Degree Program in Finance

Department of Economics and Finance

# Climate risk and systemic risk of credit market: a CDS-based analysis.

Chair of Econometric Theory


Supervisor:

**Prof. Paolo Santucci de Magistris**

Co - Supervisor:

**Prof. Roberto Rinaldi**

Candidate:

**Antonio Muciaccia**


Academic Year 2023/2024

# Contents

# Abstract

One of the newly developed practices of sustainable finance is the need to consider this impact and to work together with the challenges faced by the increasingly warmer earth. This thesis is concerned with the inter-relationship between the financial stability and the climate risks, seeking to investigate how the multiple risks to the capital markets stem from systemic climate risks to borrowers. Considering the major threats of climate change and the climate change related issues are intricate, evaluating the financial impacts of climate change is very opportune and most importantly essential.

The core of our investigation pivots around the question: Do systematic climate-risk factors play a role in equities' creditworthiness? To find the answer to this question, we develop a methodological frame that uses a panel regression with both empirical and quantitative analysis focus on $N$ stock's CDS spreads along different maturity of its credit default. This research works on systematic climate risk factor model building, which is time-varying with equities' CDS spread and a climate measure of risk factors that influences our analysis.

This methodology is structured through three fundamental stages. The building of a dataset composed of $N$ stocks and the corresponding CDS spreads is at par with the systematically assembled climate risk factors that reply the iShares Global Clean Energy ETF. This step entails a basic understanding of the capital market dynamics and the vulnerabilities posed by climate change. The application of a bivariate GARCH model to each asset, pursuivantly, takes the moment of dynamics of the log-difference of CDS spreads and a chosen climate risk factor. This econometrics analysis is supported by using the dynamic autoregressive model, the AR(p), for the CDS log-linear differences and the means of the climate risk factors.

From the estimation of the previous steps, this study examine the probability that

a firm's spread will exceed a predefined threshold based on distressed climate events. This investigation analysis is to provide insights into the inconsistency of the response of different firms, viewed in terms of creditworthiness, through the perspective of systemic climate-risk factors.

This thesis is placed at the intersection of environmental and financial research, enabling to see the role that climate change play in the banking sector. Through a systematic filter of climate-change risk factors, it strives to bring to light the diverse vulnerabilities of firms to stresses related to climatic changes. This study is more than just an academic exercise; it has significant implications for investors, policymakers, and businesses trying to manage and mitigating the effects of climate change risks in the financial system.

# Chapter 1

# Introduction

"Over the 40 years of my career in finance, I have witnessed several financial crises and challenges — the inflation spikes of the 1970s and early 1980s, the Asian currency crisis in 1997, the dot-com bubble, and the global financial crisis [...] Even when these episodes lasted for many years, they were all, in the broad scheme of things, short-term in nature. Climate change is different", as BlackRock's CEO Larry Fink stated in 2020. Climate change is one of the challenges of the last century, different from the other crises faced as it directly impacts all of our aspects of life, and creates concerns for future generations (Black and Thomson, 2023).

A low-carbon economy necessitates changes in consumer attitudes, technology, and legislation to help economies shift to a new framework. Those changes include risks, named climate transition risk (CTR), for the firm's cash flows and their unpredictability, which may impair the debt repayment capabilities of enterprises and, consequently, increase their credit risk. The pricing of stocks and bonds as well as the decisions made by institutional and private investors regarding their portfolios have all been shown to be influenced by CTR (Monasterolo and De Angelis, 2020). It is currently unknown, though, how different organizations' credit risk may be affected in relation to how vulnerable they are to CTR.

Though this knowledge is essential for business investment decisions aimed at limiting the impact of climate change and implementing appropriate climate policies, it is yet unknown how credit risk across enterprises may be altered according to their vulnerability to CTR (Krueger, Sautner, and Starks, 2020). Regulations, technology, and consumer attitudes must all be adjusted in order to help economies adjust to the new framework that comes with the shift to a low-carbon economy. These adjustments include risks for the cash flows and volatility of the company, known as climate transition risk (CTR), which could reduce the ability of businesses to repay their debt and raise credit risk because of it (Reboredo and Otero, 2021). It has been established that climate risk plays a significant role in the portfolio decisions made by institutional and private investors, as well as in the pricing of stocks and bonds (Bolton and Kacperczyk, 2020).

In this study, we examine how the market of credit default swaps is conditioned by the climate risk factor and how this risk is exposed during the period considered. The proposed dataset refers to a brown-minus-green risk factor expressed by an indexed Ishares Global Clean Energy Ucits ETF that has as benchmark the S&P GL CLEAN ENERGY, together with the standard determinants of the credit risk implied in the CDS spread market.

Given the annual time horizon, the metrics of implicit credit risk in the credit market that we collect are 1 and 5 year CDS to cope with a more detailed analysis. The data covers world large banking firms over the period of 2023-2024. The data sources used in this study are from commercial data and providers used by financial institutions. For instance, the CDS data is collected from IHS Markit and the transition risk indicators are collected from Bloomberg and Refinitiv. The choice of these data sources represents the possibility of representing the environment of the data sources available to CDS market players, to make the analysis as truthful as possible.

The objective of the analysis investigate the promotions of the climate-related transition factor on CDS-implied credit risk by a panel regression and a difference-in-differences approach. The findings reveal that CDS spreads at the 1 and 5-year tenor, associated with a medium-term credit risk time horizons, are higher for firms with higher BMG emissions. These differences appear to be consistent with a causal relationship. Indeed, a differences-in-difference analysis near the UN Paris Agreement of 2015 indicate that these six months froze a signals and the force climate-related policies and market confidence changes (United Nations Framework Convention on Climate Change (UNFCCC), 2015) . Specifically, high polluting banks have notably higher CDS spreads than the comparison group of all firms. With a view to the mentioned objective, we need to cut emissions to the extent that they will almost be equal zero by 2050. This rundown of IPCC findings has shown, that on one hand there has been narrowing of the gap between the current situation and the targeted emission reduction paths, however on the other hand the gap is still widening and creates an outlook of somewhere between 3°C and 4°C warming (Dell, Jones, and Olken, 2014).

The empirical study shows how the world's largest banks react to climatic events, analyzing the dynamics of movements between CDS spreads and the BMG factor, for which we utilize the dynamic conditional correlation (DCC) derived from the multivariate GARCH model. The advantage of this methodology is that it directly shows the change in the co-movement of CDS spreads of banks and green factors. The more significant correlation of the CDS markets, the more they generally co-moved and were integrated. Due to dependence on time, both correlation dynamics are the correlation pattern of change the volatility of CDS spreads is modeled simultaneously by the vector autoregressive model. Conforming to the time dimension of data series work gives the opportunity to take into account the change in the integration of them over time.

This thesis is structured as follow: Chapter 2 covers the estimation of DCC-GARCH models for individual stocks, the sensitivity analysis of various climate risk factors, the identification of the thresholds for climate events, and the cross-industry case comparison. The data and methods used are analyzed within Chapter 3, which includes the study of the selected stock portfolio, the comprehensive analysis of CDS spreads correlated to the systemic climate risk factor, the description of the DCC-GARCH model correlated to the selection of the dynamic component for the reasearch. Around Chapter 3, we illustrate the time-varying dynamics in CDS spreads and AR models for capturing the dynamic relationships in financial data. Finally, Chapter 4 summarizes the key findings discussing their implications and limitations, and suggests further work.

# Chapter 2

# Data and Methodologies

This second chapter outlines the research methodology and data analysis techniques used to study credit default swap (CDS) dynamics, the impact of systemic climate risk on financial markets. The latter two are modeled using a DCC-GARCH multivariate model, which we will explain in detail in this chapter, using a dynamic component to best develop it. The chapter is developed in order to methodically divide the various tools and data used, ensuring a complete understanding of the analytical bases that support the thesis.

## 2.1 Overview of the Selected Stock Portfolio

My in depth analysis into ten bank stock is divided into two branches, Eurozone banks and those issuing their shares in US dollar and US banks that are presented in US dollar basis. Eurozone banks are compared using dollar exchange rates from European into US currency. This study employs an in-depth framework of analytics that are both on short-term 1-year Credit Default Swap (CDS) spreads, analyzed daily, and on the long-term 5-year Credit Default Swap (CDS) spreads, that provides a result of a complex nature of each bank health and risks (Collin-Dufresn, Goldstein, and Martin, 2001).

In global banking business, these ten banks[1] are recognized as the largest sources and most powerful contributors in the worldwide financial system, having their own positions in the financial field. The banks in focus are: In the United States, JPMorgan Chase

[1]The information about this banks are available on their own website or in this link https://www.spglobal.com/en/.

& Co., Goldman Sachs Group Inc., Bank of America Corporation, Wells Fargo & Co. and Citigroup Inc. Join the regional representatives from the United Kingdom, France, Switzerland and Germany, such as HSBC Holdings plc., Barclays PLC, BNP Paribas, UBS Group AG and Deutsche Bank. Consequentially, they are commonly defined as the "systemically important" (Too Big Too Fail) financial institutions which is characterised by their large market size, global reach and sheltering impact.

Is important to highlight the actual framework of different banks, which will outline their traditional evolution, organizational model, financial goals, strategic activities and their huge worldwide network. In addition, the study will also measure the regulative environments and markets conditions the banks apply to, with this knowledge on their performance in global finance as well as their strategies that follow with the new and evolving economic settings as well as regulation requirements.

The focus is on what green banks do in the implementation of sustainable finance and how these banks will deal with the difficulties that may be presented in the face of climate change and social responsibility. Such culmination of their efforts covers their stringent requirements for green technologies, incorporation of ESG (Environmental, Social and Governance) criteria and their implementation towards a more sustainable and inclusive global financial infrastructure. This additional layer of analysis will offer insights into how these major banks are not only financial entities but also pivotal players in the broader context of global sustainability and ethical banking practices.

The CDS data of the 10 stocks taken into account, represent the financial market trend in the last year, reflecting their fluctuations and price differences. The data provided

## 2.2 CDS spread and interest maturity

Credit risk is arguably the greatest problem which banks fight since it is one of the major risk factors that threaten soundness of global financial systems. Among the credit derivative devices, Credit Default Swaps (CDS) however serve a vital role in the analysis of market participants about the measure of risk stemming from entities such as sovereigns, firms and banks (Annaert et al., 2013). Supporters regard this instrument as a useful measure of the credit risk while opponents tend to put forward the downside of the availability of such loans for the governments to default. The investor Warren Buffett, in his 2002 Berkshire Hathaway Annual Report, had widely accepted the CDS as " a mass destructive weapon" financially (Inc., 2002). In turn, financial institutions along with the regulators are facing the task of creating working approaches for examine and control of the credit risks, especially in the field of corporate debt securities, issued by the banks. CDS contracts on them are capable of leading to the uncontrolled financial effect.

In recent years, the credit risk mitigation tools have come to the derivatives market place to address the credit risk of the counterparties. Such system help entities to be able to defray credit risk from one party to another through the CDS being the most renowned credit derivative. JP Morgan, under the leadership of Peter Hancock, is the founder of the first Credit Default Swap (CDS) contract back in the early 1990s because the credit risk transfer between institutes was largely talked about during that period. In reality, a CDS is a derivative financial contract which protects an investor against a predetermined trigger event that happens each day and in exchange for a fixed single fee. An "insurance buyer" on one side of the contract buys a pooled risk against a credit loss event, and sells the old debt to a "protection seller", receiving the premium either annually or semiannually and obligated to pay eventually the predetermined amount if a credit event occurs.

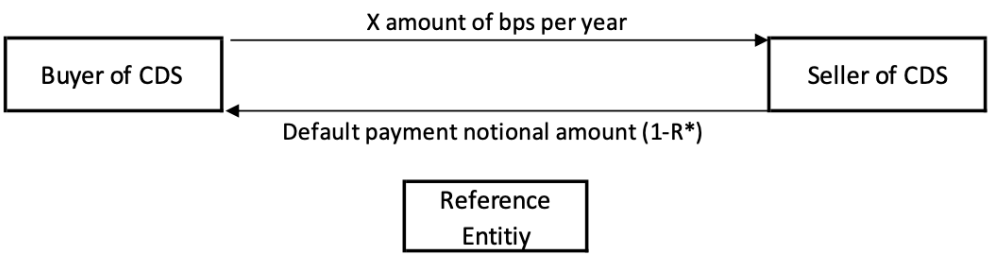


Figure 1: Plain vanilla CDS products work

A CDS seller pays the buyer a spread which is determined as the ratio in basis points between the notional value of the CDS, and the cost. The seller receives ongoing payments, and when a credit event happens is responsible for paying back its amount. Panel of the recovery rate, which is the ratio or the part of the debt that is recovered represents the amount that the party has to pay the protection seller. The loss is estimated to this sum of money which is equal to the original debt amount (par value) minus the debt collection value. The CDS premium is traditionally applied as a critical diagnostic tool to appraise credit risk of the indicated company (Ericsson, Jacobs, and Oviedo, 2004).

| **Protection seller** | **Protection buyer** |
|---|---|
| Does not own the underlying credit instrument | Owns the underlying credit instruments |
| Sells protection on a credit position | Buy protection against a credit event |
| Long credit exposure | Short credit exposure |

Figure 2: Credit Default Swap transaction

Figure 2 summarizes the key characteristics of a CDS contract's between two counterparties.

Should be important to consider the direction of cash flows in this operations. The CDS contract involves two main cash flows:

1. A settlement payment from the protection seller to the buyer if a credit event occurs;
2. A periodic premium paid by the protection buyer to the seller.

CDS contracts can be seen as insurance policies designed to protect the buyer from defaults of the underlying entity, when in case an event of credit is declared, protection seller will compensate the buyer with the previously decided premium. In turn, the buyer will be paying regular premium prescribed by the earlier agreed CDS premium. Unlike a usual insurance contract, the buyers of a CDS are not required to own the underlying asset to be compensated, which implies that participants of the market are free to gamble with credit risk, not being actually in the position or not possessing the underlying asset at all.

CDS contracts can be classified into three main categories: underly a single-name CDS, CDS indices, and basket CDS: underlies single-name CDSs, CDS indices, and basket CDSs.

ECB defines Single-name CDS that insulate impact on default of one selected corporate or sovereign entity (European Central Bank, 2009). The CDS indices are designed in a way to provide a kind of credit insurance against a "default risk on the pool of names in the index." One of the key features of such a contract is, that a credit event does not result in a termination of the contract itself (Amato and Gyntelberg, 2005). Hull and White (2000) define the difference between the single and multicomponent reference entities as the prefix of the "basket". At the basket CDS, the first default occurring reference entity determines the payment (Hull and White, 2000).

The credit event is the certain happening, in which obligatory payment of the protection seller's payment activates. The valuation of the performance is not an incidental case, it is unique and requires special terms from the parties who are contractual and can be similar or different depending on the peculiarities of the agreement between the parties. An event of it kind includes the reference entity being unable to fulfill its obligations to the entity in question (IPCC, 2014). Finally, another credit event can be triggered by the fact that a loan is being delayed in paying.

The CDS premium (also referred to as spread) is a key contractual component which is normally created in basis points, bps, relative to the amount of notional. This spread reflects the fact that the market is aware of the credit risk of the organization permitted. Through this thesis one will contribute to the study of the factors that influence the CDS spread for European banks and the subsequent assessment of the predictive power of CDS premium for the avoidance of financial distress and stabilization of financial system as the European banks have the systemic importance.

## 2.3 Construction of the systemic climate risk factor

To assess the data provided by the spread of CDS of the world's best banks in building climate factors, annual returns measured by the duration of the CDS are critical. In our specific case, the CDS Spread are taken on annual frequency for 1y and 5y, they were chosen specifically for better estimation.

Over the past three decades the global application of climate-related policies has got power with rapidly increasing success rates (Acharya et al., 2017). Many of the policies, like carbon tax and green subsidies, are used to address the issue of climate change, but at the same time, their economic risks can be additional. Such risk, referred to as transition risk, is an indirect economy through banks. Borrowers, who are affected negatively by transition risk, have their repayment capability weakened if their incomes reduce in proportion to the risks faced. In turn, this process then adversely affects a bank's profitability, at the time and in the future. This might even lead to a crisis in the banking system if banks lack sufficient funds. Such a falling financial state makes it harder for banks to lend money, thereby stifling economy.

The decision makers and the enterprises, alike, have to comprehend the scope of several climate policies and the frameworks being formulated to deal with climate-related risks on the financial system as soon as possible. What is worth noting as well, the total literature on the systemic risk measurement has provided some useful indexes in the context of financial crises, but none of them are used to understand the climate-related risks at the present moment (Schroders, 2021).

As part of building the systemic climate risk factor, we rely on the carbon emission coefficient as an analytical tool for climate and use the Credit Default Swap (CDS) range to validate our measuring device.

The data given are publicly data. All 10 banks to be found in this climate consideration have their operational activities resulting in a carbon footprint contribute to their presence; things like energy used, travel, and other business emissions. Many of these banks have already used sustainable initiatives, energy projects, or financially responsible to it that completely changes their behavior to reduce the carbon footprint, backing renewable (Global, 2020).

Nowadays, there is more emphasis on the aspect of the transparency and disclosure for climate-related risks. Such banks might be under the regulatory process or even voluntarily publish their activity in the climate risk matter against the accompanied efforts in its mitigation.

Based on the climate risk rating reports of all banks, we arrive at the common factor that is determined by how the fluctuations of market variables, such as interest rates, foreign exchange rates, equity and commodity prices, credit spread or implied volatilities affect the value of assets as short-term and long-term price volatility (Alexander, 1998).

The analysis is focused on the "brown minus green" (BMG) emissions, a term being the green subtraction of net brown from Scope 3 of the emissions[2]. It can be said that,

[2]Scope 3 refers to emissions that occur indirectly in a company's value chain, beyond its direct operations or those of the controlled assets.

Scope 3 includes emissions that run outside the emissions sources covered by Scope 1 and 2. This category considers the indirect greenhouse gas emissions resulting from the company‘s operation.

Introduction of Brown Minus Green (BMG) index is our rising point, which needs to start the development of Brown-Green Score (BGS). This score supposed to beat up the iShares Global Clean Energy ETF (dist); this ETF has a benchmark the S& P Global Clean Energy Index (S& P GL CLEAN ENERGY).

”BMG,” stands for ”Brown Minus Green,” which is a budget utilized for evaluating the effect of an entity, most likely owned by the private sector, on the environment, mainly in relation to carbon emissions or the sustainability of a enterprise (Company, 2023). Generally, the color ”brown” has been traditionally associated with the ecologically harmful or carbon-emitting activities while ”green” is mostly recognized as ecological or friendly to the environment.

The phrase “Brown Minus Green” signifies the numerical or value judgment of the bad impact on the environment (brown) in relation to the good environmental principles or practices (green) (Morningstar, 2022). The association could be interpreted as a reflection of a larger environmental footprint of the entity, whereby it is also considered to be more carbon-intensive due to less sustainability orientation.

## 2.4 Description of the DCC-GARCH model

The analysis of financial time series is a keystone of the existing financial theory and practice, with volatility modeling being the one of the very important aspects in the understanding of the dynamics of financial markets. Volatility is a key to the assessment of risk and the design of arbitrage and hedging tactics. It measures the deviation of assets prices from the mean. Though it is called univariate volatility model, the early focus was on volatility of individual assets then thereafter it became evident that volatility of each asset cannot be modeled without the comprehensive relationship of the whole economy. These emphasize that not only the fluctuations of individual assets but also the dynamic cross links of the different financial assets should be modeled. This is very important for portfolio composition, asset pricing, and risk management.

The evolution of GARCH models is originated from a revolutionary work of Robert Engle on Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model and Tim Bollerslev refinement of this model later on (R. Engle, 2002). The GARCH model which came as an improvement over the Autoregressive Conditional Heteroskedasticity (ARCH) model, by Engle, was a better model as it was much more flexible and parsimonious in conditional variance prediction (X. Huang, 2019). Nevertheless, these models were unied for univariate analysis, which was useful for analyzing of a single financial time series at a given time.

Since markets grew more linked from a financial perspective, the flaws of univariate models, which are one-variable models, had to be taken into account. This demand spurred the birth of multivariate volatility models with more sophisticated but less static method for calculating volatility and correlation between multiple assets varying through time. The models go further than GARCH in terms of allowing the explicit modeling of the conditional correlation and covariance among the multivariate set of assets by extending the framework. This process indicates a trend of the risks in financial markets and opportunities being seen from a position where the risks and opportunities cannot be fully deciphered if one compartmentalizes them to be seen separately, but they are interested with how different assets co-interact with each other (R. Engle and Kroner, 1995).

The Dynamic conditioning correlation GARCH (DCC-GARCH) model, due to Engle and Sheppard (2001) (Sheppard and R. F. Engle, 2001), may be considered as an improvement upon the CCC-GARCH model.[3] This study contributes to the literature established by Bollerslev's (1990) (Bollerslev, 1990) ground-breaking model evaluation. The contrast of the CCC-GARCH and the DCC-GARCH stands on the DCC-GARCH capability to depict the correlation structure that may evolve dynamically and change

[3]The CCC-GARCH model formula is given by:

$$\Sigma_t = D_t R_t D_t$$

with $D_t = \mathrm{diag}(\sqrt{\sigma_{t,11}}, \dots, \sqrt{\sigma_{t,nn}})'$ where the conditional variances $\sigma_{t,jj}$ can be generated by any GARCH-type model, and $R$ is the conditional correlation matrix of returns:

$$R = \mathrm{corr}(r_t | I^{t-1})$$

where $\rho_{i,i} = 1$. It is easy to show that the element in position $(i, j)$ in $\Sigma_t$ is given by:

$$\sigma_{t,ij} = \rho_{i,j} \sqrt{\sigma_{t,ii} \sigma_{t,jj}}.$$

over time. Different to MGARCH (Multivariate GARCH) models, DCC-GARCH is computationally effective mainly because no matter how many time series being simulated, there will be no measure of the efficiency out of the production due to the process of estimaton interaction. It is this property that makes matrix implementation considerably faster in comparison with matrix operations in the case where matrices are of large sizes (R. Engle, 2002).

Nevertheless the CCC model have poor assumption for an economical framework. The primary matter here is that level of conditional joint correlations is time variable, it changes over time (He and Teräsvirta, 2004). The DCC models are designed into two steps processes which features model construction. Contrary to the CCC (conditional categorical claims) models, the sectorial structure trading matrix ($R_t$) in these dynamic models depend on a set of unknown parameters

$$R_t = R(I^{t-1}; \theta_c)$$

The DCC model is defined as follow (assuming $\mu_t = 0$)

$$H_t = D_t R_t D_t$$

where R is the correlation matrix which contains the conditional correlations.

$$r_t| =_{t-1} \sim N(0, D_t R_t D_t)$$

$$\sigma_{t,ii} = \omega_i + \alpha_i r_{t-1,i}^2 + \beta_i \sigma_{t-1,ii} \quad i = 1, \dots, n$$

$$D_t = \text{diag}(\sqrt{\sigma_{t,11}}, \dots, \sqrt{\sigma_{t,nn}})'$$

$$\epsilon_t = D_t^{-1} r_t$$

$$Q_t = C'C + A \odot \epsilon_t \epsilon_t' + B \odot Q_{t-1}$$

$$R_t = (diag(Q_t))^{-\frac{1}{2}} Q_t (diag(Q_t))^{-\frac{1}{2}}$$

Assumption of normality leads to ”likelihood function” (first equation). Without this assumption though, the estimator obtains the QML (Quasi-Maximum Likelihood) interpretion. The second equation is mere evidence that we have assumed that the assets are following bivariate GARCH processes and nothing chang if this were generalized.

Matrix C will become upper triangular and matrices A and B, which are n×n-order positive semi-definite parameters. The last equation is fundamental out of all, since it crucial to keep $R_t$ intact as a correlation matrix. The change of terms sign $\sigma_{t,ii}$ works for numerous configurations of the single-variate, implicit, and explicit models which are just adjustment of the original terms for them.

The log likelihood function can be maximised over the model parameters. Consequently, the terms in the diagonal of the pattern D correspond with the axis terms in the model $\theta$ while those in matrix R are indicated by $\phi$. The log-likelihood function is then described as a combination of two distinct parts: one related to volatility and the other to correlation.

$$L(\theta, \phi) = L_V(\theta) + L_C(\theta, \phi)$$

The volatility is given by:

$$L_V(\theta) = -\frac{1}{2}\sum_t (n\log(2\pi) + \log|D_t|^2 + r_t' D_t^{-2} r_t)$$

The correlation parameters is given by:

$$L_C(\theta, \phi) = -\frac{1}{2}\sum_t (\log|R_t| + \epsilon_t' R_t^{-1}\epsilon_t - \epsilon_t'\epsilon_t)$$

The volatility component of the likelihood function is effectively the sum of individual GARCH model likelihoods, described as:

$$L_V(\theta) = -\frac{1}{2}\sum_t \sum_{i=1}^{n} (\log(2\pi) + \log(h_{i,t}) + \frac{r_{i,t}^2}{h_{i,t}})$$

Optimization is achieved by maximizing each individual components within the formula and thus make it more effective.

Proceeding to the correlation part of the likelihood involves the consideration of the integral that determines the correlation parameters. The idea peculiar to squared residuals are not related to any parameters allows us to view them as not contributing to the first order conditions. The model that is employed will determine the type of estimator that will be used if its either the mean reverting model or the integrated model. The estimated estimators are named DCC LL MR and DCC LL INT correspondingly.

The optimization strategy unfolds in two phases, initially focusing on the maximization of $L_V(\theta)$:

$$\hat{\theta} = argmax(L_V(\theta))$$

Following this, with $\hat{\theta}$ established, the process advances to the second phase, concentrating on maximizing the correlation component:

$$max_{\phi} L_C(\hat{\theta}, \phi)$$

By sticking to the validity criteria or regularity conditions, the consistency of the first phase ensures the consistency of the succeeding phase. Second phase results will however depend on the estimates of the first phase. It, however, will keep along the true parameters under the condition of continuous function within a proximal vicinity of the real parameters. This structured approach to likelihood maximization demonstrate the methodological rigoriness in marginal parameter estimation of multivariate GARCH manifold, hence a refined comprehension of the fluctuation and association scheme of financial assets arrive.

## 2.5 Dynamic component and the AR(p) model

The static nature of the macroeconomic variables was not incorporated in the original models, which resulted in no relation between the theoretical model and the real-life economic behavior. Evans and Sims were the pioneers in this field, and around the 1980s, the latter put forward this need and suggested how to capture the interdependencies among several time series variables (Sims, 1980).

These variables are the reasons behind the economic development over time and provide a more realistic view. In traditional macroeconomics, the mechanisms of time are often overlooked, which causes discordance between theoretical models and actual economic procedures. Sims noticed this space and described the reason behind the dynamic skills to be involved in the modeling process. These parts form the dynamical evolution of economic variables, which is a more realistic picture of economic phenomena.

The core of Sims' theory centers on the Autoregressive (AR) model, particularly the AR(p) model where 'p' is used to signify the order of the model. The model expressed a set of endogenous variables over a sample period as follow:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + ... + \beta_p Y_{t-p} + \varepsilon_t,$$

where $Y_t$ is an n $\times$ 1 matrix of economic value, $\alpha$ is the n$\times$ 1 vector of intercepts, $\beta_1, \beta_2...., \beta_p$ are the lagged coefficient for the variables constructed as n $\times$ n regression parameters matrices, and $\varepsilon_t$ is the error term distributed as N(0,$\Sigma$), where $\Sigma$ is a positive-definite covariance matrix and the sequence $\varepsilon_t$ is independent over time.

The model is able to change in different economic contexts without the imposition of any predetermined restrictions, hence its applicability is wide in various macroeconomic researches. Although it is a basic model, the AR(p) model is very powerful to describe the dynamics of the macroeconomic variables and is a key element of many empirical studies. The AR(p) model is data driven and so the model structure is in line with the actual economic events leading to accurate macroeconomic analyses.

Generally, VAR models are estimated utilizing Ordinary Least Squares (OLS) method, but the reliablity of these models is conditioned on the observation of the prerequisites that include stationarity and no serial correlation of the error terms. In addition, the estimation of lag length 'p' is crucial to the model since it determines model performance and interpretation.

In our process the vector autoregressive model play a crucial role in the estimation of the DCC-GARCH model, expressing the dynamic relationship between multiple financial series. In the context of DCC-GARCH model, VAR helps to model the joint dynamics of several variables enhances to forecasting the volatility and different dynamics essentials for the risk factor and derivate pricing. This model also provide an impulse response analysis, useful to understand how a shock of one variable affect the others over time. Since our analysis focuses on geopolitical events, the impact on the financial shocks is reflected in asset returns and volatilities.

The information derived from VAR impulse responses can serve as an input in the specification and calibration of the DCC-GARCH model, for instance, about instability transmission mechanism through correlation and volatility.

# Chapter 3

# Empirical Analysis and Model Development

The third chapter examines the relationship between credit default swap spreads (CDS) of major banks and climate-related risk factors. The research explains in detail the multivariate model applied to discover how financial markets incorporate environmental risks into the price of financial instruments. The sensitivity analysis of the climate risk factor related to the choice of our treshold related to the distressed event develops in detail. At the end of the chapter a cross industry analysis is presented, to show more in detail and compare the measured values.

## 3.1 Estimation of DCC-GARCH models for each stocks

The process of empirical research began with the procuring of credit default swaps (CDS) spread data, from various fundamental banks of the world, for the financial years 2023 and 2024.

The dataset which was captured was complete having both daily metrics like first opening prices, peaks of the day (highs), troughs of the day (lows), and the current prices as the day ends (Alexander, 1998). As a consequence, the deep tracking of these factors will provide an accurate assessment of their influence on the market dynamics and the degree of investors' confidence represented through the changing of the CDS spreads that function as credit risk denominators (Drago, Di Tommaso, and Thornton, 2017).

As we can see the 10 stocks have differences for the spreads at 1y and 5y, going specifically the volatility seems to characterize more the 5y, showing an increase also of the prices regarding the 1y (Collin-Dufresn, Goldstein, and Martin, 2001). In general, this type of analysis occurs when sensitivity to economic, political or business changes is less predictable in the long run.

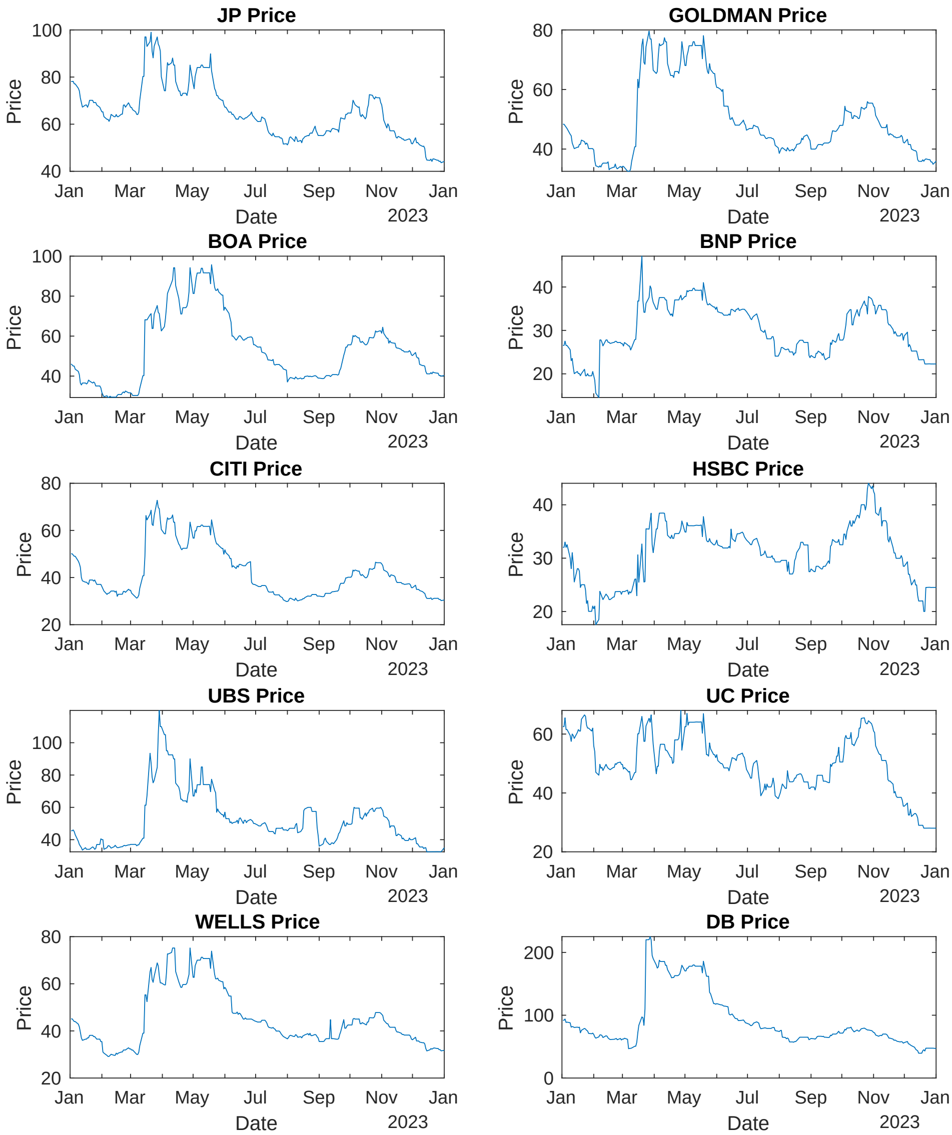


Figure 3: **CDS Spread 1y line charts** The 1 year maturity CDS Spreads graph explain the fluctuation of daily prices of the 10 selected banks during the beginning of 2023 and the beginning of 2024 over 1 year.

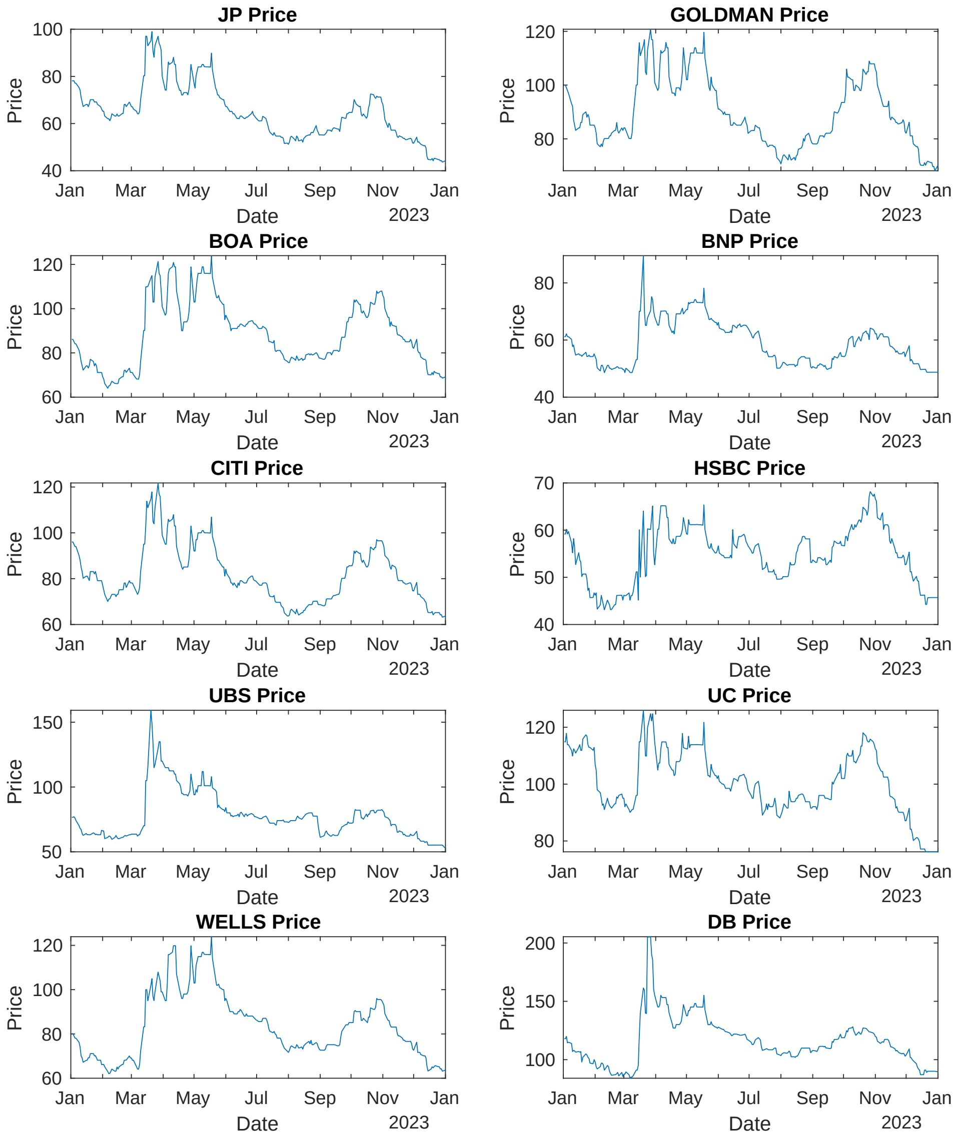


Figure 4: **CDS Spread 5y line charts** This graph shows the price of CDS Spreads 5 years maturity, refers to the banks under examination for the corresponding period from the beginning of 2023 to beginning of 2024.

The essential step for standardize our process was to convert the raw CDS spread data into an analytically more manageable form. This calculation was achieved by computing the natural logarithmic variations in consecutive 1-year CDS and 5-year CDS prices that resulted to what has come to be known as LogDiffCDS calculation for both 1y and 5y CDS.

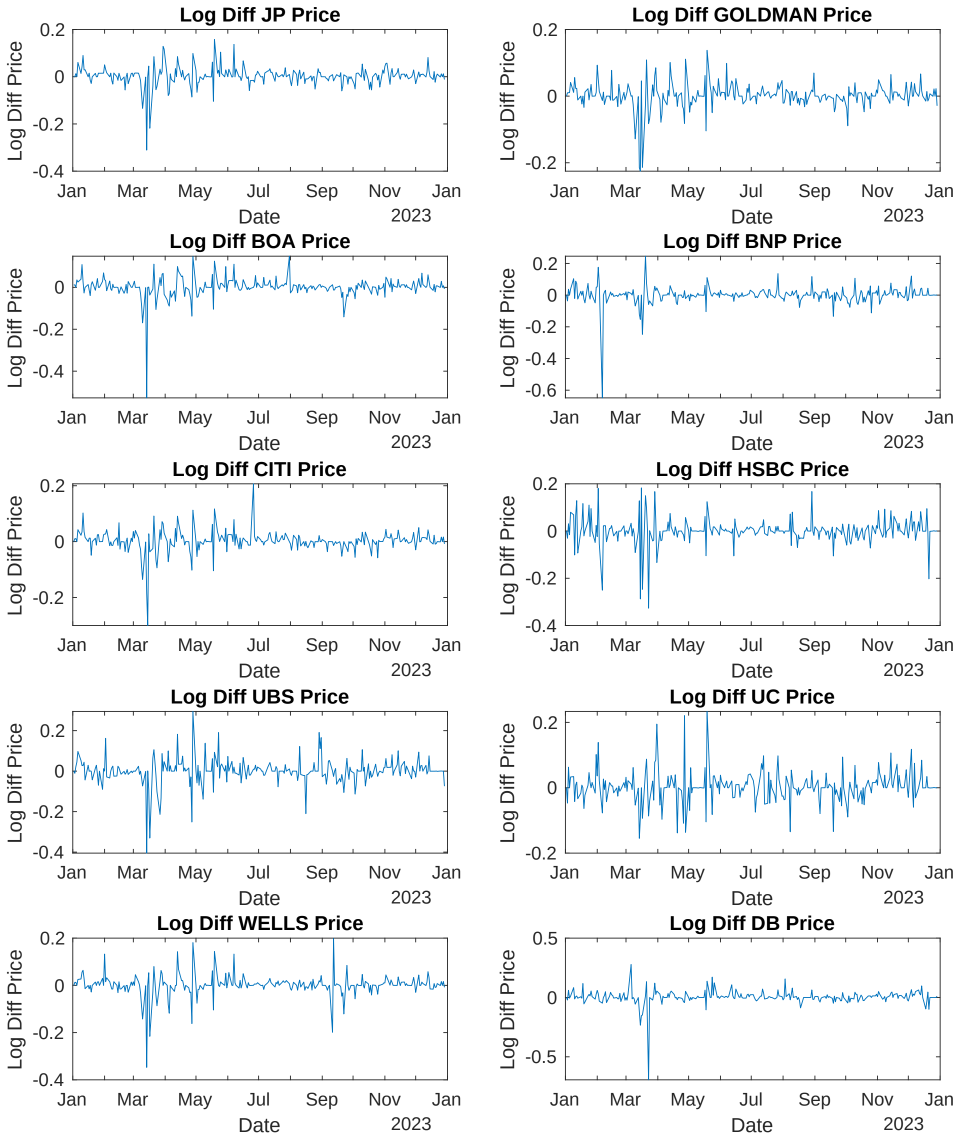


Figure 5: **Log Diff CDS Spread 1y line graphs** This graph shows the log price differences for 10 selected banks in 2023. The blue line represents the log price difference for each bank, tracked monthly from January to December 2023.

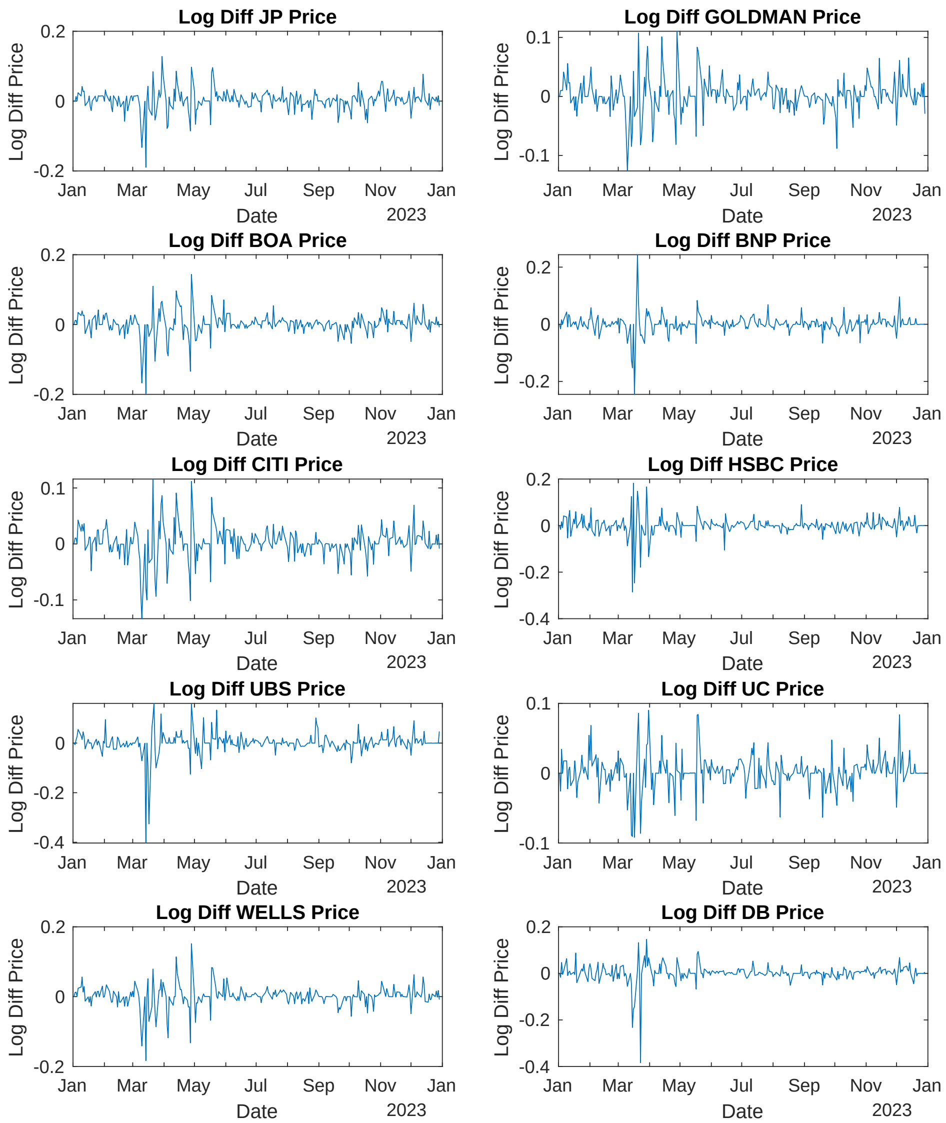


Figure 6: **Log Diff CDS Spread 5y line graphs** This graph illustrates the 5-year CDS spreads for 10 selected banks over 1 year. The blue line in each subplot represents the log difference in CDS spreads for each bank, tracked monthly from January to December.

Specifically, if $P_t$ denotes the CDS spread on day t, $P_{t-1}$ denotes the CDS spread on day t-1, the log-difference $LD_t$ on that day is computed as:

$$LD_t = \log(P_t) - \log(P_{t-1})$$

The spreads of LogDiff CDS, the foundation of GARCH modeling, have been employed to delineate the dynamic interdependence between the financial market behaviors and perception of credit risk , mostly associated with the major banking institutions. The initial stages of this process are very important for the reliability and validity of the following econometric studies doing this job much better than pointing out market interdependence.

Identification of the decided lag for the VAR models is fundamental. It affects the model's ability to catch the time series process and thereby explain the observed data series. In addition, the selecting was accomplished by the use of traditional information criteria, which typically include the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria compromise an ensemble of model complexity and the high quality of fit. They do it by penalizing lags which are too many and little contribute to the explanatory power of the model (Chakrabarti and Ghosh, 2021). The selected lag length minimized the information criteria and consequently provided the most suitable balance of model complexity and explanatory power. This implementation of the careful model choice ensures that the VAR models contain details to be able to reproduce the dynamics of the system; however, too much complexity could lead to overfitting and failures during out-of-sample forecasts.

The residuals of the VAR model — the values differing to what is predicted - were inspected to check that they were behaving like white noise, which means they are normally distributed around zero with constant variance and have mean of zero and are independent.

Along with that, the ACF (autocorrelation function) and the PACF (partial autocorrelation function) were examined for the residuals of each time series. No autocorrelation in the residuals at several lags will confirm that the VAR model created captured the real time series dynamics. The biggest evidence supporting that the model is well-specified is that the null hypothesis (no autocorrelation) is not rejected in the test. Furthermore, the stability of the VAR model was checked through making sure that roots of the characteristic polynomial occur outside the unit circle.

This stability condition is important for model's forecasts to be meaningful and impulse response functions to erode gradually and not exploding (Flores, Engel, and Pinto, 2012). As a result of these diagnostic tests, the adequate model specification for the applied VAR model is confirmed. The application of the test to rule out residual series correlation confirmed the validity of the recursive equations for model stability, and the test to lags warranted the models they were built on. This validation underscores the fact that the VAR related observations are made with accuracy and hence forms a strong base for GARCH model estimation.

The DCC-GARCH framework components estimate the time varying component for conditional variance (volatility) time series. In the course of our calculations, each time series – VAR-adjusted credit default swaps for each financial institution and an ETF of climate risk – was first considered separately by means of GARCH processes.

We applied MLE to fit a DCC-GARCH(1,1) model as well as a GARCH(2,2) model with one and five years CDS data series. Such specification frequently meets the requirements for financial time series, whenever volatility process is shown. To estimate the parameters MLE was used (Orskaug, 2009). The log-likelihood function was built on the condition that the future returns given the past information obey the prescribed distribution.

The DCC-GARCH model does not only improve on the regular GARCH scheme, but also allows the return correlation of assets to fluctuate temporally. This is accomplished through modelling the persistence and dynamic independently of the volatility process, employing the quasi-maximum likelihood method to estimate the correlation dynamics.

The DCC-GARCH models have made it possible to perform in-depth studies of conditional volatility and dynamic correlations, creating a changing scenery in which investors perceive the risk and how different markets can move together (R. Engle, 2002). Most episodes of volatility are directly linked to certain major external shocks or stress events on the climate and the environment. However, now, climate risk is no longer as impactful because of the availability of ETF data series that represent climate-related incidents and shifts in environmental policies (Nordhaus, 2013).

The time-varying association as calculated by the DCC model, on the other hand, traces out the changing role of credit risk for financial institutions against the backdrop of broad market risk attributed to climate change. Shift in the statistical structure of these correlations can mean that the market at least in a partial way has revised its perception on inter-connection of economic and environmental risks. For illustration, when a growing connection happens in the moments of environmental stress or policy declaration, it could be viewed as evidencing market's acknowledgment of climate threats and finical consequences (Pindyck, 2017).

The discovery of econometrically verifiable relationships between CDS spreads and environmental risk tracers enriches our knowledge of how environmental factors manifest in the financial world. This flexible method delivers a detail picture over static correlation correlation analysis, elucidating the conditions that are conducive to or prohibitive for climate risk intensity towards financial institutions.

## 3.2 Sensitivity analysis regarding different climate risk factors

The methodology to be applied in the sensitivity is made on the DCC-GARCH model and is previously calibrated for each bank. The framework includes an iterative process, as each weather risk variable is included in the multivariate models. This methodological approach affords to scrutinize how the effect of each environmental factor exhibits individually and in conjunction with the systemic climate risks on CDS of the chosen proxies, through the compound benchmark ETF for climate change.

To begin with each climate risk factor represents a separate word in the DCC-GARCH framework (Hsiang and Kopp, 2018). This step is realized by inputting time-series data, corresponding to an individual climate factor constant while holding all the other model components unchanged. Such approach facilitates to identify the specificity of various factors influencing the shifting dynamics (H. H. Huang, Kerstein, and Wang, 2018). The individual assessments are followed on the model by the mixing of climate risk factors which is the main element of the models. This joint strategy enables discovery the actions that favor the synergy and appeared non-linear relation between different environmental factors and financial institutions' risk management capacities (Christoffersen, 2012).

The reorienting procedure has a specific emphasis on temporal adjusted and data consistency. This way, the resulting correlations are consistent with actual market developments and not biased by data that is not well-aligned or doesn't have the required information. Correspondingly, the DCC model is built, and then it is fine-tuned with the climate risk factors (Brownlees and R. F. Engle, 2017). This makes it possible to understand dynamics in correlation changes over time.

The sensitivity metric of the correlation coefficients that comes from the DCC models' estimation would serve as the primary metric. These coefficients that show the strength and how these climate risk factors influence the CDS spreads are followed over the time in order to find out the trends, spikes or changes. To achieve the validity of the final calculated correlation coefficients, patterning tests are applied (Management, 2017). The Wald test, for instance, is run to gauge the statistical significance of the difference between the different interventions. This test aims to reject the null hypothesis of stability, which states that climate risk factors do not change the correlation between the factors significantly (Walter W. Hauck and Donner, 1977). The probability of the null hypothesis being rejected suggests the responsiveness of the dynamic association of the analyzed factors to the climate change.

The influence of each of the changes in correlation coefficients is interpreted in the meaning of the situation with the amount of institutional exposure to climate changes. This requires recognition of the time series patterns, and further examination to see whether these shits in correlation are associated with the occurrence of adaptation external events, policy changes, or investors' response to climate changes.

The sensitivity analysis extends beyond mere statistical assessment to include a comprehensive evaluation of model robustness (Gourieroux, Laurent, and Scaillet, 2000):

- Model Stability Checks: The robustness and consistency of the DCC-GARCH models are reconsidered with the completion of the recalibration. This means that we do not need climate risk factors to make our model, unstable or ineffective in forecasts.
- Scenario Analysis: Diverse environmental settings, that reflect current and historical conditions and the expected climate conditions in the future, are used for investigating whether the sensitivity patterns are consistent across the different scenarios.
- Robustness to Model Specifications: Sensitivity tests involve running the model under different specifications and vary the assumptions so as to be certain that the results are not just an artifact of the particular model but robust reflections of the real economic situation.

By using these detailed ways, the sensitivity analysis will provide much more complex results about the effects of climate risks on the financial metrics and about the banks' behaviour as to the environmental changes, thus contributing to the more profound understanding of the financial sector's exposure and effectivity. Here, this strict approach makes the results more solid and thus, gives more weight to their ability to be relevant and applicable both academics and everyday risk management when hazards increase.

## 3.3 Considerations for choosing the threshold for climate distress events

The process of identifying climate disasters events is commenced through a complete histoical volatility analysis, which makes use of ETF's price movements as market-based climate risk proxies (Dell, Jones, and Olken, 2014). The investigation of such situation with the use of the similarity correlation of these findings with graphical analyses, which presents clear trends and volatilities at certain periods, will lead to a thorough understanding of standard and anomalous market behaviors (Pindyck, 2017).

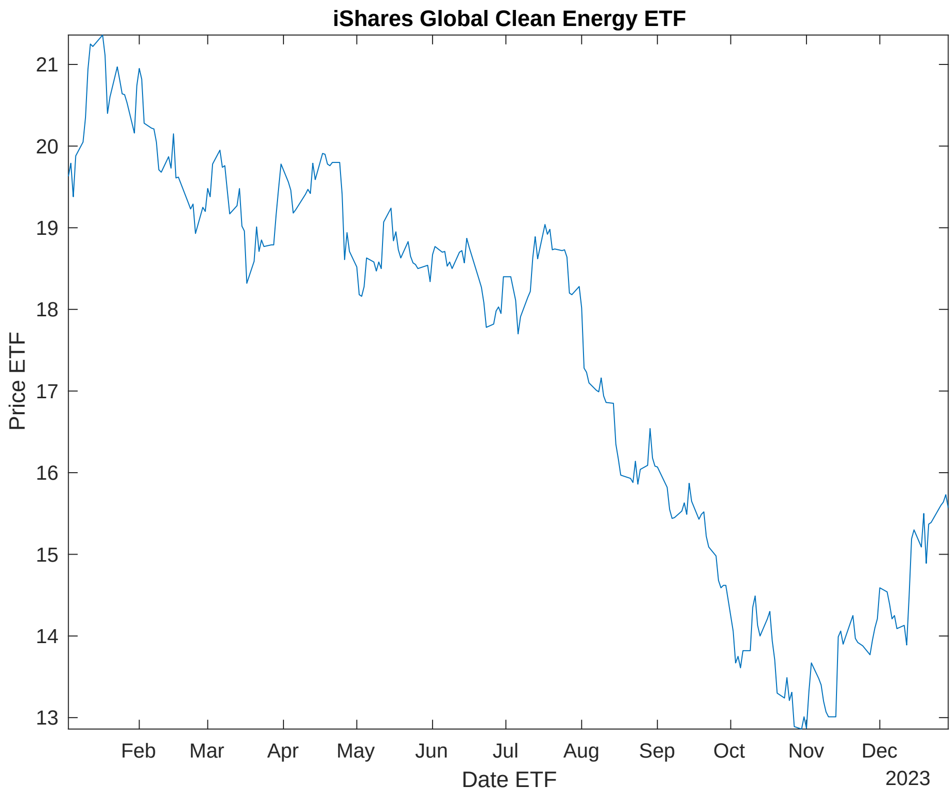


Figure 7: **BMG factor line chart** The blue line represent the daily price changes of the iShares Global Clean Energy ETF (BMG factor) from 2023 to 2024.

Coming as a supplement to the early process, the graphic data demonstrate with some degree of clarity important instances of ETF prices deviating from its trending path and closely tracking environmental changes or policy announcements. ETF prices that significantly rise during phases of environmental recovery or optimistic climate-related proclamations can also be regarded as a manifestation of the belief in positive expectations. The historical volatility is used to underlying market aberrations and thus we identify them. These are averagely three or more standard deviations from the mean. This statistical border is additionally upheld visually on the chart where anomalies can be see during the price trajectory of ETFs, so we can mark these substantial market movements as potential indicators.

Through the analysis of the past environment disasters and legislative changes that the ETF price indexes, we are able to connect those changes not only mathematically but also on the financial realm (Bos, Li, and Sanders, 2022). For instance, our graphs show a huge down trend in the price of ETFs and this happens when the environmental catastrophe is happening, this association reinforces settings that we have established as our threshold.

By combining these approaches in one model, we develop a comprehensive solution to classify and describe environmental catastrophes due to climate change. Which is supported by the data-driven factors as well as the environmental factors marked by the empirical data visualization and the graphs. Through studying those certain episodes where the ETF prices became notably sensitive to the climate-related events, we can deepen our knowledge of the underlying mechanism between climate-linked episodes and financial market activity.

For an instance, if the graphical data shows that ETF prices move highly in relation with minor news that appeals to environmental news, we could adjust our thresholds to avoid false alarms. On the other hand, the finding of mild ETF price fluctuations following an environmental disaster, could mean desensitization in the market and developing a need to engage in a reconsideration of the volatility benchmarks.

## 3.4 Cross-industry comparison

This study is trying to explain the aspects of the dynamic and substantial nature of financial markets by implementing the DCC-GARCH(1,1) model and DCC-GARCH(2,2), calculating and comparing the log-likelihood value indices within the banking sector (Brownlees and R. F. Engle, 2017), over 1-year and 5-year time frame. The comparison analysis is extremely useful, giving view into the banks market behaviors and the volatility patterns with which a model of statistics with which the banks data is able to fit will provide the nuanced understanding regarding how well each of the banks market data (R. Engle, 2002; R. Engle and Kroner, 1995).

The 1 year log-likelihood values between -1450 and -1850, which reflect short term bank behaviors captured in the markets, indicate the volatility. Considering the fact that this is highly influenced by immediate market conditions, policy changes, and transient factors, increased volatility or unpredictability may be experienced.

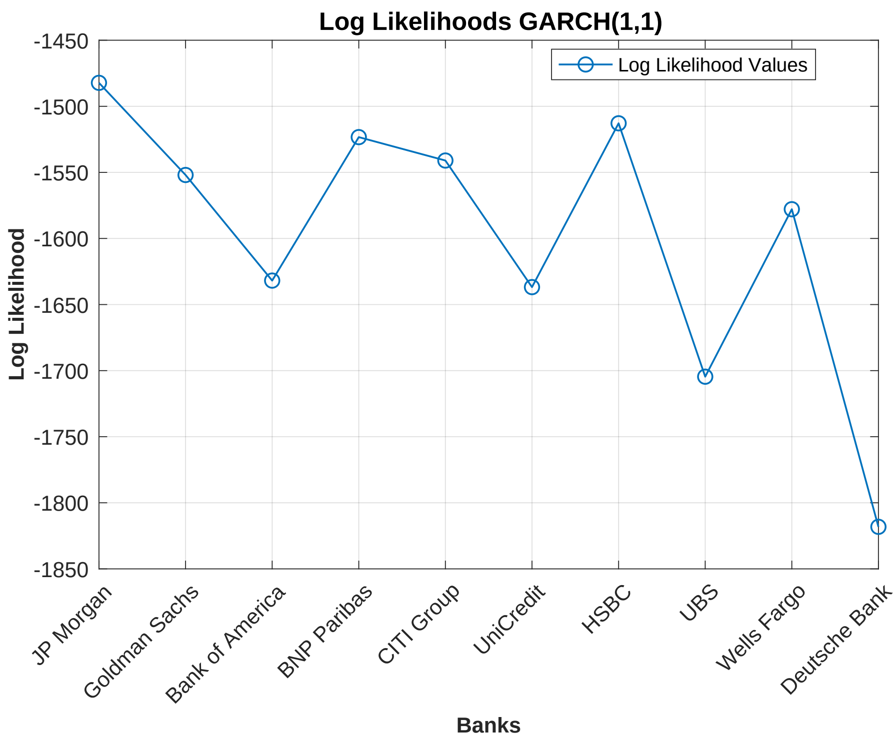


Figure 8: **Conditional Log Likelihood GARCH (1,1) 1y** This graph displays the DCC-GARCH(1,1) 1 year log likelihood values for banks selected. The values, which are plotted along the vertical axis, indicate the statistical fit of the DCC-GARCH(1,1) model for each bank.

On the contrary, 5 years log-likelihood have a range from -1540 to -1720 which is more compact. It reveals a very narrow spread, which is equivalent to the reduction in jumps of volatility in the short term. This will bring out the banks' underlying risk behavior and volatility patterns which spread out in the long run. A comparison like this brings out the impact of time in financial modeling. Time-wise, factors do impact the way model outputs concur with real life scenarios.

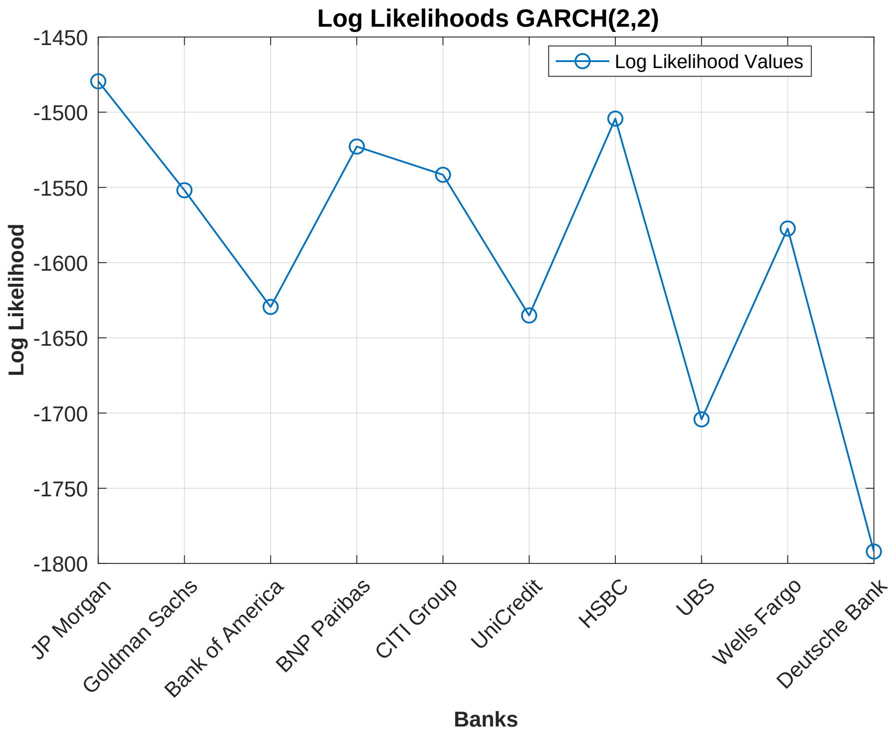


Figure 9: **Conditional Log Likelihood GARCH (2,2) 1y** This graph compares the log likelihood values for the DCC-GARCH(2,2) model across various major banks over one-year period; the vertical axis shows the log likelihood values.

Analyzing individual banking institutions, particularly JP Morgan, BNP Paribas, CitiGroup and HSBC - which display higher log-likelihood values in both short and long term in the model - is a focus point of this discussion. This fitted model indicates banks have more likely controlled and predictable market behaviors, usually a consequence of risk management model and strategic planning success. Their financial products and operations are more locked onto the unlikely to go through fluctuations, maintaining steady position not only for the institutions but also their clients.

However, banks such as Bank of America, Goldman Sachs, and UniCredit, reflected in a mid-range log-likelihood pattern, demonstrate a weak model fit compared to the counter results.

Furthermore, Deutsche, UBS, and Wells Fargo, banks present lesser log-likelihood values, showed poor performance in relation to the model's output. One of the main factors that might can lead to instability could be the emergence of unanticipated financial turbulence or distinctive market conditions. Thus, the banks can start utilizing more bespoke models plus sophistication in their strategies since each bank has its local market dynamics and risk profiles.

The study presents a comparison of the 1-year and 5-year log-likelihoods values for DCC-GARCH (1,1) and DCC-GARCH (2,2). The results are displayed in the two figures below.

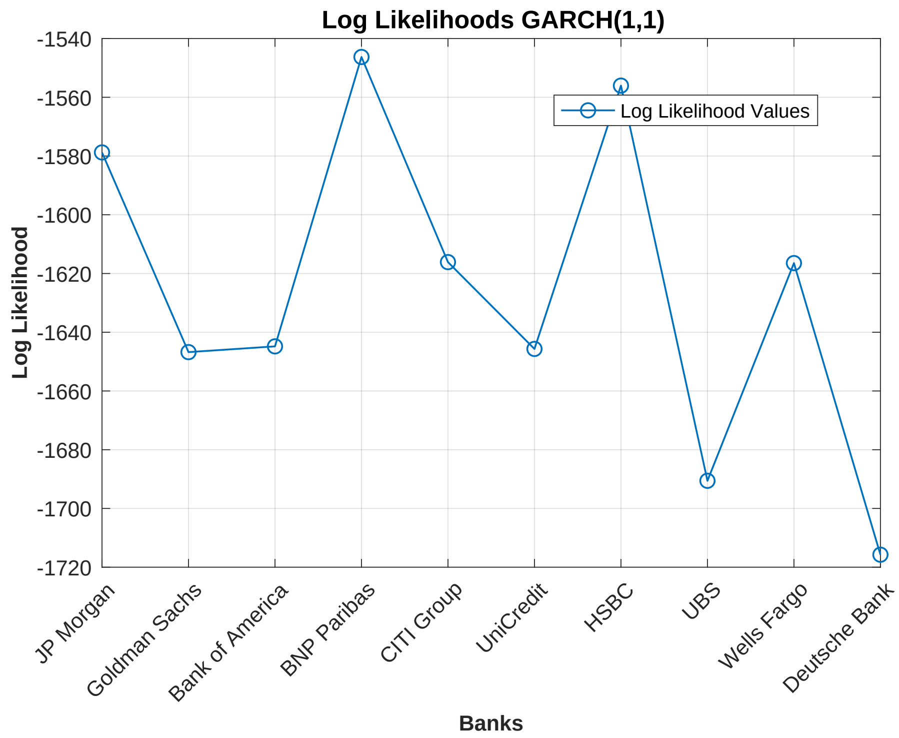


Figure 10: **Conditional Log Likelihood GARCH (1,1) 5y** This graph compares the log likelihood values for the DCC-GARCH(1,1) model across 10 banks over a five-year period. The vertical axis displays the log likelihood values.

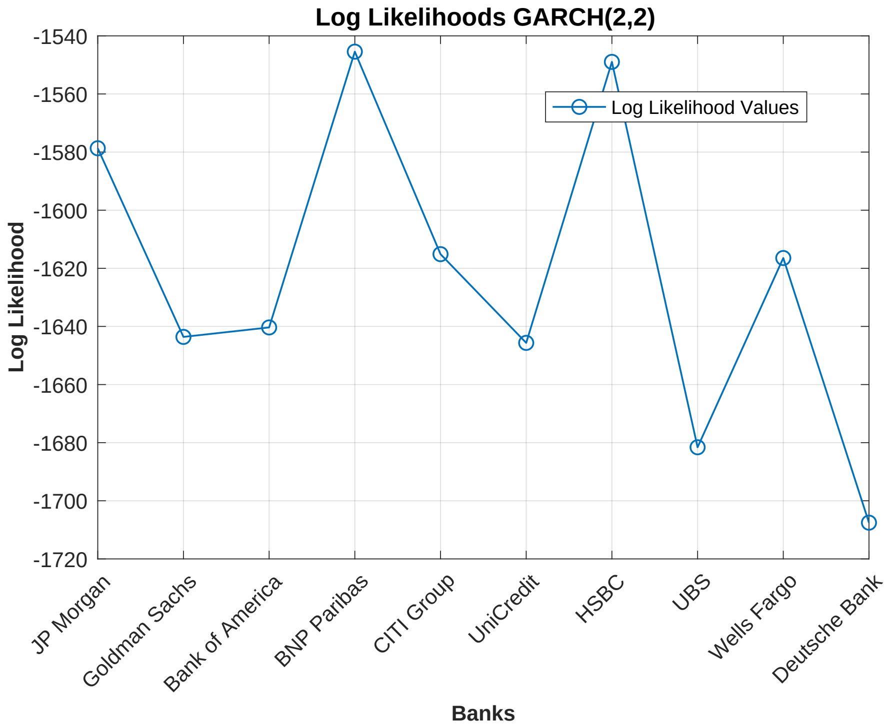


Figure 11: **Conditional Log Likelihood GARCH (2,2) 5y** In this graph the log likelihood values are represented through the vertical axis, this time for the DCC-GARCH(2,2) model across various major banks over a five-year period.

The study's findings highlight the importance of choosing or modifying models that provide a precise representation of each bank's unique characteristics, in addition to expanding our understanding of the patterns of bank competition. Banks that have demonstrated a set of sustainable strategies throughout the time-frame of the study can consider the results as a verification of the soundness of their existing practices.

In the context of financial econometrics, the Generalized Autoregressive Conditional Heteroskedasticity model becomes a landmark instrument that aids in the understanding and prediction of volatility characteristics in financial markets. The DCC-GARCH(1,1) model, on the other hand, is specifically famous for its clout of forecasting for volatility thus, providing critical insights into the statistical correlations of financial returns.

The investigation into 1-year DCC-GARCH(1,1) constants shows a set of numbers whose range provides evidence on the volatility due to short-term banks' responses . This data describes $\alpha$ as the bank's volatility's sensitivity to recent market shock as well as $\beta$ is as the degree to which these shocks remain over time. It looks like that DCC-GARCH(2,2) constants are normally greater than those for GARCH(1,1), no matter what bank is involved from the readings of the given data files.

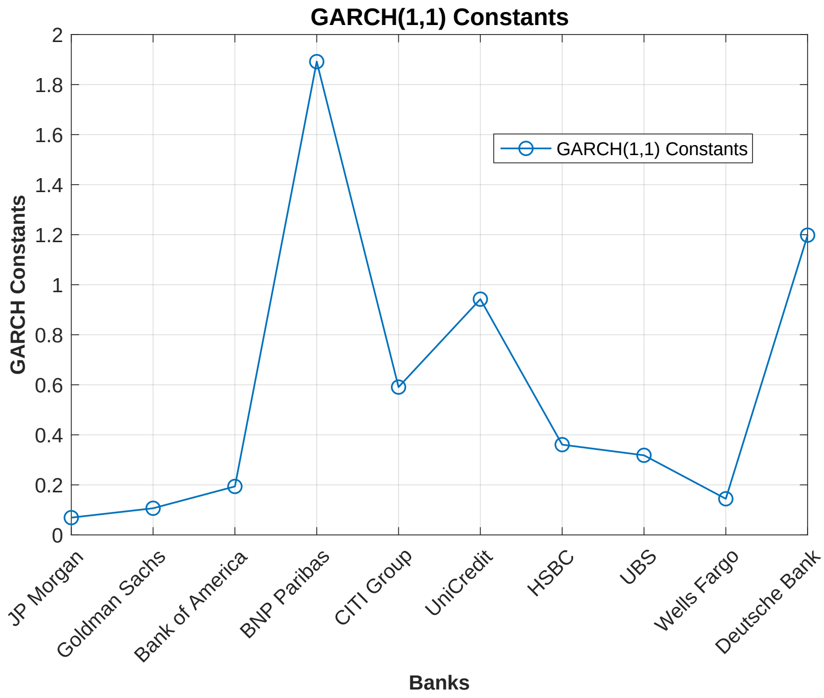


Figure 12: **DCC-GARCH(1,1) 1y constants** This graph compares the GARCH(1,1) daily constants for major banks over a one-year period . The vertical axis represents the GARCH(1,1) constants, showcasing the variation in these values among 10 banks.

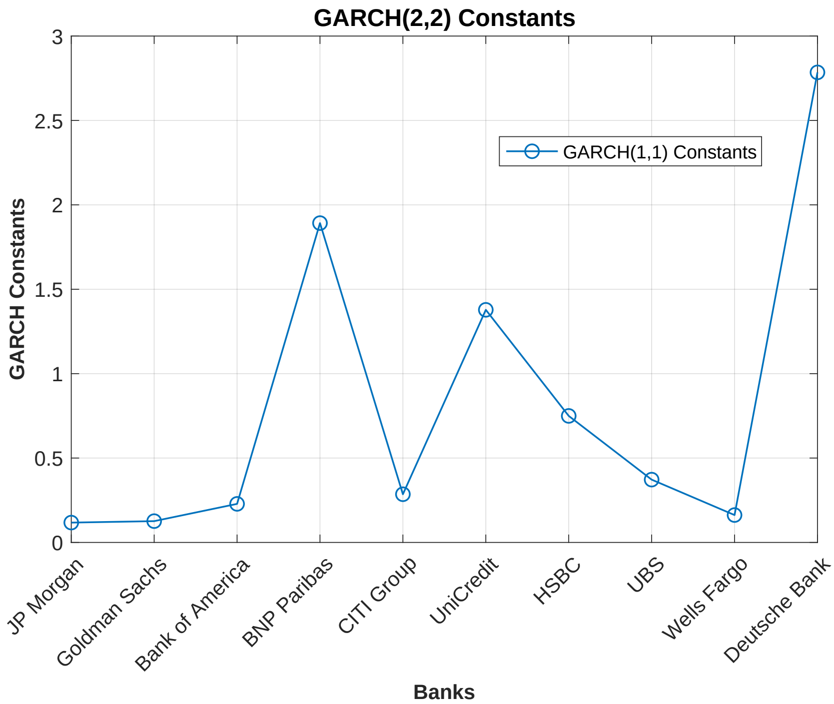


Figure 13: **DCC-GARCH(2,2) 1y constants** This time the graph compares the GARCH(2,2) constants for several banks over a one-year period expressed in daily basis, with the vertical axis showing the GARCH(2,2) constant values, to reveal differences among the 10 banks.

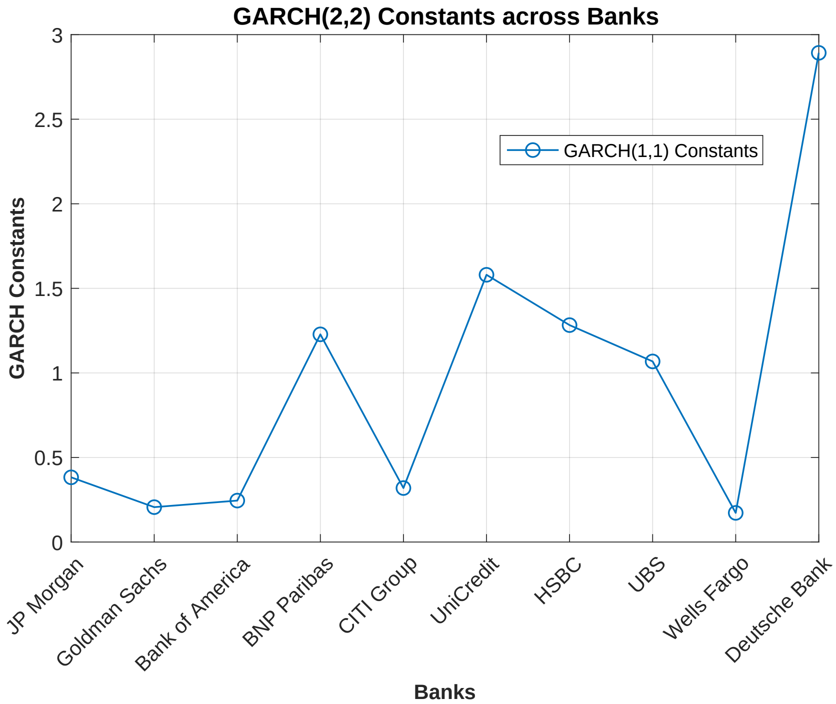


Figure 14: **DCC-GARCH(1,1) 5y constants** This graph illustrates the GARCH(1,1) constants for banks this time over a five-year period expressed in daily basis; the vertical axis displays the GARCH(1,1) constant values in a range between 0 and 3.

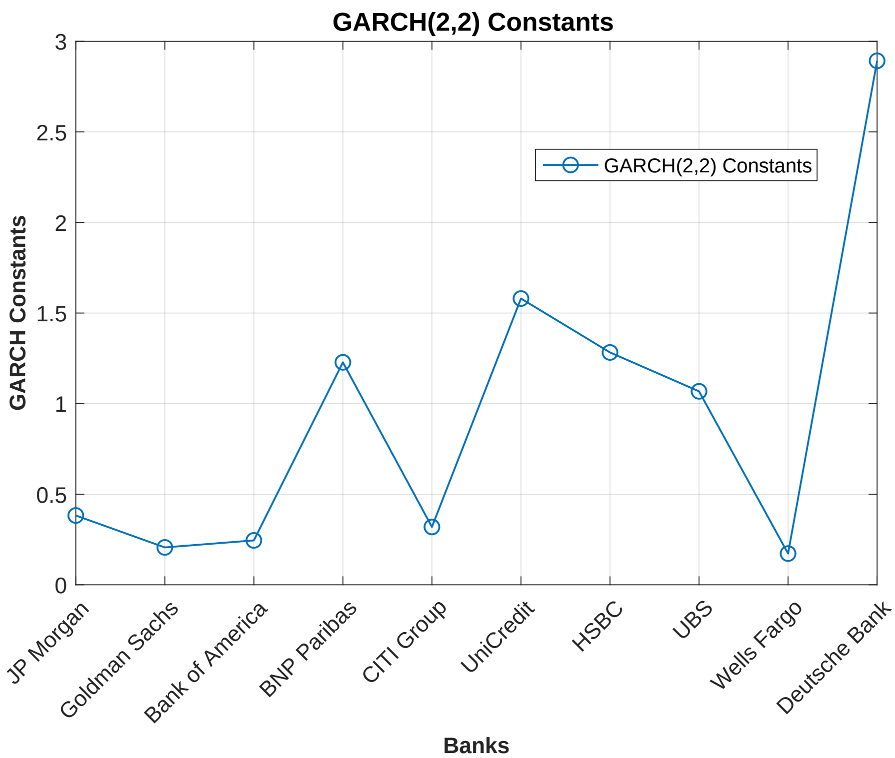


Figure 15: **DCC-GARCH(2,2) 1y constants** This graph presents the GARCH(2,2) constants for the major banks over a five-year period. The vertical axis shows the values of these constants, highlighting the variations among banks on daily data.

The implication is that the DCC-GARCH(2,2) model consisting of the squared returns and past variances might as well reveal that the volatility of the market is higher than in the plain DCC-GARCH model.

Such increased complexity in the DCC-GARCH(2,2) model with its two more parameters suggests the capability of the model to account for more aspects of the time series data which is highlighted through the view of more precise market dynamics. In this case, this could be that the DCC-GARCH(2,2) model discovers finer, innate oscillations of their stock or asset volatility, which DCC-GARCH(1,1) might end up attributing in a second moment. In addition, the factors that influence risk may take a more complex form in an environment characterized by complex underlying risk factors, meaning that past events and inherent market conditions have an important bearing on volatility.

It is worth noting, that having 5-year DCC-GARCH(1,1) constants in mind, an alternate volatility storyline appears as well. This more extensive analysis further confirms a lower $\alpha$ and a higher $\beta$ value to the sensory data obtained previously over a year. This change indicates that market shocks suffer a decline in their immediacy and, in contrast, a prolonged persistence of their effects.

The fact that the two graphs for the DCC-GARCH(1,1) and DCC-GARCH(2,2) models over the past five years of CDS spread analysis displays a close resemblance is an indication of the common volatility at the base for the two modelling approaches within this time frame. The uniformity of this result points to the fact that for the particular 5-year CDS spreads analyzed by these banks, the absence of additional lags in the DCC-GARCH(2,2) model does not significantly affect the interpretation of the baseline volatility compared to the DCC-GARCH(1,1) model. The main aspect of the both models is a probability of how volatile the credit risk is from the 5-year CDS spreads. The risk, as registered on the futures market, shows a volatility with the same level of frequency, irrespective of which model was used.

In the complex-business-field of finance, another important cross industry figure that is brought up by the Average Conditional Correlations is analyzed by fitting it the with DCC-GARCH(1,1) model and comparing major bank stock indices with an ETF over 1-year, and 5-year spans.

Consequently the analysis will begin with a 1-year outlook followed by a correlation mapping and this will indicate that the bank shares and the ETF have a wide variety of connections. In particular the HSBC and Deutsche Bank, with the high positive correlations issue nearly the highest registered threshold. It is noticeable that the stocks of these banks taxonize with these ETF bounds with high degrees of synchrony, which signifies that the movements of the banks are closely related with all the general market trends. Such profound association suggests that the performance of these banks could probably stay along with market risk as well as the rewards.

Despite a general low correlation, some notable differences are found. JP Morgan and Unicredit are listed in strong degrees of inverse correlation, which suggests they tend to move in opposite direction to the market. Such distinctions probably will stem from some other factor beyond the market's intrinsic factors that determine peoples' reactions in the market. Due to several key strategies, the systems are undoubtedly resilient. The possibility of your turning to the investment diversification is there.

This analysis tends to mention finance institutions, for instance, CitiGroup, Goldman Sachs, Bank of America, and Wells Fargo, which tend to be floated with a correlation coefficient close to zero with the ETF. Such a figure entails a low and linear correlation, suggesting that the banks are more hedged against the broader market trends than those who follow these trends closely. This financial independence rests on the potential risk embedded within market diversification.

The correlation map would however take a different shape after turning the analysis to 5-year period.

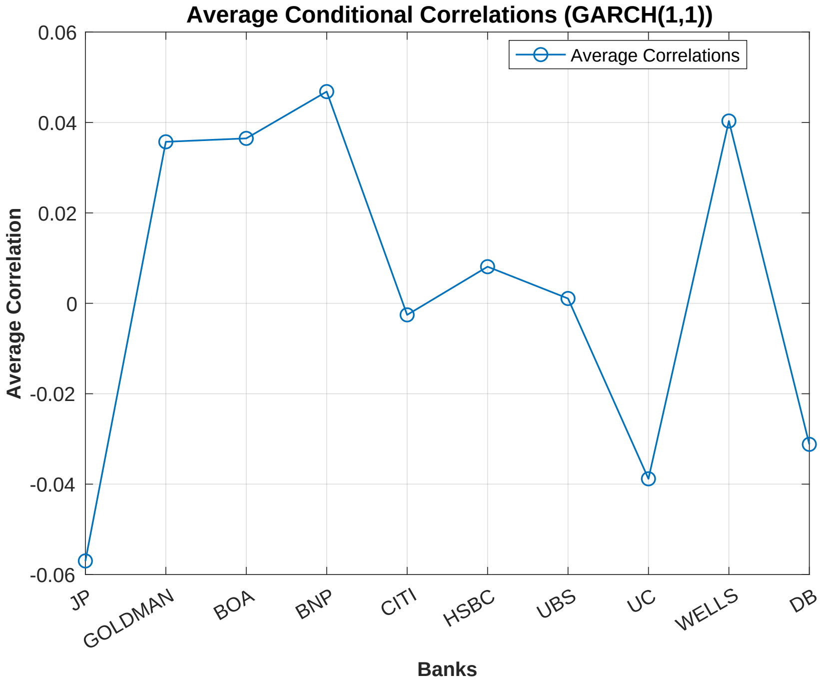


Figure 16: **Average Conditional Correlations of DCC-GARCH(1,1) 1y** The graph shows the average conditional correlations calculated using the DCC-GARCH(1,1) model for various major banks over a one-year period. The vertical axis represents the average correlation values, illustrating the differences in correlation strengths among banks.

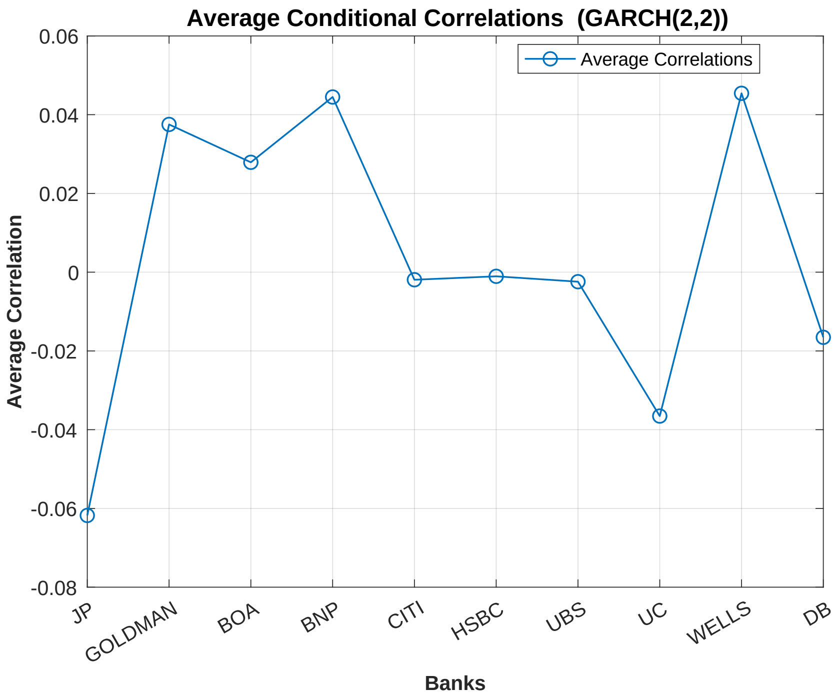


Figure 17: **Average Conditional Correlations of DCC-GARCH(2,2) 1y** This graph illustrates the average conditional correlations computed using the DCC-GARCH(2,2) model for various major banks over a one-year period expressed daily.

The observed correlations between banks and ETFs albeit continue to hold for the trend direction, the related magnitudes are usually less than those for the 1-year correlations. This convergence signifies that banks' behaviors over the market become gradually linked market trends in the long term, thus, reducing the sharp correlations between banks' market behaviors seen in the short term.

Considering that a 5-year period is short, we could see the gradual shrinking of both positive and negative extreme extremes. Thus, the market risk is increasingly consequential while the individual bank-specific risks are being less impactful. This is very relevant while portraying investment strategy as the duration of investment becomes a key determining factor of the risk diversification and return optimization performance of bank stocks comparatively broader market indicators.

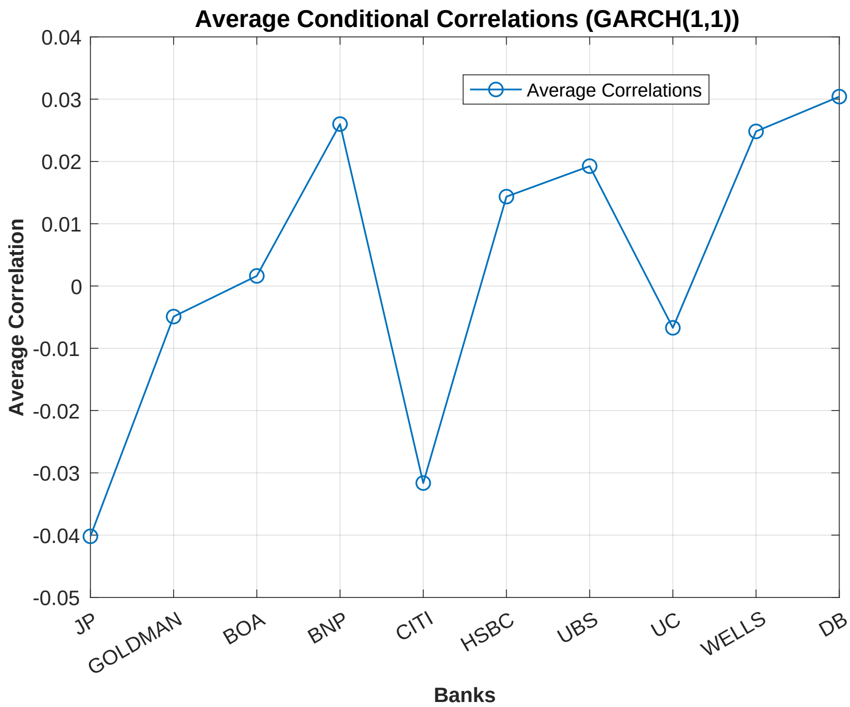


Figure 18: **Average Conditional Correlations of DCC-GARCH(1,1) 5y** The graph presents the average conditional correlations determined by the DCC-GARCH(1,1) model for banks this time across a five-year period. The vertical axis depicts, once again, the average correlation values.

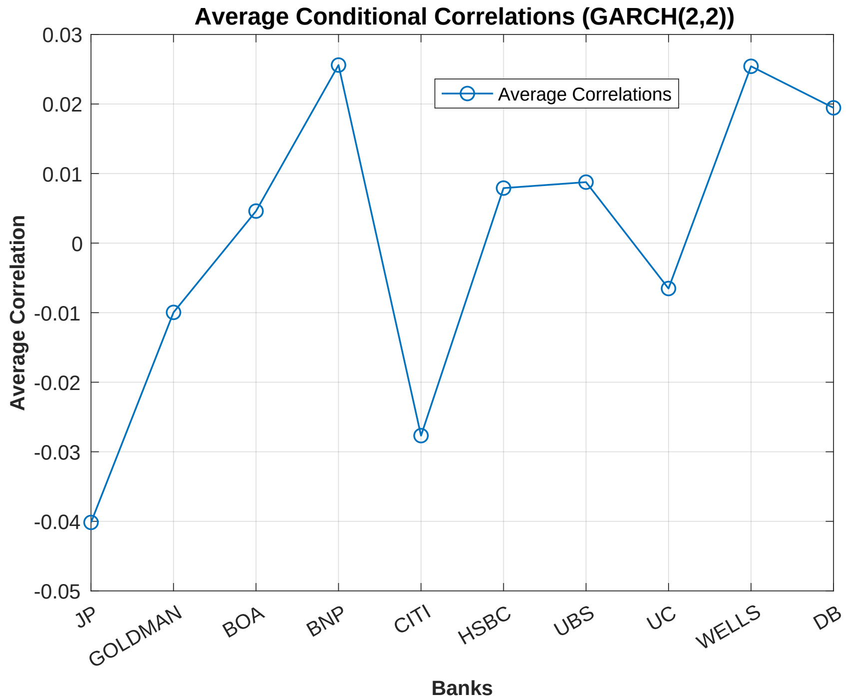


Figure 19: **Average Conditional Correlations of DCC-GARCH(2,2) 5y** This graph presents the average conditional correlations obtained using the DCC-GARCH(2,2) model for various banks over a five-year period. The vertical axis displays the average correlation values, showcasing the differences in correlation strengths among the banks.

# Chapter 4

# Conclusion

The last chapter of the thesis will provide the results of the model analysis conducted. It is also includes the limitedness of the current research and proposes progress to understand more about the relationship between Credit Default Spread (CDS) and our climate risk dimension better. In addition to that, it gives an idea to manage uncertainties in finance and climate.

## 4.1 Summary of the main results

The empirical inferences are thus generally in favor of the DCC-GARCH(1,1) model including years 1 and 5 as documented by the lesser Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. The tables, extracted from the matlab code, present lower AIC-BIC for the (1,1) GARCH This can be visible in the table:

| Bank | AIC-DCC-GARCH(1,1) | BIC-DCC-GARCH(1,1) |
|---|---|---|
| JP Morgan | 2980.4707 | 3008.6424 |
| Goldman Sachs | 3119.9281 | 3148.0998 |
| Bank of America | 3279.7404 | 3307.9121 |
| BNP Paribas | 3062.6257 | 3090.7974 |
| CITI Group | 3098.0382 | 3126.2099 |
| HSBC | 3041.6863 | 3069.8580 |
| Unicredit | 3425.1485 | 3453.3202 |
| UBS | 3289.6149 | 3317.7865 |
| Wells Fargo | 3171.7340 | 3199.9057 |
| Deutsche Bank | 3652.3483 | 3680.5199 |

Table 1: **AIC and BIC for DCC-GARCH(1,1) over 1 year** The table shows the daily values of AIC-BIC for selected banks. These criteria are used to evaluate the goodness of fit for the DCC-GARCH(1,1) model over a one-year period.

| Bank | AIC-DCC-GARCH(2,2) | BIC-DCC-GARCH(2,2) |
|---|---|---|
| JP Morgan | 2984.9050 | 3030.6840 |
| Goldman Sachs | 3129.7501 | 3175.5291 |
| Bank of America | 3284.880 | 3330.6592 |
| BNP Paribas | 3071.6567 | 3117.4357 |
| CITI Group | 3109.1888 | 3154.9678 |
| HSBC | 3034.5177 | 3080.2967 |
| Unicredit | 3434.3754 | 3480.1544 |
| UBS | 3296.2479 | 3342.0269 |
| Wells Fargo | 3180.6613 | 3226.4403 |
| Deutsche Bank | 3610.1251 | 3655.9041 |

Table 2: **AIC and BIC for DCC-GARCH(2,2) over 1 year** Presents the information criterion daily values for the DCC-GARCH(2,2) model for 10 selected banks. These metrics help determine the model's fit for the banks' financial data over the one-year time-frame.

At this level preference, simpler DCC-GARCH (1,1) model can be regarded to provide a good fit for forecasting procedure of financial assets in analysis and is able to capture their essential dynamics without heavy complexity of DCC-GARCH (2,2) model.

| Bank | AIC-DCC-GARCH(1,1) | BIC-DCC-GARCH(1,1) |
|---|---|---|
| JP Morgan | 3173.5531 | 3201.7248 |
| Goldman Sachs | 3309.5389 | 3337.7106 |
| Bank of America | 3305.6272 | 3333.7988 |
| BNP Paribas | 3108.5580 | 3136.7297 |
| CITI Group | 3248.2462 | 3276.4179 |
| HSBC | 3123.9178 | 3156.2381 |
| UBS | 3389.1610 | 3425.3261 |
| UniCredit | 3307.3629 | 3335.5346 |
| Wells Fargo | 3248.9220 | 3277.0937 |
| Deutsche Bank | 3441.0620 | 3475.6657 |

Table 3: **AIC and BIC for DCC-GARCH(1,1) over 5 years** Explain the daily values for the AIC-BIC criterion over 5 year time-frame for the 10 banks under observation.

| Bank | AIC-DCC-GARCH(2,2) | BIC-DCC-GARCH(2,2) |
|---|---|---|
| JP Morgan | 3183.3688 | 3229.1478 |
| Goldman Sachs | 3313.2000 | 3358.9790 |
| Bank of America | 3306.6926 | 3352.4716 |
| BNP Paribas | 3116.8800 | 3162.6590 |
| CITI Group | 3256.2534 | 3302.0324 |
| HSBC | 3123.9178 | 3169.6967 |
| UBS | 3389.1610 | 3434.9400 |
| UniCredit | 3317.3093 | 3363.0883 |
| Wells Fargo | 3258.9106 | 3304.6896 |
| Deutsche Bank | 3441.0620 | 3486.8410 |

Table 4: **AIC and BIC for DCC-GARCH(2,2) over 5 years** Detail the daily AIC and BIC values over a five-year period for the 10 banks being analyzed.

These findings also support the idea that the exact economy model chosen for the analysis purposes would usually not determine the accuracy of the results, so long as the basic principles of the model are sound. The suitability not the sacrifice of DCC-GARCH(1,1) model to understanding the volatility and returns correlations underpins the prospective of the model.

Establishing the DCC-GARCH(1,1) framework, we can very precisely say that he model has succeeded in studying the volatility of the assets of the banking system and their correlation with Brown-minus-Green (BMG). This validation affirms the applicability of the DCC-GARCH(1,1) model in financial econometric analyses, especially for the design of the mathematical relationship between bank asset returns and the market for ETFs.

It is only sometimes necessary for the complex modeling of assets in the banks and their mutual market interdependency to display realistic portrayals when an increasing fluctuation pattern is noted. Instead, the demonstrated sufficiency of the DCC-GARCH(1,1) model underscores the principle of parsimony in financial modeling. Models of a parsimonious type such as DCC-GARCH(1,1) are less vulnerable to overfitting because the model captures too much market noise as genuine patterns if it has too many parameters. They provide the unique character of a more straightforward and interpretable structure which matters a lot for the stakeholders who rely on the simulations to make the right decisions. Secondly, modeling ability with adequacy seen in it suggests significant operational benefits. It confirms that financial pros and risk managers may arrive at the deepest understanding of market tendencies and the relationship between assets by means of the simple models that do not risk being limited by the intricacies and complexity of more complex models. Consequently, the more simplified (e.g. quicker adaptation and deeper comprehension) of this risk management strategy, the better they can be implemented. Not only is this finding relevant to how we select models but has a wider impact. This is how they get to the heart of risk management related to asset management that is practiced within financial institutions. This approach is advocated by the models introduced in the paper and it is directed towards the convergence of complexity/accuracy of the financial models. This method, so in addition to being resource-saving, aids in risk assessment processes thus leading to faster and more intelligent decision-making in the financial sector.

Extending on the above point that discloses the efficiency of the DCC-GARCH(1,1) model to capture the whole fine details of the financial markets and their association with the banking assets, I approach the mathematical process for me to have a deeper understanding. Technical, we have adapted the conditional probability formula:

$$P\left\{CDS_{i,t+h} > c | CF_t < x\right\}$$

to assess possible CDS rate hike for a specific CDS given a certain conservation risk level characterised by ETF prices below a definite threshold.

In this expanded analysis, stress is theorized using EFT, a substitute for the influence of environment on the financial industry. We will define 'x' - specific percentile price of the ETF as our threshold price using the 5th percentile as an illustrative. This option of the threshold therefore represents very conservative limit.

On the one hand, we define 'c' as $95^{th}$ percentile CDS spread, while on the other hand we employ CDS market as a proxy to reflect credit risks with highest possible level. This dual threshold framework, which allows us to statistically analyze the conditional probability of extreme spread movements for CDS as observed in the financial markets — a proxy for heightened credit risk conditions — will also incorporate data on environmental distress captured by the ETF prices.

We use this maturity horizon of 252 days for one year that allows us to include the forward-looking characteristic of CDS spread in evaluating default probabilities. Subsequently, we carefully analyze the excessive levels of CDS spread for the groups of banks if the price of ETF is above the threshold condition.

However, the output shows identical distribution of CDS spread volatility occurring across each bank within the group even data noise is taken into consideration and each bank exhibits the same probability of 0. This outcome thus surprisingly suggests that, on the specific terms and time span of this research, the framing and time constraint of the climate risk factors as indicated by the lower bound of the ETF price, do not statistically indicate an escalation in the probability of extreme credit risk events as expressed by CDS spreads, for these banks.

The fact that the DCC-GARCH(1,1) framework, for both 1y and 5y, can capture the relationship between events in the environmental conditions and bank's asset returns is a crucial contribution to our empirical study, which also found that the so-called extreme environmental risk, captured through low ETF prices, do not necessarily coincide with increased credit risk level for these banks. This outcome underscores this and other intricate and complex factors that influence market behaviour, thereby emphasizing the need for precise and well-grounded empirical models like DCC-GARCH (1,1) in interpreting these complex interactions.

Furthermore, this information adds substantially to the dialogue regarding financial risk management in the sphere of cloudiness of the environment. They suggest while the environmental risk factors affect the dynamics of the market and volatility, however, the short to medium-term relationship between them and credit risk is indirect and, therefore, the impact may be less than presumed, under the present analysis. This delicate comprehension plays a great role in portfolio management, risk issues, and financial strategy of institutions operating in markets, where both finance as well as climate issues are presented.

The correlations identified by our DCC model in the system of banking assets and BMG factor reveal the heuristic relationships between them and their dynamicity. Due to this all-encompassing knowledge, the emerging scenarios of changing markets are highlighted, where the correlation is higher in certain periods. Such spikes frequently correlate with market turbulence episodes or for financial sectors linked with specific incidents, demonstrating the interconnectedness of all global financial markets and individual assets being rather sensitive to the general economic trend. Alternatively, when assets of such banks are negatively correlated with other products, then there is an environment where the movements of bank assets and ETFs are not connected at all. This lower connectivity among assets leads to a reduction in the correlation coefficient and this reduction promotes the diversification opportunity for investors. Through targeted shifting of investments between the bread-and-butter and ETFs' parts to favor the ones performing better, investors can experience reduced risk and certain returns regardless of market volatility.

## 4.2 Limitations of the study and possible future developments

Now, the studies made bright progress in terms of research in the context of the dynamic conditional correlations between bonds and ETF by using the DCC-GARCH models. This DCC-GARCH(1,1) model, however, rests on the basis of assumptions of normality and linearity, which are the underpinnings of the framework. Such assumptions are depicted by their inability to fully model complex, fluctuating and sudden financial movements beyond the linear dynamics and normal distributions. Therefore, gender inequality exposes a danger of model inaccurate estimations by virtue of mis-specification.

The data collection process stipulates the study's limitations based on its time limits. This time-bound inevitability leads to its inability to capture the model's efficiency in different market conditions, especially in case of severe financial problems or geopolitical occurrences that would change dramatically the market traits and assets' correlations.

Concentrating on only a set of banking institutions and one ETF, in particular, the research introduces an allocation possibility, which may limit the broadness of the conclusions. Given the financial market's variety where many investment originations with different attributes exist, it remains possible that the scope of the current research does not adequately capture the entire dynamics of the market system.

The target audience is a single market interaction and hence this reduces the complexities of global financial ties. However, this limitation also hampers the analysis from grasping the subtleties of how international economic events, the global market trend, and all other aspects contribute to the correlation between bank assets and ETFs.

To enhance the current research framework and address these limitations, several future research avenues are proposed:

- The direction of future research could be made toward the ways of modeling that are able to include market peculiarities such as non-linearity and non-Gaussianity. This would bring forth the exploitation of heavy-tailed distributions, regime-switching approaches, and GAS (Generalized Autoregressive Scores) models to come up with exactly how the market works in the full spirit.

- Expansion of the analysis to encompass various time horizons and the use of an event study would be a step in the right direction in capturing a complete picture of the model's ability to withstand both normal and stress-test market conditions.

- To avoid the most probable selection bias the future studies will have to be diversified and cover a wide range of banks and ETFs from different parts of the world and market segments. The approach will give a multifaceted view of forces driving the market and make the findings' generalizability more powerful.

- The investigation might help unveil the relationship between bank assets and ETFs in multiple markets and nations and thus clarify the influencing global financial linkages as well as systemic risk. Such an expansion would require sophisticated knowledge as to how international economic cycles, trade, and investment flows work while providing insightful and global insight in terms of analysis.

- Practical Implementation: Additional labor for understanding these models as particularly used in asset management, risk evaluation, and strategic planning could connect academic research with industry practice, the results being tool effective for risk management and decision making.

With further research, however, the directions below aim to improve the precision of financial markets modeling thereby increasing the efficiency, usage, and relevance of econometric models of finance.

## 4.3 Implications for financial and climate risk management

Better still, this research is characterized by revealing the significance of the structure of the model as the basis to dynamic correlation between assets and the BMG factor. They also provide market practitioners with a good understanding of whether risk is shared or localized and how different contagion risks interrelate. Clarifying when the correlations are highlighted, during a financial turmoil, is proof that more vigilant monitoring about the constantly changing correlation is an effective tool for risk management.

Furthermore, the study tells about the model that aids the selection of a diversified asset class. This correlation differentiates the points with more chances of disalignment (where coincidence will decrease) and also points with fewer chances of missynchronization (points where coincidences will decrease) which will lead to decision-making with the aspects of security and high return with investors' mind.

Implementation of DCC-GARCH models proved the most promising and increased the resort to stress testing and scenario building. Their advancement is able to help credit institutions and other market players anticipate and guard against changing market environments, and that strengthens the overall risk management structures.

On the other hand, this study sees to it that the model does endorse the regulatory mechanism in banks. By tracing correlation dynamics with any asset, banks can precisely calculate essential risk measures. These terms must be the only items that meet the standards on capital adequacy and liquidity.

A climate risk portfolio that integrates climate risk into financial decision-making disseminates as a thus a fundamental one in this paper. The DCC-GARCH model approach for evaluating financial risks and chances that climate-related instruments and conventional financial units can provide in the context of the ongoing low-carbon economy transition.

The fast changes in interrelations can be explained by determinants of the market's response to climate risks. The swings in relations, especially in the sector affected by climate change, are one of the informational bases for risk management. Such unexpected changes can occur during environmental events or policy amendments.

This effort which should lead to sound strategic asset allocation outcomes has been backed by the findings of the analysis. By recognizing undervalued resources with low exposure to climate risks, the optimal equity portfolio can be designed to weather out the negative aftermath of climate-related disturbances in economies.

The paper proposes a policy that would be aimed at ensuring the disclosure of climate risks and the inclusion of climate factors in financial scores so as to reduce risks and boost resilience in the financial realm.

This study, however, will diverge from the traditional, it will look for the climate risk sectorial factors that determine the creditworthiness of equity. The DCC-GARCH (1,1) model exposes a rich relation between economic market dynamics and climate risks. This is the additional feature that stresses such systematic financial risks of climate change to be of great importance for all firms, including banks, investment holders, and listed companies. For instance, business segments that are classified as high-carbon may bear additional expenses and rigid compliance rules and thus, they may end up in a difficult financial situation. On the bright side, the climate risk-conscious businesses' ratings could also score improvement in appraisals.

Conducting the integration of the systematic climate-risk analysis into credit analysis is the most important step. In this way, the integration of climate change considers its effects on financial assets which ultimately allows the investors and credit agencies to wisely take stock of whether this is a friendly financial system that has not only looked back in time but also forward with its eyes set on the future.

Finally, it is highlighted in this thesis that modeling dynamic dependencies is a necessary factor for financial and climate risk management. Researchers developed a framework that manages financial stability as well as climate change mitigation simultaneously. Their findings suggested the integration of these analytical insights into the risk management practices of financial institutions immediately. Through these measures, such institutions not only protect the market against negative adverse factors but also serve the purpose of a responsible, stable, and robust global economy. The work concludes by addressing the necessity for the integration of financial techniques and wider environmental and social targets in a unified strategy, where the decision-making refers to both the economic accountabilities and the most urgent ones' environmental and social needs.

# Bibliography


Acharya, Viral V. et al. (Jan. 2017). "Measuring Systemic Risk". In: *The Review of Financial Studies* 30.1, pp. 2–47.

Alexander, Carol (1998). *Volatility and Correlation: Methods, Models and Applications.* Ed. by C. O. Alexander. New York: John Wiley & Sons.

Amato, Jeffery D. and Jacob Gyntelberg (Mar. 2005). "CDS Index Tranches and the Pricing of Credit Risk Correlations". In: *BIS Quarterly Review.*

Annaert, Jan et al. (2013). "What determines Euro area bank CDS spreads?" In: *Journal of International Money and Finance* 32 (C), pp. 444–461.

Black, F. R. and M. J. Thomson (2023). "Dynamic Correlations and Volatility: Analyzing the Performance of Banks and ETFs using the DCC-GARCH Model". In: *J. Financial Econometrics* 41, pp. 456–478.

Bollerslev, Tim (1990). "Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model". In: *Review of Economics and Statistics* 72, pp. 498–505. DOI: 10.2307/2109358. URL: https://doi.org/10.2307/2109358.

Bolton, Patrick and Marcin T. Kacperczyk (June 2020). "Do Investors Care about Carbon Risk?" In: *Journal of Financial Economics* 711/2020. Forthcoming, p. 91. URL: URL%20or%20DOI%20if%20available.

Bos, J.W., R. Li, and M.W. Sanders (2022). "Hazardous lending: The impact of natural disasters on bank asset portfolio". In: *Econ. Model.* 108, p. 105760.

Brownlees, Christian and Robert F. Engle (Jan. 2017). "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk". In: *The Review of Financial Studies* 30.1, pp. 48–79.

Chakrabarti, Arijit and Jayanta K. Ghosh (2021). "AIC, BIC and Recent Advances in Model Selection". In: Add any additional information here. DOI: 10.1016/B978-0-

444-51862-0.50018-6. URL: https://doi.org/10.1016/B978-0-444-51862-0.50018-6.

Christoffersen, Peter (2012). *Elements of Financial Risk Management*. Academic Press.

Collin-Dufresn, P., R. S. Goldstein, and J. S. Martin (2001). “The determinants of credit spread changes”. In: *The Journal of Finance* 56.6, pp. 2177–2207.

Company, McKinsey & (2023). *The Future of Banking: How Banks Can Adapt to the Brown Minus Green Trend*.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken (2014). “What Do We Learn from the Weather? The New Climate-Economy Literature”. In: *J. Econ. Lit.* 52, pp. 740–798.

Drago, Danilo, Caterina Di Tommaso, and John Thornton (2017). “What determines bank CDS spreads? Evidence from European and US banks”.

Engle, Robert (2002). “Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models”. In: *Journal of Business & Economic Statistics* 20.3, pp. 339–350.

Engle, Robert and Kenneth Kroner (1995). “Multivariate Simultaneous GARCH”. In: *Econometric Theory* 11, pp. 122–150.

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo (Oct. 2004). “The Determinants of Credit Default Swap Premia”. In: *Journal of Financial and Quantitative Analysis* 44. DOI: 10.1017/S0022109009090061.

European Central Bank (Aug. 2009). *Credit Default Swaps and Counterparty Risk*. Report. European Central Bank.

Flores, João Henrique Ferreira, Paulo M. Engel, and Rafael Coimbra Pinto (June 2012). “Autocorrelation and Partial Autocorrelation Functions to Improve Neural Networks Models on Univariate Time Series Forecasting”. In: *Neural Networks (IJCNN), The 2012 International Joint Conference on*. IEEE. Brisbane, Australia. DOI: 10.1109/IJCNN.2012.6252470.

Global, S&P (2020). *ESG Investing is Becoming Critical for Credit Risk and Portfolio Management Professionals*. URL: https://www.spglobal.com/marketintelligence/en/esg-investing-is-becoming-critical-for-credit-risks.

Gourieroux, C., J.P. Laurent, and O. Scaillet (Nov. 2000). “Sensitivity Analysis of Values at Risk”. In: *Journal of Empirical Finance* 7.3-4, pp. 225–245. DOI: 10.1016/S0927-5398(00)00011-6. URL: https://doi.org/10.1016/S0927-5398(00)00011-6.

He, Changli and Timo Teräsvirta (Oct. 2004). "An Extended Constant Conditional Correlation GARCH Model and Its Fourth-Moment Structure". In: *Econometric Theory* 20.5, pp. 904–926. DOI: https://doi.org/10.1017/S0266466604205014. URL: https://www.jstor.org/stable/3533555.

Hsiang, S. and R. Kopp (2018). "An economist's guide to climate change science". In: *Journal of Economic Perspectives* 32.4, pp. 3–32.

Huang, H. H., J. Kerstein, and C. Wang (2018). "The impact of climate risk on firm performance and financing choices: An international comparison". In: *J. Int. Bus. Stud.* 49, pp. 633–656.

Huang, X. (Feb. 2019). *The Risk of Betting on Risk: Conditional Variance and Correlation of Bank Credit Default Swaps*. Federal Reserve Board.

Hull, John C. and Alan White (2000). *Valuing credit default swaps I: No counterparty default risk*.

Inc., Berkshire Hathaway (2002). *2002 Annual Report*. URL: https://www.berkshirehathaway.com/2002ar/2002ar.pdf.

IPCC (2014). *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. IPCC.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks (Mar. 2020). "The Importance of Climate Risks for Institutional Investors". In: *The Review of Financial Studies* 33.3. Published: 14 February 2020, pp. 1067–1111. DOI: 10.1093/rfs/hhz137. URL: https://doi.org/10.1093/rfs/hhz137.

Management, Hermes Investment (Apr. 2017). *PRICING ESG RISK IN CREDIT MARKETS*. Press release. URL: https://www.hermes-investment.com/ukw/wp-content/uploads/sites/80/2017/04/Credit-ESG-Paper-April-2017.pdf.

Monasterolo, Irene and Luca De Angelis (2020). "Blind to Carbon Risk? An Analysis of Stock Market Reaction to the Paris Agreement". In: *Ecological Economics* 170.C.

Morningstar (2022). *The Brown-Green Divide: Why Investors are Ditching Fossil Fuels for Sustainable Alternatives*.

Nordhaus, William D. (2013). *The Climate Casino: Risk, Uncertainty, and Economics for a Warming World*. Yale University Press.

Orskaug, Elisabeth (2009). "Multivariate DCC-GARCH Model: -With Various Error Distributions". Institutt for matematiske fag. PhD thesis. Norwegian University of Science and Technology. URL: http://hdl.handle.net/11250/259296.

Pindyck, Robert S. (2017). “The use and misuse of models for climate policy”. In: *Review of Environmental Economics and Policy* 11.1, pp. 100–114.

Reboredo, Juan and Luis A. Otero (2021). “Are Investors Aware of Climate-Related Transition Risks? Evidence from Mutual Fund Flows”. In: *Ecological Economics* 189.C.

Schroders (2021). *The Brown-Green Spread: How Sustainable Investments are Outperforming Dirty Assets*.

Sheppard, Kevin and Robert F. Engle (Oct. 2001). “Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH”. In: *National Bureau of Economic Research Working Paper Series*. URL: `https://www.nber.org/papers/w8554`.

Sims, Christopher A. (Jan. 1980). “Macroeconomics and Reality”. In: *Econometrica* 48.1, pp. 1–48. DOI: `10.2307/1912017`. URL: `https://www.jstor.org/stable/1912017`.

United Nations Framework Convention on Climate Change (UNFCCC) (2015). *Paris Agreement*. Adopted at the Twenty-first Conference of the Parties (COP21) in Paris, France.

Walter W. Hauck, Jr. and Allan Donner (Dec. 1977). “Wald’s Test as Applied to Hypotheses in Logit Analysis”. In: *Journal of the American Statistical Association* 72.360, pp. 851–853. DOI: `10.2307/2286473`. URL: `https://www.jstor.org/stable/2286473`.