ETF is traded daily and prices incorporate real-time information such as market sentiment, news, and expectations, which are not captured in annual financial statements. In contrast, annual reports reflect historical data with a time lag and do not account for forward-looking information. Using market prices therefore allows for a more timely and dynamic measure of systemic risk and returns, making the analysis more relevant and responsive to current market conditions.

An alternative would have been to construct a synthetic "system ETF" that aggregates the returns of all institutions in the sample. However, this would introduce bias, an inflated R^2, and generate multicollinearity problems, because the predictors would be used to explain a dependent variable—*system*—that, by construction, already incorporates those same predictors. For this reason, the index representing the German financial system used in the analysis must be exogenous and not constructed from the institutions in the sample.

Annual closing prices as of December 31st were collected for the proxy over the period

2007-2024, and returns were calculated using the equation

$$R_t^{\text{system}} = \frac{P_t^{\text{system}} - P_{t-1}^{\text{system}}}{P_{t-1}^{\text{system}}} \tag{4}$$

where P_t^{system} represents the closing price of the system index at time t, P_{t-1}^{system} is the closing price of the system index at time $t-1$, and R_t^{system} is the simple return of the system index at time t.

For consistency, system returns are also standardized, and the logarithmic returns for the Financial System ETF are computed as

$$r_t^{\text{system}} = \log\left(1 + R_t^{\text{system}}\right) \tag{5}$$

4.3 VaR Estimation

There are several methodology to estimate the Value at Risk of a financial istutition, such as Historical Simulation that is probably the most straightforward method, quantile regression that consist in a flexible method that directly estimates the conditional quantile , GARCH and others. For some of them such as Historical Simulation we don't have to assume any specific distrubiton, and the same is for Quantile Regression that has the advantage of being nonparametric and suitable method even in the presence of non-normal or asymmetric returns. However,this methods can be unreliable when the number of data points is limited. In our case since we have only 17 observations -annual accounting returns from 2008 to 2024- the quantile estimates and inference result unstable. Specifically to estimate the VaR at 5% with Historical Simulation we would need a minimum of 20 observation to get one single value representing the VaR. Given these limitations, an alternative approach is adopted for this analysis based on an approximation procedure known as the *Cornish–Fisher expansion.*

The approach propoesd by Cornish and Fisher (1938) is an asymptotic expansion used to approximate the quantiles of a probability distribution based on its cumulants, which are special transformations of the moments of a random variable designed to isolate information specific to each order. This means that while moments are not independent—the higher order moments contain information about the lower order moments—the cumulants are moments that extract the unique information of each order and are constructed to be independent from each other.

In this way, through the cumulants of a variable, it is possible to adequately reconstruct the probability distribution function. Recall that cumulants do not correspond to moments. More specifically, only the first cumulant coincides with the first moment (i.e., the mean). From the second order onwards, cumulants do not coincide with moments. Indeed, while the second moment measures the average squared magnitude around zero and therefore mixes location with scale, the second cumulant corresponds to the variance and isolates pure dispersion. It is precisely thanks to cumulants that the Cornish–Fisher expansion can be applied subsequently (see Appendix B).

4.3.1 Cornish Fisher pitfall

In order to use this approach, we don't need to assume normality of the return distributions, however Cornish Fisher expansion should avoid his main pitfall: exiting the domain of validity of the formula (Maillard (2018)). Specifically, as stated by Maillard in his guidelines for a proper use of the Cornish Fisher expansion, this approach is a way to transform a standard Gaussian random variable z into a non Gaussian Z random variable.

Said that, the transformation in order to conserve the quantile of the distribution requires that

$$\frac{dZ}{dz} > 0 \quad \forall z \in R,$$

where

$$\frac{dZ}{dz} = z + (z^2 - 1)\tfrac{S}{6} + (z^3 - 3z)\tfrac{K}{24} - (2z^3 - 5z)\tfrac{S^2}{36}.$$

Here the parameters are defined as $k = K/24$ (excess kurtosis) and $s = S/6$ (skewness parameter).

After the calculation, Maillard derived the condition:

$$|S| \leq 6(\sqrt{2} - 1) \approx 2.485.$$

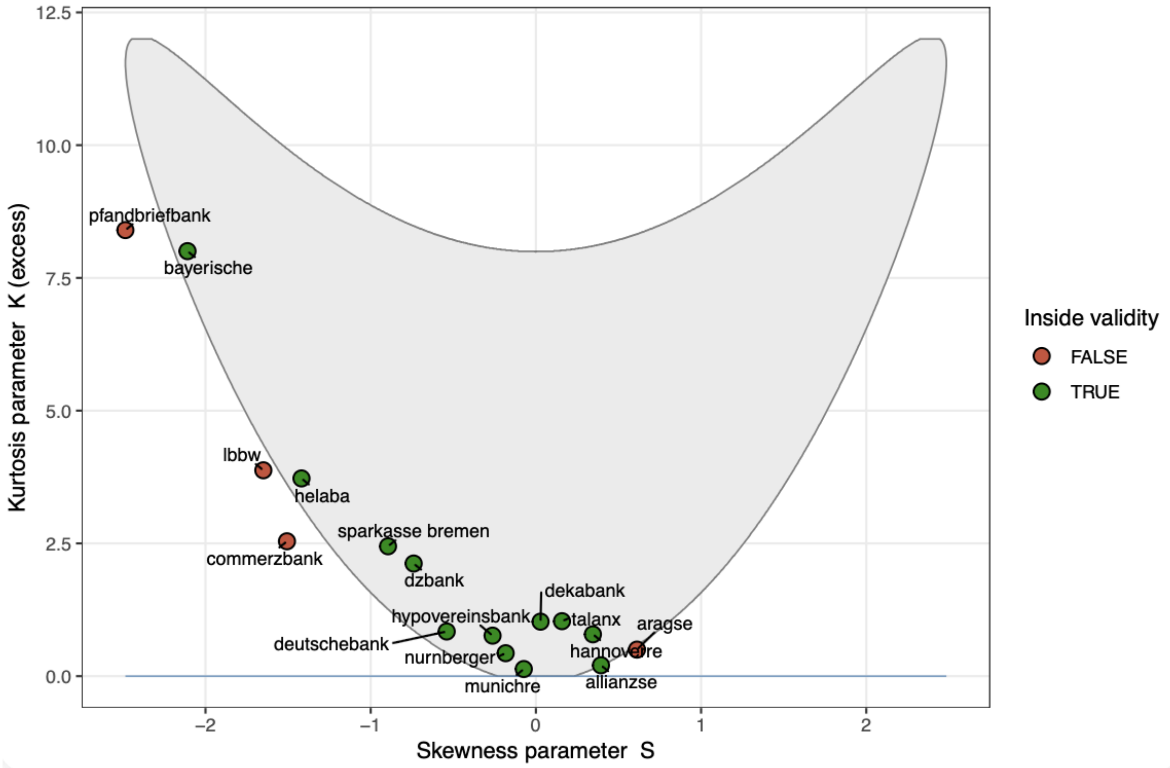
Moreover, the area under the curves can be expressed as

$$k' = \frac{1 + 11s^2 - \sqrt{s^4 - 6s^2 + 1}}{6}, \qquad k'' = \frac{1 + 11s^2 + \sqrt{s^4 - 6s^2 + 1}}{6}.$$

To check whether the Cornish–Fisher expansion can be applied, Maillard suggests that the skewness and kurtosis parameters must lie within the region defined by *k'* and *k"*. I specify that it is the parameters that must be considered, not the empirical skewness and kurtosis obtained from the sample moments of the institutions' return distributions.

Figure 1: Cornish Fisher Expansion Domain of Validity by Maillard.

Admissible region (Maillard, App. 2) for the second-order Cornish–Fisher in the (S, K) plane: green points lie within the reliable CF domain; red points fall outside.



Therefore, once the empirical moments have been computed, they must be transformed to obtain the skewness and kurtosis parameters[4] According to Maillard (2018), for those financial institutions whose transformed skewness and kurtosis parameters fall within the domain of validity, the Cornish–Fisher expansion can be considered a statistically acceptable and suitable approximation of the quantile.

For the others (highlighted in red), the methodology may not provide reliable estimates. In our analysis, institutions lying outside this domain were therefore excluded. However, ARAG SE was retained since its parameters lie exactly on, or very close to, the boundary of the validity region; given the already limited size of our dataset,

[4]See Maillard (2018), Appendix 2.

excluding it would have further reduced the representativeness of the sample.

4.3.2 Quantile Adjustment

To estimate the quantile of a non-normal distribution based on its standardized moments, through the CF expansion, we approximate quantiles by adjusting the corresponding quantile of the standard normal distribution. Specifically, it introduces corrections that depend on the skewness and kurtosis of the distribution.

Let x denote the quantile of the standard normal distribution corresponding to a given confidence level (for instance, the 5% quantile when computing Value at Risk). The Cornish–Fisher expansion provides an adjusted value w_p, which approximates the quantile of the actual (non-normal) distribution that exhibits non-zero skewness γ_1 and excess kurtosis γ_2. This adjusted quantile accounts for the deviation from normality and is therefore more accurate in risk estimation contexts.

The relationship between the normal quantile x, the moments γ_1, γ_2, and the adjusted quantile w_p is described by the following expression, truncated at the second-order terms:

$$\begin{aligned} w_p &= x + \gamma_1 h_1(x) \\ &\quad + \left[\gamma_2 h_2(x) + \gamma_1^2 h_{11}(x)\right] \end{aligned} \tag{6}$$

Here, the functions $h_1(x)$, $h_2(x)$, and $h_{11}(x)$ represent combinations of the so-called probabilists' Hermite polynomials.

These polynomials are defined as follows:

$$\mathrm{He}_1(x) = x$$

$$\mathrm{He}_2(x) = x^2 - 1$$

$$\mathrm{He}_3(x) = x^3 - 3x$$

The adjustment functions in equation (6) are then given by:

$$\begin{aligned}
h_1(x) &= \frac{\mathrm{He}_2(x)}{6} = \frac{x^2 - 1}{6} \\
h_2(x) &= \frac{\mathrm{He}_3(x)}{24} = \frac{x^3 - 3x}{24} \\
h_{11}(x) &= \frac{-\left[2\,\mathrm{He}_3(x) + \mathrm{He}_1(x)\right]}{36} = \frac{-(2x^3 - 6x + x)}{36} = \frac{-(2x^3 - 5x)}{36}
\end{aligned}$$

By computing w_p as shown, we obtain an adjusted quantile that incorporates the effects of skewness and kurtosis in the underlying data. This corrected quantile is then used in the estimation of the Value at Risk (VaR) and, subsequently, in the calculation of systemic risk measures such as ΔCoVaR.

4.3.3 VaR Adjustment

The values γ_1 and γ_2 represent the skewness and excess kurtosis of the random variable, respectively. The values within each set of brackets correspond to the terms at that polynomial level, and all must be calculated and combined for the Cornish–Fisher expansion at that level to be valid. What has been done is to estimate the quantile corresponding to p (0.05) by extending the normal quantile x and adjusting it with the third (skewness) and fourth order moments (kurtosis) to fit non-normal distributions.

The formula used is the following:

$$y_p \approx \mu + \sigma w_p \tag{7}$$

$$y_p \approx \mu + \sigma \left(x + \gamma_1 h_1(x) + \left[\gamma_2 h_2(x) + \gamma_1^2 h_{11}(x) \right] \right) \tag{8}$$

The adjustment is given by equation (6): the quantile y_p is adapted to the actual skewness and kurtosis. In this way, the obtained VaR incorporates empirical non-normality, resulting in a more realistic VaR, especially for banks with non-normal return distributions (e.g., Commerzbank, LBBW, etc.).

Besides the 5% VaR (stress scenario for the institutions), the same approach has been used to calculate the 50% VaR (i.e., when institutions are in their normal state — median).

4.4 Systemic Risk Quantification Using ΔCoVaR

To quantify systemic risk, consistently with the approach introduced by Adrian and Brunnermeier (2016), the ΔCoVaR has been used.

Define

$$C_q^i := \left\{ X^i \leq \mathrm{VaR}_q^i \right\},$$

the event C of bank i being in situation of stress (i.e. at his 5% quantile)[5].

Said that, the Value at Risk (VaR) of institution i at level q is defined as the $q\%$

[5]It should be noted that the conditioning event C_q^i is defined ex post: once the 5% VaR is computed from the observed data, we can retrospectively classify whether institution i was in a stress state or not.

quantile, i.e.,

$$\Pr\left(X^i \leq \mathrm{VaR}_q^i\right) = q\%$$

where X_i is the return (or loss) of institution i under consideration.

This means that the probability that the loss X_i will be less than or equal to the VaR is $q\%$, or equivalently, Thus, the probability that the loss exceeds the VaR at level $q\%$ is $1 - q\%$. Therefore, a higher risk corresponds to a higher value of VaR_q^i.

Given this premise, the *CoVaR* (Conditional Value at Risk) is defined as the value such that the probability that X^j is less than or equal to that value, conditional on institution i being in a certain condition C_q^i, is exactly $q\%$.

Formally,

$$\Pr\left(X^j \mid C_q^i \leq \mathrm{CoVaR}_q^{j|C_q^i}\right) = q\%$$

where X^j denotes the loss of institution j (or of the entire system when j represents the system), C_q^i is the conditioning event for institution i—for instance, the event that i is exactly at its q-percentile Value-at-Risk—and $\mathrm{CoVaR}_q^{j|C_q^i}$ is the conditional Value-at-Risk of j given that event.

We then define the ΔCoVaR as

$$\Delta\mathrm{CoVaR}_q^{j|i} = \mathrm{CoVaR}_q^{j|X^i=\mathrm{VaR}_q^i} \; - \; \mathrm{CoVaR}_q^{j|X^i=\mathrm{VaR}_{50}^i} \tag{9}$$

that is, the difference between the CoVaR of institution (or system) j when institution i experiences a loss equal to its own q-percentile VaR and the CoVaR of j when i is instead in its median state (the 50-percentile of its loss distribution).

The ΔCoVaR captures the portion of systemic risk that arises solely because institution i is under financial stress. Specifically, it is the difference between the conditional VaR of the system (or of institution j) when i suffers an extreme loss and the conditional VaR when i is in its normal, median state.

The use of ΔCoVaR allows capturing and measuring the *tail-dependency* between two random return variables, that is, how two variables behave similarly in the tails of the distribution, where rare but catastrophic events occur.

ΔCoVaR is a directional measure, which implies that the two conditional risk measures are generally *not commutative*. Specifically, we typically observe:

$$\Delta\text{CoVaR}_q^{\text{system}|i} \neq \Delta\text{CoVaR}_q^{i|\text{system}} \tag{10}$$

This asymmetry reflects the fact that the systemic risk imposed *on* the system by institution i is not the same as the risk experienced *by* institution i when the system is in distress. For risk management purposes, it may be useful to calculate both conditions, but in this analysis we limit ourselves to calculating $\Delta\text{CoVaR}_q^{\text{system}|i}$, which quantifies the marginal increase in systemic risk when institution i is under stress relative to its median state. Thus, we obtain the formula used to calculate the ΔCoVaR of the system conditional on institution i at confidence level q, as proposed by Adrian and Brunnermeier (2016):

$$\Delta\text{CoVaR}_q^{\text{system}|i} = \text{CoVaR}_q^{\text{system}|X^i=\text{VaR}_q^i} - \text{CoVaR}_q^{\text{system}|X^i=\text{VaR}_{50}^i}$$

4.4.1 Estimation model

To obtain the CoVaR, this section discusses the model used. The analysis relies on a set of univariate linear regression models of the form:

$$r_t^{\text{system}} = \alpha_i + \beta_i \cdot r_{i,t} + \varepsilon_{i,t}, \tag{11}$$

where r_t^{system} is the aggregate return of the financial system at time t (dependent variable), $r_{i,t}$ is the return of institution i at time t. The coefficient β_i is associated with the return of institution i and ε_t is the error term at time t.

This approach follows the original CoVaR framework proposed by Adrian and Brunnermeier (2016), and allows the systemic impact of each institution to be evaluated independently. Compared to a multivariate regression approach, this method avoids instability resulting from strong co-movements among institutions' returns, which typically leads to multicollinearity, insignificant coefficients, and overly aggressive model reduction when variable-selection procedures (such as forward stepwise selection) are adopted.

In a few words, the univariate approach therefore provides more stable and interpretable β_i estimates for systemic risk assessment.

4.4.2 Calculation of ΔCoVaR

Once the coefficients are extracted from the model, the CoVaR for each institution i is given by

$$\text{CoVaR}_q^i = \text{VaR}_q^{\text{system}|X^i=\text{VaR}_q^i} = \alpha_q^i + \beta_q^i \cdot \text{VaR}_q^i$$

where VaR_q^i is obtained from the estimation of the $q\%$ quantile of institution i using the Cornish–Fisher Expansion.

From this, the Delta Conditional Value at Risk is calculated as:

$$\Delta\mathrm{CoVaR}_q^i = \mathrm{CoVaR}_q^i - \mathrm{CoVaR}_q^{\mathrm{system}|\mathrm{VaR}_{50}^i} = \hat{\beta}_q^i \left(\mathrm{VaR}_q^i - \mathrm{VaR}_{50}^i\right) \tag{12}$$

where $\hat{\beta}_q^i$ is the coefficient of institution i extracted from the previously estimated regression on returns.

An empirical calculation procedure and respective interpretation for Nürnberger Versicherung is provided as an example in Appendix E.

5 Results

This section presents the empirical findings of the analysis. The focus is on quantifying the systemic relevance of German financial institutions through ΔCoVaR and on illustrating the network of equity interconnections that shape potential contagion channels. The results are reported using both accounting-based and market-based returns, allowing for a comparison between backward-looking balance-sheet measures and forward-looking market indicators. The estimated values are summarized in tables and visualized through systemic-risk network graphs, which display the magnitude, sign, and relative importance of each institution's contribution. In addition, alternative methodological approaches are compared, namely Quantile Regression and the Cornish–Fisher expansion, in order to highlight how different estimation strategies affect the computation of systemic risk contributions. Finally, robustness and sensitivity checks are provided by contrasting Cornish–Fisher estimates with Historical Simulation quantiles, to verify the stability of results in the presence of a limited sample size. Together, these analyses give a comprehensive picture of systemic linkages in the German financial sector and the reliability of the methods employed. Having outlined the overall structure of the empirical analysis and the methodological approaches employed, the next step is to present the estimation results obtained from the univariate regression specification.

5.1 Regression Results

The system return is regressed separately on each institution's return: this approach avoid overfitting and multicollinearity problems that arise in the multivariate model, given the limited sample size (17 annual observations).

Table 2: Individual institutions' impact on the system return.

This table reports the results of separate univariate regressions in which the system return is regressed on each institution's individual return in order to avoid overfitting and multicollinearity issues of the multivariate model.

Institution	**Intercept**	β	**Std. Error**	**p-value**	R^2
Deutsche Bank	-0.032	0.770	0.159	<0.001***	0.609
Nürnberger	-0.034	0.560	0.657	0.4075	0.046
Hannover Re	-0.197	1.024	0.265	0.0015**	0.499
Munich Re	-0.152	1.194	0.403	0.0097**	0.369
Allianz SE	-0.134	1.393	0.206	<0.001***	0.752
Commerzbank	-0.025	0.618	0.160	0.0015**	0.498

Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

The univariate regression results(11) are shown in Table 2. Large insurer such as Allianz SE, Munich Re and Hannover Re, and main banks such as Deutsche Bank and Commerzbank exhibit positive coefficients that are statistically significant showing that changes in their performance are closely associated with the performance of the financial system as a whole. The estimated slope coefficients measure how each istitution's return co-moves with the system return. A positive coefficient indicates that when an institution performs poorly, the system is also likely to experience a downturn. This approach makes it more suitable for the computation of CoVaR and ΔCoVaR than the multivariate regression, where the beta estimated appear unreliable due to the small sample. In a few words, statistically significant coefficients provide stable and economically interpretable estimates of how a situation of stress of an institution affects the entire system.

5.2 Robustness and sensitivity checks

An important aspect of any risk measure is the extent to which its value depends on the underlying distributional assumptions and on the chosen estimation procedure. In particular, the Cornish–Fisher expansion has been employed in this thesis to approximate quantiles of the returns distribution and, consequently, to compute the Value-at-Risk (VaR) and ΔCoVaR. Although the Cornish–Fisher approach is widely used in the risk management literature, it is essential to verify whether its outcomes are robust in the specific empirical context considered here, namely annual accounting and market returns with a limited time span.

Can we assume that the approach employed is robust, or is it producing problematic quantile values? One potential concern is that, with a small sample size ($n = 17$ in this case), higher-order adjustments for skewness and excess kurtosis may either over- or under-correct the tail quantiles, thereby producing values that deviate significantly from more direct empirical estimates.

To keep things simple, we can run a robustness check by comparing the VaR values, for those institutions that fall within Maillard's domain of validity, with the 5% quantile computed by weighted interpolation between the first and second order statistics (given the small sample size). A numerical example is provided in Appendix D. The idea is simple: if the Cornish–Fisher expansion provides reasonable and stable approximations, then the CF-based VaR should not diverge excessively from the empirical HS quantile. At the same time, some differences are expected and even desirable, because Cornish–Fisher explicitly incorporates distributional features (skewness and kurtosis) that are ignored by Historical Simulation. In other words, the Cornish–Fisher expansion shifts more probability into the worst outcomes, giving a more conservative measure of risk.

While the numbers are often very close, the Cornish–Fisher expansion is generally more reliable, as it explicitly accounts for skewness, excess kurtosis, and the distributional characteristics of returns. The comparative results are reported in Table 3, see Appendix F for comparative results related to Italian financial system. For most institutions, the two approaches produce fairly similar results, suggesting that the Cornish–Fisher expansion does not lead to distortions even with the limited dataset available.

For example, Deutsche Bank's 5% quantile is only slightly more negative under CF than under HS (a difference of -0.29 percentage points), confirming the robustness of the adjustment. In other cases, such as Sparkasse Bremen or Hannover Re, the difference is somewhat larger, indicating that skewness and kurtosis corrections significantly affect the lower tail of the return distribution. Notably, Munich Re is the only institution where the Cornish–Fisher adjustment increases the quantile, producing a less conservative estimate; this reflects the positive skewness of its returns distribution.

Table 3: VaR at 5%: Historical Simulation vs Cornish–Fisher.

Table comparing 5% VaR computed via Historical Simulation (HS) and Cornish–Fisher (CF) for the selected institutions. The difference (CF − HS) captures the adjustment for skewness and kurtosis. Values are expressed in percentage.

Financial Institution	**HS (5%)**	**CF VaR (5%)**	**CF − HS**
Sparkasse Bremen	−2.88	−7.17	−4.29
Deutsche Bank	−10.20	−10.50	−0.29
DZ Bank	−0.09	−8.36	−8.28
Munich Re	0.63	1.65	1.02
Hannover Re	9.78	7.54	−2.23
Nürnberger	3.04	2.03	−1.01
ARAG	8.53	6.51	−2.02

Overall, the evidence suggests that the Cornish–Fisher expansion provides VaR estimates that are generally consistent with empirical quantiles, while introducing adjustments that better reflect the statistical properties of the data. Given the limited sample size and the potential pitfalls of Historical Simulation in such contexts, the Cornish–Fisher expansion can be considered a more reliable choice for estimating tail risk in this study. At the same time, the robustness check highlights the importance of carefully interpreting results: differences across institutions are not uniform, and in small samples, methodological choices can have a non-negligible impact on the estimated magnitude of systemic risk contributions. This underlines the necessity of reporting robustness checks alongside the main results, as they provide reassurance that the findings are not merely an artifact of the chosen methodology.

In the case of DZ Bank and Sparkasse Bremen, the difference between the historical simulation (HS) VaR at the 5% level and the Cornish–Fisher (CF) VaR is particularly pronounced.

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In the case of DZ Bank and Sparkasse Bremen, the difference between the historical simulation (HS) VaR at the 5% level and the Cornish–Fisher (CF) VaR is particularly pronounced.

This difference can be explained by two factors. First, the HS method relies exclusively on the empirical distribution of returns. Given the limited sample size available (17 annual observations), the lower tail is represented by very few data points, making the 5% quantile effectively determined by a single extreme observation. As a result, the HS VaR estimate is highly sensitive to the small dataset of distribution returns and may underestimate tail risk.

Second, the Cornish–Fisher expansion adjust the normal quantile by incorporating information about skewness and kurtosis. However, with small samples, the estimates of skewness and kurtosis are squite unstable and may yield large adjustments to the quantile. In this case, the CF expansion tends to exhibit more likely extreme negative outcomes, producing a lower VaR estimate than the HS method.

Overall, the divergence between the two approaches highlights a well-documented limitation: HS tends to be unreliable in small samples due to lack of granularity in the tails, while the Cornish–Fisher expansion may overcorrect when higher-moment estimates are unstable. This explains why the CF VaR for DZ Bank and Sparkasse Bremen indicates substantially higher tail risk compared to the corresponding HS estimate.

5.3 Methodological Comparison: Quantile Regression and Cornish–Fisher Expansion

This subsection contrasts two alternative methodologies for estimating systemic risk contributions through ΔCoVaR. In this case, the analysis is conducted using returns computed from market prices, rather than accounting-based measures. The rationale for introducing market-based returns lies in their forward-looking nature: unlike accounting data, which are backward-looking and tied to annual financial statements, market prices continuously incorporate new information and expectations.

By repeating the comparison between quantile regression and the Cornish–Fisher expansion on market-based returns, it is possible to assess whether the close alignment already observed with accounting-based measures also holds in a more dynamic setting. Confirming such consistency would strengthen the robustness of the findings, showing that the two methodologies yield comparable results regardless of whether returns are derived from balance-sheet data or from financial markets. From the table 4 we can observe that the 5% and 50% quantiles are very similar across all institutions, indicating that the Cornish–Fisher Expansion provides reliable estimates of the tails as well as the median when compared with the quantile regression method. The main differences arise in the ΔCoVaR values, which reflect discrepancies in the estimated coefficients β obtained via the two approaches. Although the resulting ΔCoVaR values differ in magnitude, their signs seems to remain consistent across methods in 4 out of 6 institutions.

This suggests that the Cornish–Fisher approximation mantaints the qualitative stress effect, while modest quantitative differences stem from variation in β, which directly scales the shift $\hat{\beta}_q^i \left(\mathrm{VaR}_q^i - \mathrm{VaR}_{50}^i\right)$.

Table 4: Comparison of ΔCoVaR estimates: quantile regression (QR) vs. Cornish–Fisher (CF)

This table compares ΔCoVaR estimates obtained via quantile regression and the Cornish–Fisher expansion. While the 5% and 50% quantiles are largely consistent, differences in estimated coefficients (β) lead to modest discrepancies in ΔCoVaR; no sign reversals are observed.

Financial Institution	β		$\mathrm{VaR}_{5\%}$		$\mathrm{VaR}_{50\%}$		ΔCoVaR	
	QR	CF	QR	CF	QR	CF	QR	CF
Deutsche Bank	0.413	0.770	-0.544	-0.521	-0.006	0.000	-0.222	-0.402
Nürnberger	-0.276	0.560	-0.278	-0.252	0.000	-0.007	0.077	-0.137
Hannover Re	0.503	1.024	-0.274	-0.243	0.113	0.109	-0.195	-0.360
Munich Re	-0.235	1.194	-0.195	-0.353	0.040	0.070	0.055	-0.505
Allianz SE	0.521	1.393	-0.469	-0.445	0.044	0.078	-0.267	-0.729
Commerzbank	0.300	0.618	-0.687	-0.661	-0.046	-0.017	-0.192	-0.398

Quantile regression, through the relationship $Q_{Y|X}(q) = \alpha_q + \beta_q X$, estimates how one institution affects another specifically in the tail of the return distribution, so $\beta_{0.05}$ reflects tail-specific dependence during period of stress, not on average. Cornish–Fisher applies a parametric correction to unconditional quantiles, keeping β^{CF} tied to the average (mean-based) relation. Thus, while VaR levels look similar, ΔCoVaR differs because QR captures tail dependence, whereas CF adjusts only marginal distributions

Overall, this explains the coherence of the quantiles but the discrepancy of the ΔCoVaR. In practical terms, the Cornish–Fisher approach may be suitable as a benchmarking or exploratory tool, but its ΔCoVaR values should not be used for risk oversight or policy decisions, unless more data or higher-frequency observations are available to properly estimate tail behavior.

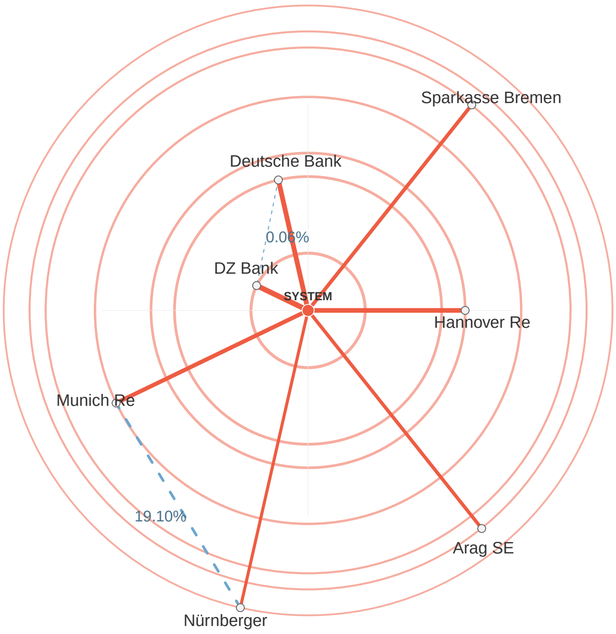
5.4 Systemic-Risk Network of German Financial Institutions

To provide a topological representation of the German financial system for the institutions under analysis, we employ an undirected graph with the system (the chosen ETF) fixed at the origin. Each peripheral node (banks/insurers) is placed on a circle at an equally spaced angle, while its radius is a monotone decreasing function of the magnitude of $|\Delta\text{CoVaR}|$ (gravitational layout): institutions with larger systemic impact appear closer to the center. System–institution connections are drawn as radial lines whose thickness scales with $|\Delta\text{CoVaR}|$ and whose color encodes the sign (green for $\Delta\text{CoVaR} > 0$, red for $\Delta\text{CoVaR} < 0$).

The numeric ΔCoVaR value can be optionally printed along each ray for readability. The adjacency matrix used to build the network includes both the system links and peer-to-peer equity participations between institutions, the latter rendered as dashed blue lines (symmetrized across pairs and labeled in percent when available). The resulting German systemic-risk topology is shown in Figure 2.

Figure 2: Systemic-risk network from accounting returns and associated ΔCoVaR values.

The figure shows the German financial system. The central node represents the aggregate system, while concentric placement of institutions reflects the relative intensity of their ΔCoVaR. The radial lines capture each bank's impact on the system (green for ΔCoVaR > 0, red for ΔCoVaR < 0). Dashed blue lines show ownership links between institutions.



Institution	**ΔCoVaR**
Sparkasse Bremen	-0.137
Deutsche Bank	-0.356
ARAG SE	-0.109
DZ Bank	-0.486
Nürnberger	-0.065
Munich Re	-0.221
Hannover Re	-0.316

Focusing on *DZ Bank*, a value of $\Delta\text{CoVaR}_{0.05}^{\text{system}|\text{DZ Bank}} = -0.486$ (in log–return units) implies that, conditional on Munich Re being at its 5% VaR (stress state), the system's 5% quantile shifts left by 0.486 log points relative to the case in which DZ Bank is at its median (normal state). Translating this log change into a percentage change of the quantile gives

$$e^{\Delta\text{CoVaR}} - 1 \;=\; e^{-0.486} - 1 \;\approx\; -0.385 \quad (\text{i.e.,}\ -38.5\%).$$

In short, stress at DZ Bank is associated with an approximate -38.5% deterioration of the system's left–tail quantile compared with the institution's median state. For institutions that exhibit a positive ΔCoVaR, the interpretation is symmetric to the negative case: conditioning the institution on its 5% VaR (stress state) shifts the system's 5% quantile to the right by ΔCoVaR log points, implying a mitigation of left–tail risk. By contrast, *Nürnberger* therefore does not appear to significantly worsen systemic risk with a ΔCoVaR slightly below 0: its marginal impact is comparatively limited when set against the larger banks and insurers in the sample.

This type of result highlights the subtle interplay between regression coefficients and quantile shifts in determining the final sign of ΔCoVaR and underlines that positive systemic contributions are not necessarily synonymous with strong fundamentals, but rather with statistical co-movements that in certain cases can lead to attenuation of system-wide stress.

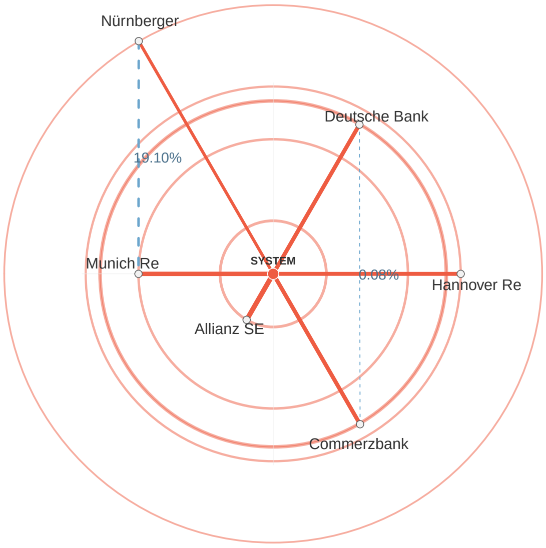
These results should be interpreted with caution, given the small sample (17 annual observations), which limits statistical power and can lead to unstable magnitudes or sign flips. This analysis is not a regulatory proposal; rather, it is an illustrative proof-of-concept that could be refined by practitioners or supervisors who have access to richer and higher-frequency data.

I also present (Figure 3) results based on publicly traded banks using market returns, which are more timely, incorporate investor expectations, and cover a longer sample than accounting data.

The use of market-based returns provides a complementary perspective: while accounting data reflect realized performance over discrete reporting periods, stock-price data embed forward-looking assessments of profitability, risk, and solvency that investors continuously update.

Figure 3: Systemic-risk network from market returns and associated ΔCoVaR values.

The central node represents the system, with institutions organized according to their ΔCoVaR size, while dashed blue edges denote equity participations. The table reports the corresponding ΔCoVaR values.



Institution	ΔCoVaR
Allianz SE	-0.729
Commerzbank	-0.398
Munich Re	-0.505
Deutsche Bank	-0.402
Hannover Re	-0.360
Nürnberger	-0.137

This means that systemic risk measures derived from market returns may be more sensitive to shifts in sentiment, liquidity conditions, and macro-financial shocks, making them particularly relevant for stress-testing exercises. From the market-based network it emerges that institutions such as *Allianz SE* and *Munich Re* contribute negatively to systemic stability (with $\Delta\text{CoVaR} = -0.729$ and -0.505, respectively), indicating that their distress scenarios are associated with substantial leftward shifts of the system's quantile. Here *Nürnberger* displays a lower value (-0.137) than before, while *Deutsche Bank* and *Hannover Re* higher ones (-0.402 and -0.360).

Similarly, *Nürnberger* displays a small but positive contribution (+0.026), while *Deutsche*

Bank and *Hannover Re* each record moderately negative values (-0.106 and -0.172).

These divergences between accounting and market-based measures are not contradictions but rather reflect the different informational content of the two data sources.

Market returns tend to anticipate distress and react quickly to shocks, while accounting returns are backward-looking and may smooth over short-term volatility. The fact that some institutions (e.g. Munich Re) can face changes in their ΔCoVaR values depending on the measure emphasizes that systemic importance is not a fixed attribute but context-dependent, varying with the lens through which financial fragility is assessed. Overall, the results derived from market returns underline the importance of complementing accounting-based systemic risk measures with market-implied indicators. This dual perspective provides a richer understanding of systemic linkages: while accounting returns highlight structural vulnerabilities tied to balance-sheet exposures, market returns capture dynamic, expectation-driven vulnerabilities that are crucial for anticipating contagion in real time.

5.5 Systemic-Risk Network of Italian Financial Institutions

Starting from the results obtained for the German banking system, the analysis can also be extended to the Italian case. The Italian financial system is characterized by a greater presence of commercial banks with strong territorial roots and by a historically important role of insurance intermediaries in the financing of the real economy. The application of the ΔCoVaR approach to the Italian landscape makes it possible to quantify how stress situations in individual institutions may spread within the system as a whole, distinguishing institutions that contribute to stability (ΔCoVaR greater than or equal to 0) from those that amplify systemic risk (ΔCoVaR less than 0). By including the shareholdings between institutions, it is also possible to capture the concrete links through which the contagion of a financial shock can spread from one institution to another.

For the institutions considered, returns were collected from annual financial statements for the period 2002–2024 using the same methodology presented for the German landscape in Section 4, including both accounting returns and market returns. The results of the set of univariate linear regression (11) are shown in Table 5.

Table 5: Univariate regression results: individual italian institutions' impact on the system return.

This table reports the results of separate univariate regressions. The system return is regressed on each institution's individual return.

Institution	**Intercept**	β	**Std. Error** (β)	**p-value**	R^2
UniCredit	-0.021	-0.012	0.323	0.9712	0.000
Intesa Sanpaolo	-0.107	0.781	0.473	0.1132	0.115
Monte dei Paschi di Siena	-0.021	0.026	0.192	0.8945	0.001
Banco BPM	-0.050	0.507	0.336	0.1463	0.098
BPER Banca	-0.034	0.042	0.260	0.8721	0.001
Banca Popolare di Sondrio	-0.399	3.276	1.105	0.0074***	0.295
Credito Emiliano	-0.184	0.998	0.859	0.2586	0.060
Generali	-0.027	0.082	0.066	0.2259	0.069
Unipol	-0.048	0.143	0.457	0.7571	0.005
Allianz SE	-0.296	1.505	0.719	0.0488**	0.172

R2 is a measure of the goodness of fit of a model. In regression, the R2 coefficient tells us how well the regression predictions approximate the real data points.

The univariate regressions indicate that most Italian institutions exhibit weak or statistically insignificant links with the system return under normal conditions, as reflected in low R^2 values and non-significant β coefficients. For instance, UniCredit (with a R^2 so close to 0) basically moves on its own here: when it struggles, the system does not visibly follow. The ΔCoVaR value close to zero confirms this. Two institutions stand out: BPSO and Allianz SE, whose coefficients are positive and statistically significant, suggesting that shocks to these financial institutions translate into strong co-movements at the system level. This highlights the systemic relevance of Allianz SE as a major insurer, and suggests that BPSO may transmit localized stress into broader market dynamics.

For the remaining banks and insurers, systemic influence may emerge primarily in tail events rather than average conditions, which is consistent with the use of ΔCoVaR as a complementary tail-risk measure.

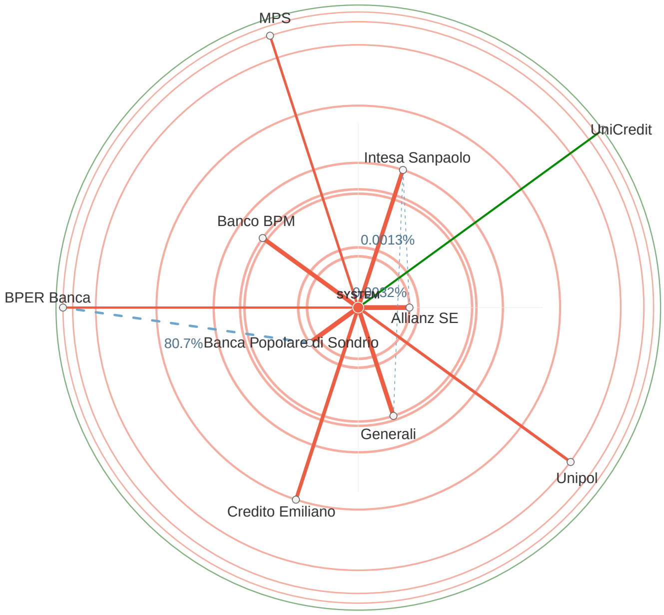
To see what happens during shocks, it is necessary to compute the ΔCoVaR, which measures how the risk of the system changes when any institution is in distress (VaR at the 5% level) compared to normal conditions (median VaR).

A topological representation of the Italian financial system is presented in Figure 4.

However, the ΔCoVaR of UniCredit is slightly positive, suggesting that under extreme stress conditions, the marginal effect of UniCredit on systemic risk is stabilizing: the additional loss of the system is lower than what would be expected based solely on average correlations. In contrast, Intesa Sanpaolo, Banco BPM, BPER Banca, Banca Popolare di Sondrio, and especially Generali exhibit negative ΔCoVaR values, indicating that their stress tends to propagate to the system, highlighting a central and interconnected role within the Italian financial network.

Figure 4: Visualization of the Italian financial system, with the corresponding ΔCoVaR values estimated from accounting returns.

The central node represents the system, with institutions organized according to their ΔCoVaR size, while dashed blue edges denote equity participations. The table reports the corresponding ΔCoVaR values.



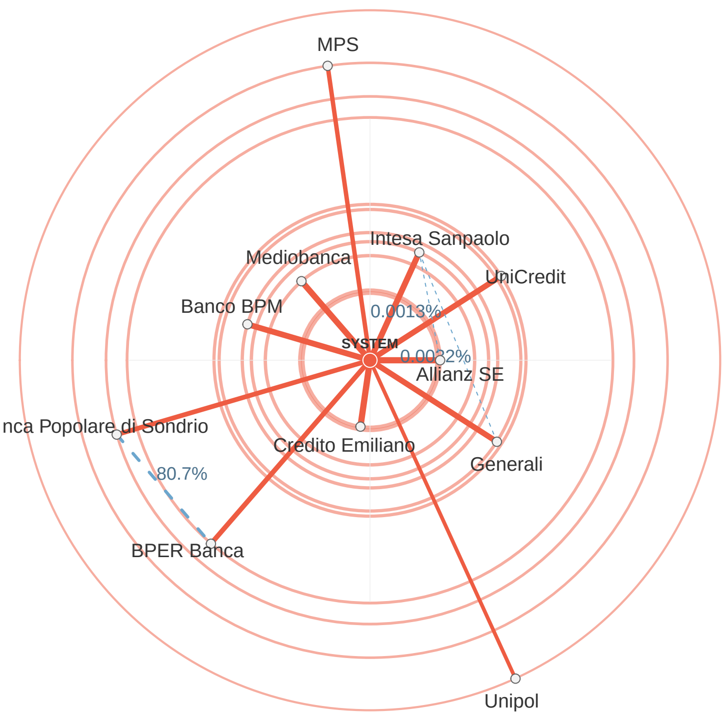
Institution	**ΔCoVaR**
UniCredit	+0.005
Intesa Sanpaolo	-0.158
Monte dei Paschi di Siena	-0.021
Banco BPM	-0.183
BPER Banca	-0.012
Banca Popolare di Sondrio	-0.240
Credito Emiliano	-0.102
Generali	-0.188
Unipol	-0.043
Allianz SE	-0.248

I also present results based on publicly traded banks using market returns in Figure 5. An interesting aspect that emerges from the comparison concerns the difference between ΔCoVaR based on accounting data and ΔCoVaR estimated from market returns.

Unicredit shows almost no explanatory power in the univariate regression (R^2 almost 0): in normal market conditions, Unicredit's returns do not co-move with the overall market. With a ΔCoVaR estimated of +0.005 using accounting returns, suggests that the bank is not a strong source of stress and does not significantly worsen systemic risk. This can happen because of the stabilizing role of capital requirements, capital buffer, ECB supervision and the "too-big-to-fail" framework which keep their reported figures stable. However, when market returns are used, the picture changes. Unicredit shows a negative ΔCoVaR (-0.387) indicating that in periods of mark tension, UniCredit tends to contribute to the propagation of losses into the whole system. In simple terms: on balance sheet data Unicredit appear stabilized by regulatory protections during the major crisis of the period we are considering, but market prices reveal Unicredit's role as a potential amplifier in short run contagion mechanisms.

Figure 5: Visualization of the Italian financial system, with the corresponding ΔCoVaR values estimated from market returns

The central node represents the system, with institutions organized according to their ΔCoVaR size, while dashed blue edges denote equity participations. The table reports the corresponding ΔCoVaR values.



Institution	**ΔCoVaR**
UniCredit	-0.387
Intesa Sanpaolo	-0.446
Monte dei Paschi di Siena	-0.165
Mediobanca	-0.468
Banco BPM	-0.432
Banca Popolare di Sondrio	-0.218
BPER Banca	-0.251
Credito Emiliano	-0.527
Unipol	-0.082
Generali	-0.395
Allianz SE	-0.522

The opposite dynamic is observed for Credito Emiliano: in balance sheet data its role is slightly worsening the systemic risk, while in market data a more pronounced negative ΔCoVaR emerges. This does not indicate structural riskiness, but rather reflects the low liquidity of the stock, which during stress amplifies the intensity of price adjustments, transmitting volatility to the system, displaying a form of “illiquidity spillover” contagion. Credito Emiliano, with a ΔCoVaR of -0.102, is sufficiently destabilizing but the effect is weak, as being a small bank it has limited systemic weight in fundamentals. Regarding the market ΔCoVaR of -0.527, it appears to be destabilizing not because it is risky per se, but because it is a low-liquidity stock and therefore reacts more sharply.

6 Discussion and Conclusion

This thesis has investigated the systemic relevance of major German financial institutions by applying the ΔCoVaR methodology to both accounting-based and market-based returns. The objective was to quantify how stress at the level of individual institutions propagates to the system as a whole. By combining statistical measures of systemic risk with a topological network representation, the analysis provides a multidimensional perspective on financial contagion.

The results show that not all banks and insurers affect the financial system in the same way: some make the system more fragile during stress, while others have only a small effect. Institutions such as *DZ Bank*, *Deutsche Bank* regarding the german financial system and *Allianz SE*, *Banca Popolare di Sondrio* and *Generali* display markedly negative ΔCoVaR values, suggesting that their stress scenarios coincide with a material deterioration of system-wide tail risk. Conversely, institutions such as *Nürnberger* or *Unicredit* occasionally exhibit almost zero or slitghlty positive ΔCoVaR values, which, although it may seem surprising at first, simply reflects how their price movements line up with the system in a way that reduces stress in certain situations. This asymmetry underlines the importance of carefully interpreting systemic risk indicators, as positive contributions do not necessarily imply superior fundamentals but simply that it moves differently with the rest of the system.

Second, the comparison between accounting-based and market-based returns reveals important discrepancies. Accounting data offer a retrospective view absed on annual financiall statements, while market data reclets forward-looking expectations and investor sentiment.t. As a result, certain institutions—most notably *Nürnberger*—switch from slightly to heavily destabilizing roles depending on the return measure employed. This finding underscores the complementarity of the two approaches: accounting-based measures reflect realized performance and balance-sheet resilience, whereas market-based measures are more sensitive to contemporaneous shocks and expectations. For supervisors and policymakers, this duality suggests that robust systemic risk assessments should integrate both perspectives.

Third, the robustness checks seems to confirm that the Cornish–Fisher expansion provides tail-risk estimates broadly consistent with historical simulation, while also accounting for skewness and kurtosis. Although differences were observed for specific institutions (e.g., Munich Re, Nürnberger, Monte dei Paschi di Siena, Banco BPM, BPER Banca) [6], these appear economically meaningful as they capture the effect of distributional asymmetries on systemic risk. This support the idea that the approch used, despite the relatively small sample size, produces stable and interpretable results.

Nevertheless, the analysis is subject to limitations. The small dataset (17 annual observations) constrains the power of multivariate models, necessitating the use of

[6] See Table 4 and Table 9

univariate regressions for coefficient extraction. While this choice is methodologically justified under the circumstances, it limits the ability to capture complex interaction effects.

With larger and higher-frequency datasets, a multivariate approach that includes interaction terms produce by cross-partecipations between institutions would be able to capture interdependencies more precisely, leading to a more detailed and reliable evaluation of systemic risk. Also, the ownership network we used is only one way in which shocks can spread. Banks are linked in many other ways too — for example through interbank lending, derivatives, or by holding similar assets — and these channels could also play an important role in the systemic risk propagation.

Overall, this thesis demonstrates the usefulness of ΔCoVaR as a tool for quantifying systemic risk and visualizing financial interconnectedness. The findings show that under certain conditions, smaller or less central players may contribute to stabilizing dynamics. For regulators, these insights highlight the importance of adopting a perspective that combines quantitative risk measures with structural mapping of financial linkages between institutions. Future work could improve this analysis by using more detailed data and models that capture how these relationships change over time.

A List of Institutions and Data Sources

Table 6: Selected institutions and corresponding tickers (Germany)

Institution	**Ticker**
Market-Traded Institutions	
iShares STOXX Europe 600 Banks UCITS ETF (DE)	SX7PEX.DE
Commerzbank AG	CBKG.DE
Deutsche Bank AG	DBKGn.DE
Deutsche Pfandbriefbank AG	PBBG.DE
Allianz SE	ALVG.DE
Münchener Rückversicherungs-Gesellschaft AG	MUVGn.DE
Hannover Rück SE	HNRGn.DE
Nürnberger Beteiligungs AG	NLVGn.DE
Talanx AG	TLXGn.DE
Non-listed / Cooperative / Public Institutions	
Sparkasse Bremen[1]	–
DekaBank[2]	–
DZ Bank AG[3]	–
Landesbank Baden-Württemberg[4]	–
Bayerische Landesbank[5]	–
UniCredit Bank GmbH[6]	–
ARAG SE[7]	–

Table 7: Selected institutions and corresponding tickers (Italy)

Institution	**Ticker**
UniCredit S.p.A.	UCG.MI
Intesa Sanpaolo S.p.A.	ISP.MI
Banca Monte dei Paschi di Siena S.p.A.	BMPS.MI
Banco BPM S.p.A.	BAMI.MI
Mediobanca S.p.A.	MB.MI
BPER Banca S.p.A.	BPE.MI
Banca Popolare di Sondrio S.p.A.	BPSO.MI
Credito Emiliano S.p.A. (Credem)	CE.MI
Assicurazioni Generali S.p.A.	G.MI
Unipol Gruppo S.p.A.	UNI.MI
Allianz SE (Italian operations)	ALV.DE*
Cassa Depositi e Prestiti (CDP)	–
Banca d'Italia (supervisory role)	–
ICCREA Banca (BCC Cooperative Network)	–

*Listed in Germany; included due to systemic relevance in Italy.

B Appendix I: Cornish–Fisher Expansion

For a random variable X with mean μ, variance σ^2, and cumulants κ_n, the quantile y_p at probability level p can be approximated using the Cornish–Fisher expansion as follows:

$$y_p \approx \mu + \sigma w_p \tag{13}$$

where w_p is an adjusted quantile derived from the standard normal distribution and corrected for skewness and kurtosis. Cornish and Fisher (1938)

where:

$$\begin{aligned} w_p = x &+ [\gamma_1 h_1(x)] \\ &+ \left[\gamma_2 h_2(x) + \gamma_1^2 h_{11}(x)\right] \\ &+ \left[\gamma_3 h_3(x) + \gamma_1\gamma_2 h_{12}(x) + \gamma_1^3 h_{111}(x)\right] \\ &+ \cdots \end{aligned} \tag{14}$$

$$x = \Phi^{-1}(p)$$

$$\gamma_{r-2} = \frac{\kappa_r}{\kappa_2^{r/2}}, \quad r \in \{3, 4, \ldots\}$$

$$h_1(x) = \frac{\mathrm{He}_2(x)}{6}$$

$$h_2(x) = \frac{\mathrm{He}_3(x)}{24}$$

$$h_{11}(x) = \frac{-\left[2\mathrm{He}_3(x) + \mathrm{He}_1(x)\right]}{36}$$

$$h_3(x) = \frac{\mathrm{He}_4(x)}{120}$$

$$h_{12}(x) = \frac{-\left[\mathrm{He}_4(x) + \mathrm{He}_2(x)\right]}{24}$$

$$h_{111}(x) = \frac{[12\mathrm{He}_4(x) + 19\mathrm{He}_2(x)]}{324}$$

where $He_n(x)$ is the Hermite polynomial of order n, γ_1 and γ_2 represent the skewness and excess kurtosis, respectively, andκ_n are the cumulants of the random variable X.

C Appendix II: Application Example of Adjusted Quantile

To illustrate the practical implementation of the Cornish–Fisher expansion, we consider the annual accounting returns of Sparkasse Bremen for the period 2008–2024. The observed returns are:

0.001434	0.029902	0.067030	0.057820	0.085028	0.050557	0.024620	0.076977	0.178593
0.076762	0.074266	-0.149809	0.012838	0.091282	0.100147	0.146331	0.128277	

From this sample, we compute the sample moments: Sample mean: $\mu \approx 0.0619$, Sample standard deviation: $\sigma \approx 0.0695$, Skewness: $\gamma_1 \approx -1.284$, and Excess kurtosis: $\gamma_2 \approx 2.78$.

Assuming we are interested in the 5% lower quantile (i.e., the left tail), the corresponding standard normal quantile is:

$$x = \Phi^{-1}(0.05) \approx -1.645$$

Using the formulas for the Hermite-based adjustment terms:

$$
\begin{aligned}
h_1(x) &= \frac{x^2-1}{6} = \frac{(-1.645)^2-1}{6} \approx 0.2843 \\
h_2(x) &= \frac{x^3-3x}{24} = \frac{(-1.645)^3-3(-1.645)}{24} \approx 0.0201 \\
h_{11}(x) &= \frac{-(2x^3-5x)}{36} \approx \frac{-(2(-4.45)-5(-1.645))}{36} \approx 0.0188
\end{aligned}
$$

We plug the skewness and kurtosis into the Cornish–Fisher expansion:

$$
w_p = x + \gamma_1 h_1(x) + \left(\gamma_2 h_2(x) + \gamma_1^2 h_{11}(x)\right)
$$

$$
\begin{aligned}
w_p &= -1.645 + (-1.284)\cdot 0.2843 + 2.78\cdot 0.0201 + (-1.284)^2\cdot 0.0188 \\
&\approx \boxed{-1.923}
\end{aligned}
$$

This adjusted quantile $w_p \approx -1.923$ reflects the empirical asymmetry and tail behavior in Sparkasse Bremen's return distribution. It is less negative than the standard normal quantile due to the presence of positive skewness and slightly negative kurtosis. By multiplying w_p by the standard deviation and adding the mean, we recover the Cornish–Fisher-adjusted VaR for the institution:

$$
\mathrm{VaR}_{0.05} = \mu + \sigma\cdot w_p \approx 0.0619 + 0.0716\cdot(-1.923) \approx \boxed{-0.0717}
$$

This value can then be used in the ΔCoVaR regression framework as a left-tail stress event.

D Appendix III: Empirical Quantile Calculation

As an illustration, consider a sample of size $n = 17$ returns. Sorting the values in ascending order yields the minimum $x_{(1)}$ and the second minimum $x_{(2)}$. For a tail probability $p = 0.05$, we obtain

$$h = 1 + (n-1) \cdot p = 1.8, \qquad k = \lfloor h \rfloor = 1, \qquad \gamma = h - k = 0.8.$$

Hence, the empirical 5% quantile is given by the linear interpolation

$$Q_{0.05} = (1-\gamma)\, x_{(1)} + \gamma\, x_{(2)}.$$

Said that, for *Deutsche Bank* we have $n = 17$ returns. Sorting in ascending order yields the minimum $x_{(1)} = -0.1515$ and the second minimum $x_{(2)} = -0.0892$. With $p = 0.05$,

$$h = 1 + (17-1) \cdot 0.05 = 1.8, \qquad k = \lfloor 1.8 \rfloor = 1, \qquad \gamma = 1.8 - 1 = 0.8.$$

Hence the empirical 5% quantile is the linear interpolation

$$Q_{0.05} = (1-\gamma)\, x_{(1)} + \gamma\, x_{(2)} = 0.2 \cdot (-0.1515) + 0.8 \cdot (-0.0892) = \boxed{-0.1017}$$

E Appendix IV: Empirical ΔCoVaR Calculation for Nürnberger Versicherung

Said that, for Nürnberger Versicherung with a $\hat{\beta}^{\text{Nürnberger}}$ equal to 3.73 a $\text{VaR}_{5\%}^{\text{Nürnberger}}$ of 0.02029, and a $\text{VaR}_{50\%}^{\text{Nürnberger}}$ of 0.11143, then:

$$\Delta\text{CoVaR}^{\text{system}|\text{Nürnberger}} = 3.73 \times (0.02029 - 0.11143) = -0.3403$$

Since the returns used are logarithmic, I perform the inverse transformation to obtain the percentage change. Given that returns are computed as logarithmic returns:

$$r = \log(1 + \text{return}) \quad \Rightarrow \quad \text{return} = e^r - 1$$

We apply the inverse transformation to the computed $\Delta\text{CoVaR} = -0.3403$:

$$\text{Percentage change} = e^{-0.3403} - 1 \approx -1 = -0.2884$$

Therefore, conditional on Nürnberger Versicherung being under stress (i.e., at its 5% worst return), the 5% quantile of the system return shifts leftward by about −28.8% compared to the case in which Nürnberger is in its median state. This reflects a deterioration of systemic downside risk.

F Appendix V: Results for the Italian Financial System

This appendix reports supplementary estimation outputs for the Italian financial system, including both the comparison between Historical Simulation and Cornish–Fisher VaR estimates and the ΔCoVaR estimates obtained via quantile regression and CF expansion.

Table 8: Comparison of ΔCoVaR estimates: quantile regression (QR) vs. Cornish–Fisher (CF)

Financial Institution	β		$VaR_{5\%}$		$VaR_{50\%}$		ΔCoVaR	
	QR	CF	QR	CF	QR	CF	QR	CF
UniCredit	0.054	0.582	-0.579	-0.627	-0.010	0.039	-0.031	-0.387
Intesa Sanpaolo	0.485	0.834	-0.354	-0.436	0.165	0.099	-0.252	-0.446
Monte dei Paschi di Siena	-0.105	0.283	-0.871	-0.845	-0.236	-0.262	0.067	-0.165
Mediobanca	-0.780	0.971	-0.327	-0.396	0.103	0.086	0.336	-0.468
Banco BPM	-0.311	0.620	-0.669	-0.641	0.111	0.056	0.243	-0.432
Banca Popolare di Sondrio	0.657	0.622	-0.292	-0.324	0.016	0.027	-0.203	-0.218
BPER Banca	-0.126	0.563	-0.408	-0.428	0.060	0.017	0.059	-0.251
Credito Emiliano	0.839	0.971	-0.400	-0.433	0.120	0.109	-0.436	-0.527
Unipol	-0.011	0.215	-0.535	-0.505	-0.076	-0.122	0.005	-0.082
Generali	0.398	1.170	-0.244	-0.294	0.048	0.044	-0.116	-0.395
Allianz SE	0.617	1.330	-0.165	-0.282	0.108	0.111	-0.168	-0.522

Table 9: VaR at 5%: Historical Simulation vs Cornish–Fisher (Italian Financial System)

Institution	**HS (5%)**	**CF VaR (5%)**	**CF – HS**
Unicredit	-0.211	-0.205	0.006
Intesa Sanpaolo	-0.064	-0.080	-0.016
Banco di Campania	-0.602	-0.734	-0.132
Banco BPM	-0.275	-0.259	0.016
BPER	0.007	-0.052	-0.059
BPSO	0.053	0.044	-0.010
Cassa di Risparmio	0.089	0.059	-0.030
Generali	-1.670	-1.802	-0.132
Unipol	-0.048	-0.097	-0.049
Allianz SE (Italy)	0.101	0.033	-0.067

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