Bank Equities Risk Assessment, Attribution and Stock Selection

Gian Marco Mensi, CFA

Matriculation no. 1098475

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Supervisor:

Prof.ssa Maria Cristina Recchioni

In the loving memory of my father Gian Piero.

To my mother Rosanna, my daughter Giulia, and my son Lorenzo.

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Without Prof.ssa Maria Cristina Recchioni’s inspiring guidance this endeavor would not have been possible.

General Abstract

This work aims, by using only publicly available market data, to quantify and allocate macro risks, such as systemic, climate and geopolitical risk, involving listed bank equities. It begins by implementing a bivariate appraisal of climate risk for the Eurozone banking sector to expand it by developing an innovative, frequency-based approach to attribute risk in a multifactor context, extending the scope of the analysis to include systemic, climate and geopolitical risk simultaneously. The results of this multifactor assessment indicate that coincident occurrences of multiple crises are likely to generate larger than expected capital shortfalls and that both climate and geopolitical risk have increased significantly from July 2011 to April 2022. The quantitative assessment of climate tail risk is compatible with the European Central Bank (ECB) 2022 climate exercise results, whereas the measure of geopolitical risk shows a significant positive correlation with the GPRD Threats index (Caldara and Iacoviello, 2022). Finally, these results are deployed to create sectoral portfolios robust to unexpected climate shocks: in the Eurozone, a strategy based on overweighting the banks least exposed to the climate factor would have produced superior risk-adjusted returns during the 2019-2022 period. However, the same approach applied to US lenders would have offered inconclusive evidence, likely due to the differences between the two regulatory frameworks.

General Introduction

All banks are subject to specific risks which require regulatory capital: credit risk, market risk and operational risk (Hull, 2023). Lenders are also subject to macro risk factors concerning the broad financial system, which manifest themselves following events of various natures suddenly provoking unexpected losses, thus undermining the standing of supposedly solid enterprises. Banks are particularly vulnerable to these shocks due to their structural high leverage and the confidence needed to conduct their business, prone to be shaken abruptly by unexpected situations. Given the banking system role as provider of credit to the economy and as monetary policy transmission channel, solvency is a prerequisite to ensure economic prosperity and regulators are continuously tuning their assessment of the consequences of potential crises using stress tests, risk exercises and ad-hoc measurements: these efforts identify systemic, geopolitical and climate risks as the main types of macro risks menacing the stability of the banking system.

Systemic risk materializes when supposedly isolated bankruptcies are not properly contained, escalate, and spread to other agents, implying that the failure of a single institution might lead to multiple resolutions and ultimately to a crisis affecting the entire financial system. History points to systemic risk as a most serious factor: the 1930s Great Depression and the 2000s Great Financial Crisis are examples of what can happen during such events. Systemic crises are rare, but devastating: combined losses grow so large that states are forced to use sovereign balance sheets to pay for the aggregate shortfall. In the early 2010s academic literature studying systemic risk flourished: Systemic Expected Shortfall (Acharya, 2010; 2017) and SRISK (Brownlees and Engle, 2012; 2017) provided frameworks to estimate the cost of a financial system collapse, network analysis was used to model the propagation of a shock through the system and VaR (Value at Risk), the risk framework that failed to capture the extent of the potential losses, was improved by the introduction of CVaR (Conditional Value at Risk) to better assess tail risk. Currently, systemic risk is constantly monitored with a variety of tools and is at the top of regulators' worries.

Geopolitical risk is represented by the consequences of acts of war, terrorism or political decisions threatening financial stability. These events are generally difficult to predict and potentially devastating, but, barring apocalyptic scenarios, they tend to affect specific constituencies: as an example, the consequences of the breakout of the Russo-Ukrainian war have been incredibly harsh on the banking systems of the belligerents, but have proven to be manageable, if not cheap, by the foreign banks with exposure to the region. Geopolitical risks also tend to show low persistency, especially in the case of conventional terror attacks. Historically, the largest consequences are linked to political events, such as Brexit, which also tend to have longer lasting effects on the banking systems involved. Given geopolitical risk's unpredictable nature, markets reflect increased risk premia for regions perceived as being hot spots, whereas risk frameworks tend to assess geopolitical risk using scenario analysis.

Climate risk is a relatively new factor, pushed to the forefront of financial risk management, banking supervision and regulation by climate change. Manifesting itself as physical risk, caused by climate events that destroy capital, and transition risk, induced by legislative and market modifications linked to the containment of global warming, its relevance is expected to rise dramatically with the projected increase in global temperatures. Its dual nature makes evaluating total climate risk assessment a very difficult task, which requires a structural commitment to create and maintain a database of non-financial data and a granular measurement of the greenness of an economy. So far, only the Eurozone appears to have taken all the steps necessary to fully include the climate factor within its risk framework, whereas other constituencies have been slower to adopt similar measures. Moreover, contrary to systemic and geopolitical risk, the financial system has not endured yet the effects of a serious climate crisis. The world, however, has experienced several energy crises: since the 1970s, large fluctuations in the price of hydrocarbons have provoked wide swings in the global economy and the value of related assets. Until 2020, these instances were generally characterized by a boom in the price of fossil fuels, followed by a subsequent bust. Then the Covid-19 pandemic came, with lockdowns causing a collapse in demand and a sharp fall in the price of oil and gas: European Brent crude prices fell more than 80% in three months, whereas in the USA bottlenecks in storage sent West Texas Intermediate crude prices into negative territory. This dramatic fall in the value of hydrocarbons occurred from relatively well-behaved prices and made a perfect case of what could happen if an uncontrolled planetary warming were to force governments to adopt draconian measures to contain greenhouse gas emissions. In such a scenario, companies linked to fossil fuel production and exploration, the "stranded assets", would rapidly lose value, likely impairing their ability to service debt: banks exposed to these "brown" assets would have to take material write-downs and record crippling losses. Assessing the size of these losses in case of a climate event is equivalent to estimating transition risk, which the ECB puts at approximately 75% of total climate risk in early 2022 for the Eurozone banking system.

Climate risk is the focus of the first chapter. It is inspired by CRISK (Jung, Engle and Berner, 2021), a metric constructed on the basis of the SRISK methodology: CRISK estimates transition risk using only market data. In their study on a selection of international lenders, the scholars found that aggregate CRISK showed a marked jump following the 2020 hydrocarbons demand collapse, returning alarming figures for the possible consequences of a climate event.

Since then, CRISK has been monitored regularly by the NYU Volatility Institute. We customized this approach to analyze the top Eurozone banks, modifying the key parameters and using a rolling window instead of a recursive method: the results showed that CRISK could serve as an early warning to identify a climate event affecting the Eurozone banking sector. It could also be used to assess relative climate sensitivity within the lenders comprised in the sample.

Reflecting on these findings, we realized the main drawbacks of this approach: shortfalls, as measured by SRISK and CRISK, are estimated independently, using a bivariate setup involving bank returns and a single risk factor at a time. Furthermore, the geopolitical factor is excluded from the analysis since there was no “GRISK”. Could all macro risk factors be evaluated simultaneously? Estimating one risk at a time makes the job easier since it avoids the issue of risk attribution. However, the balance sheet of a bank is always the same, offering a single buffer to absorb losses: risk should probably be assessed with a multivariate setup. Henceforth, after designing a geopolitical risk factor, we studied a frequency-based system that attributes tail risk using relative frequencies and applied it to Eurozone top banks in the July 2011 – April 2022 period, assessing all risk factors simultaneously. The results obtained within this multifactor framework are presented in Chapter 2 and show that, on average, systemic risk represents 85.0% of total risk, with climate and geopolitical risks contributing 10.9% and 2.7% respectively. Interaction risk among factors is always present, for an average of 1.4% of potential combined shortfall[1]. Our transition risk combined estimate of €47 billion calculated at the beginning of 2022 for a significant sample of large banks is compatible with the €53

[1] Median contributions: systemic risk 86.5%; climate risk 9.9%; geopolitical risk 2.3%; interaction risk 1.3%.

billion ECB Climate Stress Test (2022) appraisal, obtained using a comprehensive, bottom-up analysis of individual lenders' exposure to climate risk, while the aggregate geopolitical risk estimates show significant positive correlation with Caldara and Iacoviello (2022) GPR Threat index, based on media headlines.

We then decided to look for a practical utilization of the results obtained using this methodology to identify the greenest lenders and improve sectoral portfolio selection. Albeit ESG (Environmental, Social and Governance) investing is supposed to be driven by motivations that transcend expected return, our take is that bank equities less exposed to losses induced by transition risk should perform better than their peers during a climate event. Hence, we have checked this hypothesis on two samples comprising the top Eurozone and US lenders during the 2019-2022 period: after constructing a sectoral benchmark using market-cap weights rebalanced every quarterly cycle, we compared its risk-adjusted performance against climate-tilted test portfolios. The composition of these portfolios is varied with respect to the benchmark at each rebalancing date using weight modifiers based on deviation of each bank from the samples' average Environmental ratings, Scope 2 greenhouse gas emissions and our climate loss estimates. The findings, presented in Chapter 3, are mixed. For the Eurozone sample the hypothesis is confirmed: the climate loss modifier excels, showing a better risk-return profile than the benchmark and beating both the rating-adjusted and the emission-modified portfolios. However, in the case of the North American banks, no climate-tilted strategy shows any consistent overperformance vis-à-vis the benchmark. We think that the main reason for this regional divergence is the different climate regulatory discipline: the stronger European push for greening the economy is reflected in the higher sensitivity to climate risk shown by Eurozone lenders, whereas US banks react differently to it. Another factor is the lack of reliable emission data: we had to employ relatively homogeneous Scope 2 estimates in lieu of more comprehensive and relevant Scope 3 data, which for the foreseeable future are not going to become homogeneous enough to be used for analytical purposes.

Final remarks conclude.

Chapter 1: Bivariate Eurozone Banks Climate Risk Assessment Using CRISK

Abstract

CRISK is a market-based measure of systemic risk conditional on the occurrence of a climate crisis which may compromise banks exposed to companies engaged in fossil fuels exploration and production. We apply the CRISK methodology to estimate the climate transition risk of a sample of Eurozone banks for the period July 2011 – April 2022. While the granular measurement system required to properly evaluate the greenness of loans portfolios is being implemented, CRISK could provide a valuable contribution within the current EU climate risk framework. It may also serve as a guide to rank publicly traded bank equities on the basis of their relative climate riskiness.

1. Introduction

Regulators across the globe are studying how to implement climate risk stress tests for banks. In the European Union both the European Central Bank (ECB) and the European Banking Authority (EBA) are working towards the definition of a climate risk framework, with the central bank extending its current top-down scenario analysis and the authority complementing it with a granular bottom-up data collection effort focused on the assessment of the greenness of Eurozone lenders' books. Given the unprecedented nature of the challenge, there is no clear path forward and the current state of the art in modelling procedures is far from being perfect. Since it is difficult to precisely assess the actual amount of carbon exposure of a specific loan portfolio, most of the times measurement is carried out using industry proxies or sector averages, thus ignoring the in-sector heterogeneity due to material specificities of individual corporate borrowers inside each Climate Policy Relevant Sector (CPRS). Additionally, harmonized procedures are still developing, and medium and small-sized enterprises (SME) are de facto excluded from the analysis, with policy makers forced to rely on metrics that might not be directly comparable among institutions. For all these reasons, measuring climate risk for banks using publicly available market data could constitute a useful complement to the existing and developing tools: this paper introduces the use of capital shortfall - CRISK - as a measure of climate transition risk for a selection of top Eurozone credit institutions.

In May 2021 EBA published the report “Mapping climate risk” with the results of its first climate exercise. It was conducted with the participation of 26 banks that took part voluntarily in the assessment of the greenness of their loan portfolios and related climate risk profiles. The sample included approximately half of total EU-banks risk weighted assets (RWA) deployed vis-a-vis large non-financial enterprises. Corporate data collected in accordance with the EU-wide NACE taxonomy of business activities were reclassified and reconciled according to the (CPRS) methodology proposed by Battiston et al. (2017), finding that most of the sample RWA were deployed to companies operating in the sectors 1 to 6, heavily affected by transition risks. This classification was then integrated by the measurement of each specific debtor greenhouse gas emissions (GHG), that is necessary to identify the exposure towards the highest polluters and compute the portfolio carbon component. However, proxies had to be used for more than 80% of the RWA, since most of the specific information was missing. By comparing the classification resulting from CPRS criteria with the firm-specific GHG data, EBA found that there are several outliers represented both by relatively low-emission firms operating in CPRS 1-6 and by high-emission enterprises grouped in the supposedly greener sectors. Consequently, if CPRS allowed for a nearly integral (98%) NACE-based classification, the more granular and accurate GHG was applied only to a small portion of the sample (17%). Similarly, there were several instances in which banks' own evaluation of a borrower greenness could not follow EU taxonomy classifications or was diverging from the synthetic Taxonomy Alignment Coefficient (TAC) by Alessi et al. (2019), hindering a proper calculation of GAR across the participating entities.

In the current EU approach EBA exposure results are then elaborated within the ECB scenario analysis, so data quality could materially affect the accuracy of the capital shortfall estimations in all circumstances. Eventually, this strategy is bound to lead to a very precise assessment, but only following the adoption of common procedures across the EU. Significant improvements in the standardization of the results seem unlikely until a broader set of climate disclosures is extended to regular companies reporting , including SMEs. A possible stop-gap solution is to integrate the results obtained within the current EU framework, which heavily relies on sectoral average emissions, with alternative climate risk measures, such as CRISK.

In their paper Jung, Engle and Berner (2021) propose CRISK as a climate risk assessment measure that could potentially be included in future stress tests on the US banking sector. Being a relatively late comer , the Federal Reserve cannot rely on the extensive proprietary data set collected by the ECB and is considering a wide range of instruments to evaluate banks' climate risk. CRISK is an estimate of the capital shortfall conditional on a systemic climate stress affecting the financial industry closely linked to SRISK, a measure of systemic risk first introduced by Acharya et al. (2012) and subsequently developed by Brownlees and Engle (2017). Jung, Engle and Berner (2021) propose a 3-step CRISK estimation process applied to data encompassing 20 years of returns, up to and including the oil price collapse in mid-2020 and its detrimental effect on oil and gas equities (the "stranded assets"):

1. Transition risk is identified by the construction of a metric, the climate factor, tracking the underperformance of a group of stranded assets (a weighted basket of energy sector EFTs – de facto a proxy for CPRS 1) with respect to the market index return.

2. Bank climate correlations and betas relative to the climate factor are then calculated using the Dynamic Conditional Correlation (DCC) (Engle, 2002 and 2009) and Dynamic Conditional Beta (DCB) (Brownlees and Engle, 2017) models.

3. CRISK is measured using the results from DCC/DCB in conjunction with actual banks' balance sheet data to simulate the potential climate-induced equity shortfall conditional on the occurrence of a climate crisis affecting stranded assets and thus weighing on lenders.

Jung, Engle and Berner (2021) find that banks' climate betas move considerably across different time windows and that climate risk is material, mainly due to the fall in the lenders' equity market value caused by the exposure to hydrocarbons producers in the event of a climate crisis. This methodology has the advantage of employing only publicly available information and bypasses the need for a granular database. This feature, however, also constitutes its main limitation, making CRISK a useful measure of climate-induced capital shortfall only in the context of a broader macro and micro-prudential framework.

Given these premises, our analysis aims to understand whether a Eurozone CRISK assessment makes sense and what type of scenario can result from that.

The remainder of the paper addresses these points. Specifically, in Section 2 we define a Eurozone climate factor CFE, and the methodology implemented to compute CRISK, whereas in Section 3 we illustrate the data used to conduct the analysis, the simulation development and the results of the estimation process. Section 4 concludes.

2. A CRISK indicator for the Eurozone

The UN-sponsored Net-Zero Banking Alliance (NZBA), which comprises all major Eurozone and international lenders committed to implement a lending policy suitable to favor a material reduction in GHG emissions by 2030 and reach carbon neutrality by 2050, has pledged to follow the International Energy Agency (IEA)[2] resolution recommending the reduction of capital commitments towards industries contributing the most to GHG emission. Despite this claim, in its 2021 report regarding climate-related financial risks, the ECB notes that, in aggregate, the carbon intensity of EU banks' portfolios has increased: the central bank estimates the total credit sector exposure vis-à-vis CPRS sectors to be approximately €1.9 trillion. Given the size of the loans outstanding, climate transition could constitute a significant risk for Eurozone banks.

In this section we adapt CRISK, introduced by Jung, Engle and Berner (2021), to the Eurozone framework and determine whether it could be potentially integrated in the current EU regulators' toolbox. Several important structural differences between the US and the Eurozone have to be taken into account. If the US has become a net exporter of fossil combustibles, the Eurozone continues to rely heavily on imports to cover its demand for energy. However, the European Emission Trading System (ETS) is likely to have had a bigger impact on corporate behavior than the US cap-and-trade rules, significantly fostering the "greening" of the European energy sector. Moreover, European banks are subject to different rules and adopt

[2] See IEA (2021) "Net Zero by 2050 – A Roadmap for the Global Energy Sector", 4th revision.

IFRS accounting principles, perceived as stricter with respect to US GAAP[3]. As a result, proper adjustments have to be made, starting from climate factor selection.

Jung, Engle and Berner (2021) calculate the performance of the stranded assets benchmark portfolio as the return of a portfolio comprised by the energy ETF XLE (in combination with the coal ETF KOL until available) minus the return of the SP500 index (SPX), with negative values indicating an underperformance of stranded assets vis-à-vis the broader market. Given that the SPX is the de facto international equity benchmark, accounting for a share in excess of 60% of the MSCI World Index, the choice of this benchmark can be applied also to our study by selecting a liquid ETF listed in Europe that tracks the index, hedges the EURUSD currency risk regularly and is marked-to-market at the close of European bourses: our choice is Blackrock's iShares IUSE. Listed on 11 exchanges under different tickers, IUSE is an accumulation fund whose net asset value in November 2021 was close to €5 billion. There are valid alternatives to IUSE, such as Lyxor's SP5H/SPXH, but not with a price history encompassing the entire period considered.

IUSE was launched in the fall of 2010 and since then has tracked the dollar-denominated SPX very well: in the period considered the iShare ETF cumulated daily and yearly log returns show a 99.9% correlation with the corresponding SPX USD return statistics. Given the currency hedge and that the price of IUSE is arbitraged until the close of European business, it is our opinion that the characteristics of this ETF eliminate the need to account for lagged returns in this type of analysis.

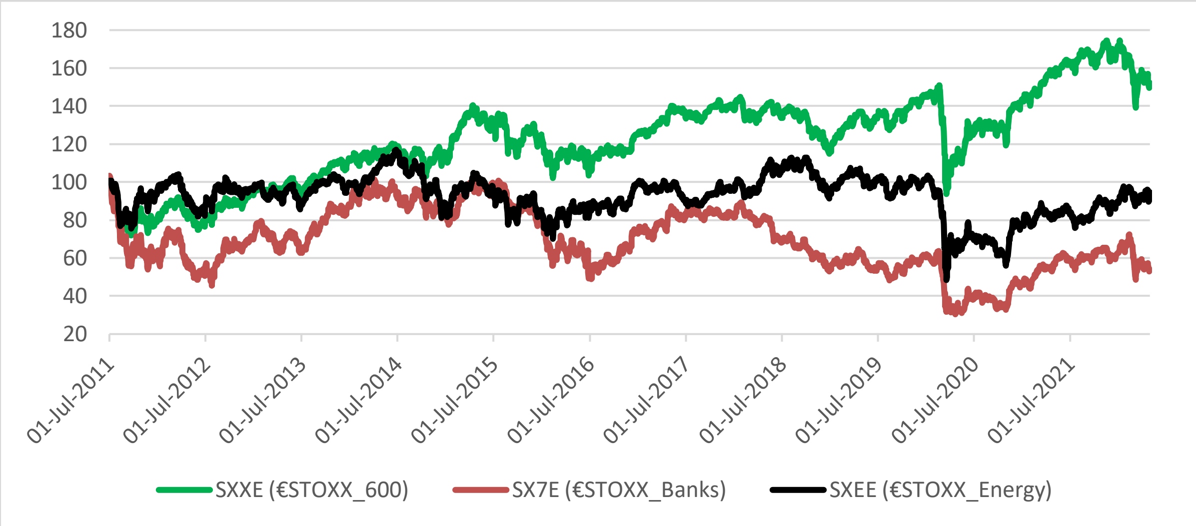
[3] See Admati and Hellwig (2013).

In terms of stranded assets, the most likely candidates are coal mining and hydrocarbons extraction companies. The largest European coal and lignite mines, however, are mainly based in Germany and Poland and are operated directly by utilities, such as RWE (Germany), whereas the largest mining stocks involved in extraction, such as BHP or Glencore, are listed in the UK. The operations of these multinational enterprises span across the world, with most of their mines based on other continents, making them unsuitable to be part of a Eurozone tracker.

Therefore, we think that the best option is to use only the EURO STOXX Energy index SXET, which represents the net return plus dividends of the SXEE Euro Energy index: it comprises companies whose main legacy business is fossil fuels exploration and production (E&P, a good proxy for CPRS 1) and does not include any renewable energy pure plays. With respect to banks, in the past decade the EURO STOXX bank index SX7E significantly lagged both the EURO STOXX (SXXE)[4] and the EURO STOXX SXEE Energy index, as shown in Figure 1. This marked underperformance is the consequence of particularly poor returns registered by banks during the 2011-12 sovereign debt crisis and the 2016 Brexit dislocation. In 2020 all sectors were heavily affected by the outbreak of the COVID pandemic, but oil and gas equities were also hit by the temporary collapse of fossil fuel prices that depressed sector returns long after the broader market recovered.

[4] The EURO STOXX index SXXE comprises only the euro-denominated securities included in the wider STOXX 600 index, thus representing a smaller, currency-homogeneous subset of stocks. As of the end on November 2021 SXXE included 291 stocks as shown by Qontigo - https://www.stoxx.com/index-details?symbol=sxxe.

Figure 1: SXXE vs SX7E vs SXEE, Cumulated Returns, 07/2011-04/2022

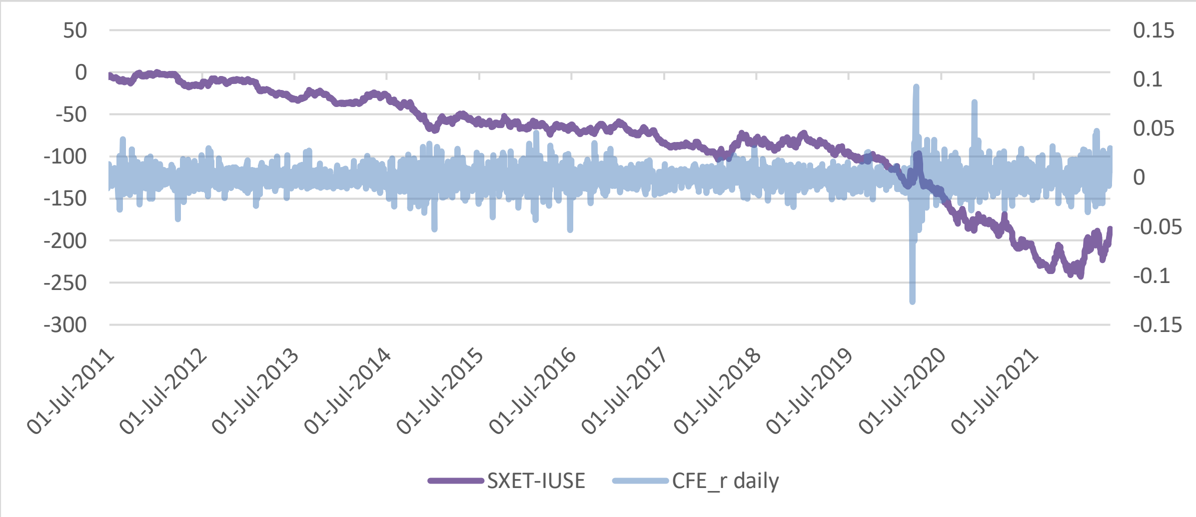


For the reasons discussed, we define the Climate Factor for the Eurozone CFE as the combined return of a long position in the Energy index SXET and a short position in the IUSE euro-hedged SPX ETF:

$$CFE = SXET - IUSE$$

Figure 2 shows both the spread cumulative arithmetic returns (long SXET and short IUSE) and the dispersion of daily CFE log returns (CFE_r) across the time window considered (on the secondary vertical axis). This definition of the climate factor makes a bank with a higher, positive, climate Beta more inclined to suffer from a drop in the market value of its traded equity during a systemic climate crisis that affects the equities of fossil fuels producers.

Figure 2: SXET-IUSE Cumulative Arithmetic Returns and Log-Returns Dispersion (right axis), 07/2011-04/2022



2.1 Eurozone banking basket selection

A good proxy for the Eurozone banking industry should include all the Eurozone-based institutions that contribute the most to systemic risk, as determined by EU and international regulators. In this process, Total Assets (TA) and Risk-Weighted Assets (RWA) represent key metrics used to identify Global Systematically Important Institutions (G-SII): in 2019, net of UK institutions, EBA determined that large French banks tended to carry the most in terms of TA and RWA, followed by a group of German, Dutch, Spanish and Italian lenders. Country-wise the situation was the same, with France, Spain, Germany, Italy and Netherlands contributing the most to the Eurozone total bank assets. Following the release of the 2021 exercise by EBA, these data were confirmed.

We then select a group of 10 of the largest G-SII as a proxy for the Eurozone banking sector: the basket includes BNP, Credit Agricole (ACA) and Société Générale (GLE) for France, Deutsche Bank (DBK) and Commerzbank (CBK) for Germany, Santander (SAN) and BBVA for Spain, Unicredit (UCG) and Intesa (ISP) for Italy, ING (INGA) for the Netherlands. Figure 3 shows the evolution of TA for the selected sample.

Figure 3: Individual Banks Total Assets in € millions, 2011Q2-2022Q1

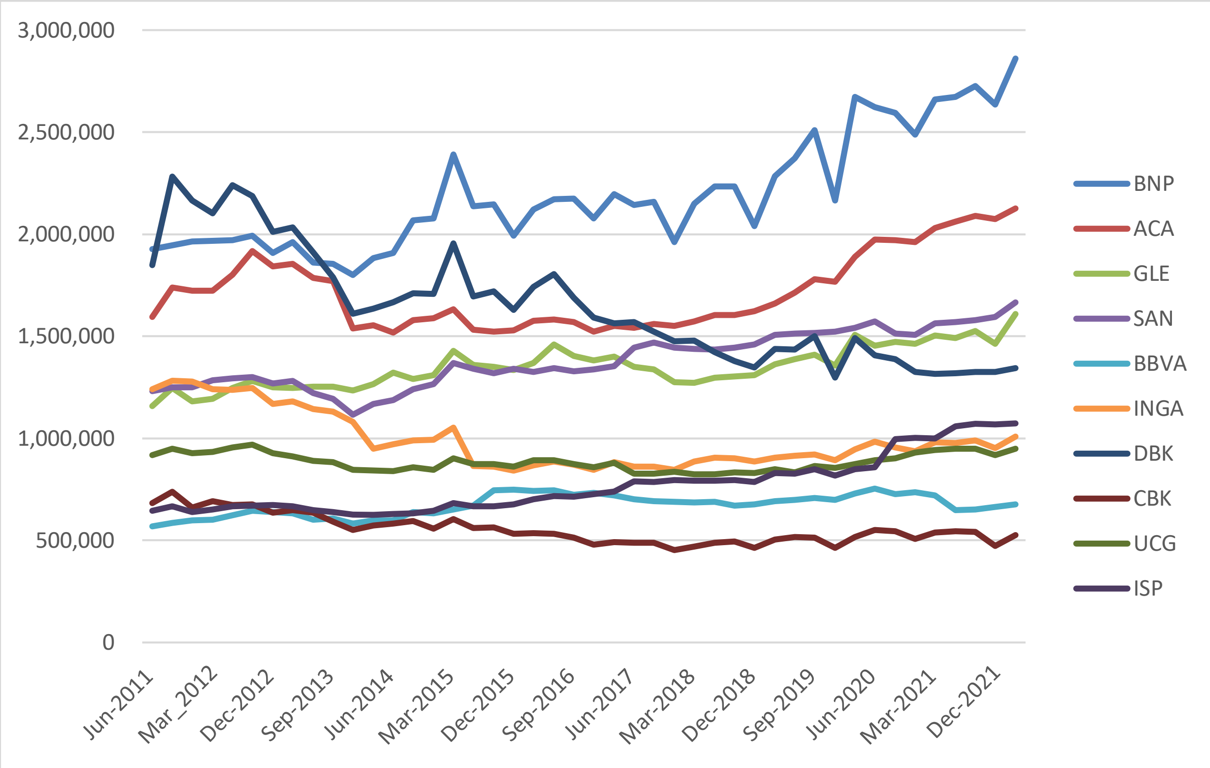
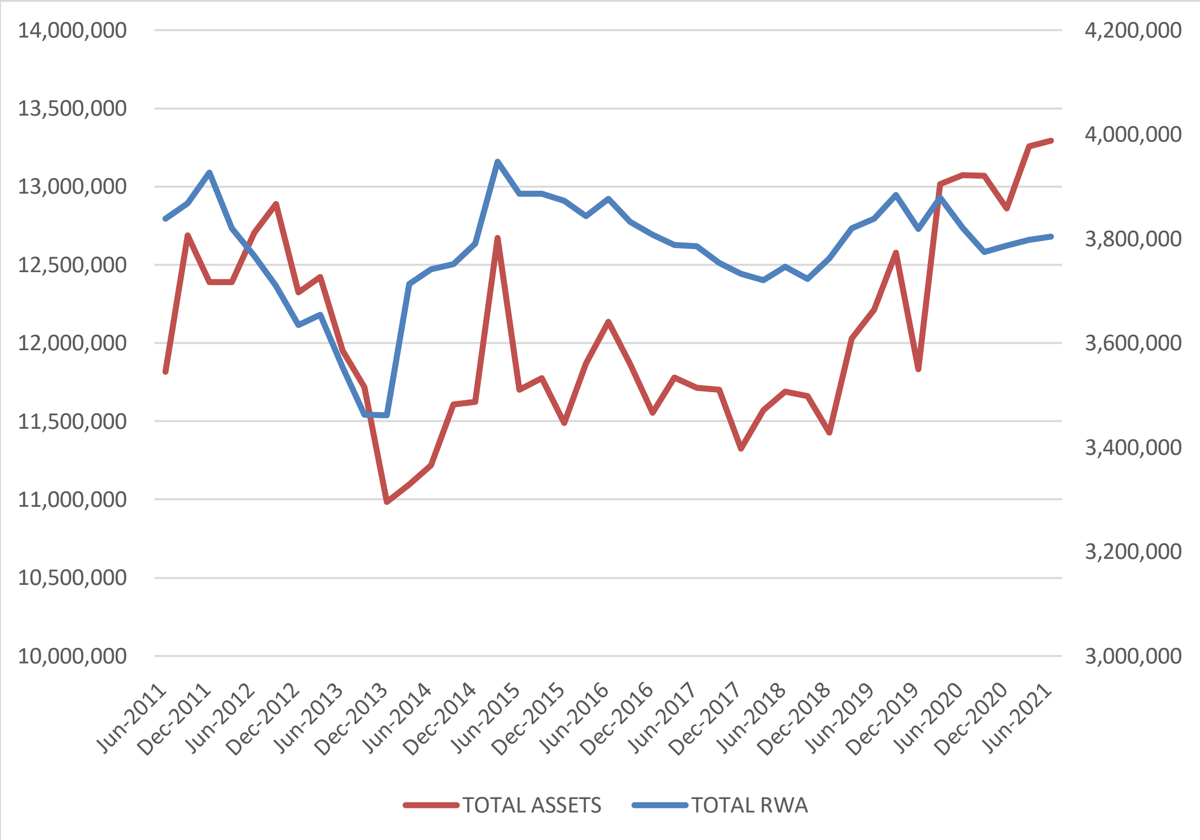


Figure 4 shows that, in aggregate, for the selected basket both TA and RWA (secondary axis) have remained rather stable: during the period considered TA increased 15.4% from 11.99 trillion to 13.84 trillion euros, whereas RWA decreased 0.6% from 3.95 to 3.92 trillion euros, with standard deviations of 5.7% and 2.8% respectively. Within the sample we can notice a clear dichotomy: in terms of TA, French banks BNP, ACA and GLE boosted their combined balance sheets by €1.87 trillion, Spanish SAN and BBVA by €0.57 trillion and Italian ISP and UCG by €0.43 trillion; in contrast, German DBK and CBK, with Dutch INGA, reduced their combined holdings by €1.03 trillion. BNP's TA registered the largest increase (+€0.86 trillion), while DBK's TA contracted the most (-€0.56 trillion).

Figure 4: Total Assets vs Total Risk Weighted Assets RWA (right axis) in € millions, 2011-2022



Given that all these banks operate in the same time zone and adopt the euro as both operating and reporting currency, we had no need to implement any lag or forex adjustment to complete our study.

2.2 CRISK calculation

Acharya and Richardson (2012, revised in 2017) introduced the concept of SRISK as a measure of the capital shortfall registered by a bank conditional on the event of a financial crisis, thus approximating the cost for the government to arrange an eventual bailout in times of a financial crisis. Brownlees and Engle (2017) show that SRISK is able to formulate a good prediction of the amount of public capital needed to strengthen the banking system following a crisis, as occurred in the US with the TARP program in the aftermath of the 2008 financial crisis. Could the same be done for climate risk? In their paper Jung, Engle and Berner (2021) apply the same exercise to the effects of the distress in the oil and gas sector due to the collapse of oil prices in 2020 and they produce an estimate for capital shortfall affecting global banks exposed to the CPRS1 borrowers. We apply the same methodology to our sample of large Eurozone lenders using CFE as climate factor.

Starting from the fundamental accounting identity that makes total book assets TA equal to the sum of total book liabilities TL and the book value of equity E we have:

$$TA = TL + E \tag{1}$$

Indicating with MV the market capitalization of the bank on a given trading day, Quasi-Assets QA are then defined as the sum of the book value of TA and (MV – E), i.e., the difference between the market cap of a bank and the book value of its equity. QA could also be expressed as the sum of its liabilities TL and its market cap MV:

$$QA = TA + (MV - E) = (TA - E) + MV = TL + MV \tag{2}$$

Assuming that the value of a bank's liabilities is generally stable around its nominal value, QA can be considered as a real-time, forward-looking market measure of the size of the balance sheet and consequently of the actual quality of the bank assets and the power they have to generate future earnings, with the ratio MV/E being equivalent to the standard Price to Book Value ratio P/BV.

$$\frac{MV}{E} = \frac{P}{BV} \tag{3}$$

A MV/E (or P/BV) larger than 1 implies a market price for the shares at a premium with respect to the book equity per share, and at a discount when it trades below 1. Interestingly, most

Eurozone lenders' shares are trading below book value, albeit with an average discount that has recently started to contract.

We now introduce the concept of Capital Shortfall CS_t at time t, defined as:

$$CS_t = k\,QA_t - MV_t = k(TL_t + MV_t) - MV_t = k\,TL_t - (1-k)MV_t \tag{4}$$

Given a prudential capital buffer k as a percentage of the bank's QA, CS identifies a minimum level of safeguard in terms of market value of its equity: a positive CS value indicates a potential burden on public finances in case of a crisis leading to a bailout. The parameter k could vary significantly among jurisdictions: according to Engle, Jordeau and Rockinger (2015) for the US GAAP standard a k=8% is adequate, whereas stricter EU rules and IFRS accounting standards make assets of Eurozone banks look larger than their counterparts, thus suggesting k=5.5% as a more appropriate value. We therefore set k=5.5% in our analysis.

Indicating with w the time span used in the projection window, $CRISK_t$ is defined as the expected capital shortfall at time t conditional to the outburst of a systemic event related to climate risks:

$$CRISK_t = E_t(k\,QA_{t+w} - MV_{t+w} \mid crisis), w > 0 \tag{5}$$

Since the market value of TL is assumed to remain close to par, the expected value of a bank's debt is equal to its nominal value[5]. By expanding and substituting we get to Eq. (6), composed by two terms, $CRISK^D_t$ for debt and $CRISK^M_t$ for market value:

[5] During times of crisis the total amount of bank debt tends to have small absolute fluctuations, even if its composition might vary: a reduction in inter-bank borrowing is usually compensated by an increase in other types of obligations, often with central banks acting as counterparts.

$$CRISK_t = E_t(k\,TL_{t+w} + k\,MV_{t+w} - MV_{t+w} \mid crisis) = CRISK_t^D + CRISK_t^M \tag{6}$$

with

$$CRISK_t^D = kE_t(TL_{t+w} \mid crisis)\,;\; CRISK_t^M = -(1-k)E_t(MV_{t+w} \mid crisis), w > 0$$

$QLev_t$ is defined as the leverage of the bank measured by the ratio of Quasi-Assets to the market cap:

$$QLev_t = \frac{QA_t}{MV_t} = \frac{TL_t + MV_t}{MV_t} = \frac{TL_t}{MV_t} + 1 \tag{7}$$

Hence, under the assumption of no debt renegotiation[6], $CRISK_t^D$ can also be expressed as:

$$CRISK_t^D = kTL_t = k\,(QLev_t - 1)\,MV_t \tag{8}$$

Eq. (8) highlights the direct influence of QLev on the risk profile of a bank: the relationship between leverage and balance sheet size is a key factor in determining the systemic relevance of an institution. Even assuming that the equity of a bank is not affected by a systemic event, leverage might generate a capital shortfall if QLev exceeds the ratio 1/k, which for k=5.5% implies a leverage just below 20. Interestingly, at end of April 2022, only BBVA showed a value for QLev below this level in our sample.

The first term of Eq. (6) represents the precautionary amount of funds to be covered by the market capitalization of the bank, which, in turn, might be affected by the expected drop in its equity value: the extent of this fall is computed as the bank equity multiperiod arithmetic return,

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[6] That is $E_t(TL_{t+w} \mid R_{f,t+1:t+w} < crisis\ threshold) = TL_t$, see Brownlees and Engle (2017).

R_t, conditional on the systemic event indicated by a factor return, R_f, lower than a certain crisis level *thresh* considered to be critical.

This value is defined as $LRMES_t$ (Long Run Marginal Expected Shortfall at time t), and it is expressed as shown in Eq. (9):

$$LRMES_t = -E_t(R_{t+1:t+w} \mid R_{ft+1:t+w} < thresh) \tag{9}$$

Following Brownlees and Engle (2017), we can derive an approximation for LRMES in a static bivariate normal framework as

$$LRMES_t^{static} = -\sqrt{w}\,\beta_t^{climate}\,E_t\left[\,r_{f,t+1}\middle|\left(r_{f,t+1} < \frac{log(1+thresh)}{\sqrt{w}}\right)\right]$$

with $\beta_t^{climate} = \rho_{bf}\frac{\sigma_b}{\sigma_f}$ being the climate Beta, calculated as the correlation between a bank return r_b and the climate factor return r_f times the ratio of their respective standard deviations.

In a dynamic context, with $I_{R_{f,t+1:t+w}<thresh}$ being the indicator function signaling a climate factor drop below the crisis threshold, $LRMES_t^{dynamic}$ is computed as the Monte Carlo average for a number of runs S of a series of simulated bank arithmetic returns R_b over the projected time span w:

$$LRMES_t^{dynamic} = -\frac{\sum_{s=1}^{S} R_{b,t+1:t+w}^{s}\ I_{R_{f,t+1:t+w}^{s}<thresh}}{\sum_{s=1}^{S} I_{R_{f,t+1:t+w}^{s}<thresh}} \tag{10}$$

Rearranging $CRISK_t^M$ we get: $CRISK_t^M = -(1-k)\,MV_t(1-LRMES_t)$

Hence:

$$CRISK_t = CRISK_t^D + CRISK_t^M = kTL_t - (1-k)\,MV_t(1-LRMES_t) \tag{11}$$

That could be expressed as $CRISK_t = kTL_t - (1-k)MV_t \, exp\left[\beta_t^{climate} \, log(1-d)\right]$, with d indicating the climate factor drop during the event. Being $log(1-d)$ strictly negative, the higher the climate Beta, the lower the market value of the bank that could be used to cover the required prudential fraction of its assets.

It is possible for the climate Beta of a bank to be negative: this feature would signal the resilience of the institution with respect to the effects of transition risks since a marked decline in value of the stranded assets would lead to a capital buffer increase. Indeed, many of the banks do show, albeit sporadically, dynamic betas close to or below zero.

In certain periods the simulation could also return negative CRISK values: such an occurrence would indicate a capital surplus despite a climate crisis. To avoid distortions, the standard CRISK calculation method puts a constraint on the result by imposing $CRISK_t = max(0, CRISK_t)$. Migueis and Jiron (2020) point out that the existence of negative values for the capital shortfall could affect the effective calculation of systemic risks, potentially leading to underestimate exposures and impairing the consistency of relative riskiness rankings: they recommend using CRISKM, a modified version of CRISK, which requires a slight change in its computation without altering the substance and the nature of the metric. With $CSM_t = max(0, kTA_t - W_t \mid crisis)$, $CRISKM_t$ is computed as shown in Eq. (12):

$$CRISKM_t = E_t(CSM_{t+w} | R_{ft+1:t+w} < thresh) \geq CRISK_t = E_t(CS_{t+w} | R_{ft+1:t+w} < thresh) \quad (12)$$

In a dynamic simulation with one or more satisfied threshold conditions, employing CRISKM instead of CRISK makes every term included in the calculation of the average[7] non-negative,

[7] See Eq. (10).

potentially increasing the capital shortfall estimate for that specific date. In our sample, however, CRISK estimation carried out using the standard method is not materially affected by this issue: negative CRISK is experienced only in a handful of cases. This is likely due to the relatively high leverage of most of the banks analyzed: as expected, negative standard CRISK measures appear to be closely linked to situations characterized by low climate betas and low leverage ratios relative to the rest of the sample.

2.3 Dynamic Conditional Climate Correlations and Betas

After analyzing the relationship between the basket return and the climate factor, we use Dynamic Conditional Correlation and Dynamic Conditional Beta to compute CRISK. DCC belongs to multivariate GARCH models and is based on a combination of time-varying conditional correlations and volatility adjusted returns, i.e., standardized residuals with mean zero and both conditional and unconditional variance equal to 1. DCC calculations are carried out in steps:

1) Volatility and standardized residuals estimation using an appropriate GARCH model;
2) Dynamic correlations estimation using the standardized residuals;
3) Rescaling.

Each series volatility is estimated using the univariate asymmetric GJR-GARCH introduced by Glosten, Jagannathan and Runkle (1993) of the variance v_t modeled, under the constraint $\alpha + \beta + \frac{\gamma}{2} < 1$, as a function of the unconditional variance ω, the lagged squared shock y_{t-1}^2, the lagged variance v_{t-1} and an indicator function $I_{y_{t-1}<0}$ that assumes the value of 1 if the lagged return is negative:

$$v_t = \omega + \alpha y_{t-1}^2 + \gamma y_{t-1}^2 I_{y_{t-1}<0} + \beta v_{t-1} \tag{13}$$

This asymmetric GARCH specification, considered to be most useful in financial econometrics, reflects the greater impact of negative shocks on volatility[8].

Subsequently it is possible to generate the conditional covariance $H_{i,j,t}$ and from there the variance-covariance matrix H_t, obtained as:

$$H_t = D_t R_t D_t \tag{14}$$

D_t is the time-varying diagonal standard deviation matrix and R_t is the conditional quasi-correlation matrix of the standardized returns that can be further decomposed into the time-varying covariance matrix Q_t:

$$R_t = diag(Q)_t^{-0.5}\, Q_t diag(\,Q)_t^{-0.5} \tag{15}$$

In the Engle (2002), (2009) specification the DCC process is mean reverting: indicating with ε_t the residual vector, with ε_t^T its transpose and using correlation targeting with $\underline{Q}$ being the unconditional variance-covariance matrix and imposing the constraint $\alpha + \beta < 1$, Q_t can be expressed as:

$$Q_t = (1 - \alpha - \beta)\underline{Q} + \alpha\varepsilon_t\varepsilon_t^T + \beta Q_{t-1} \tag{16}$$

From Eq. (17) the dynamic conditional correlation coefficient equation, necessary to conduct a simulation, can be determined to be:

$$\rho_{i,j,t} = \frac{Q_{i,j,t}}{\sqrt{Q_{i,i,t}Q_{j,j,t}}} \tag{17}$$

[8] See Rabemananjara and Zakoian (1993).

DCC calculations are executed maximizing the joint log likelihood with respect to all volatility and correlation parameters, adopting either a 2-stage or a 3-stage process. Dynamic Conditional Betas and LRMES/CRISK estimates are all based on the DCC results.

The DCC/DCB framework has been widely used in financial applications and it is still in development. Ling and McAleer (2002), Caporin and McAleer (2012) and Aielli (2013) have pointed out some theoretical flaws concerning the consistency of the DCC estimator, with Aielli introducing the DCC-A, or corrected DCC (cDCC). In our work DCC and DCC-A have returned extremely close results. There exist also alternative but conceptually similar approaches to dynamic conditional correlation, such as the DCC-TT, introduced by Tse and Tsui (2002), which we include in this analysis.

3. CRISK estimation and results

3.1 Data

The computation of CRISK requires the collection of balance sheet data. We used Datastream to gather all reported quarterly results for our sample of banks starting from Q2-2011 to Q1-2022. Adjusted price data for the 10 securities start on June 30th, 2011, and log returns are computed from the following day, July 1st, 2011, up to and including April 29th, 2022. To ensure synchronicity, only days when all the components of the basket traded have been included[9], for a total of 2735 observations per each security, index or factor and an average trading year consisting of 252 sessions.

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[9] See the Appendix for a full list of excluded dates.

3.2 Eurozone Climate Betas

Our first step in analyzing climate risk is to compute fixed climate Betas with STATA 16.1 for the sample of banks. We run an OLS regression of the log return[10] of each bank on the log returns of both the Euro Stoxx SXXE and the climate factor CFE using Newey-West standard errors robust to heteroskedasticity and optimized lag. The task is to measure the market Beta B_M and the climate Beta B_C across the entire period considered and verify the existence of a long-run relationship that can justify adding CFE as a second factor influencing the returns of the selected banks. For each bank the regression is:

$$r_{b,t} = \alpha + B_{M,b}\, SXXE_t + B_{C,b}\, CFE_t + e_{b,t} \tag{18}$$

$r_{b,t}$ being the bank daily log returns, α the constant term, $B_{M,b}$ the Beta with respect to the market log returns (SXXE), $B_{C,b}$ the climate Beta with respect to the factor CFE log returns and $e_{b,t}$ the error term. The results for the entire sample are shown in Table 1.

Table 1: Fixed Betas

	const	BM	BC
BNP	-0.00002	1.46099***	0.15336***
ACA	-0.00005	1.45905***	0.16318***
GLE	-0.00029	1.69900***	0.20445***
SAN	-0.00022	1.27862***	0.33368***
BBVA	-0.00009	1.27960***	0.25728***
INGA	-0.00005	1.53191***	0.16586***
DBK	-0.00063	1.49975***	0.06971*
CBK	-0.00064	1.52606***	0.12928***
UCG	-0.00071	1.61249***	0.24483***
ISP	-0.00002	1.50670***	0.15618***

***: significant at 1% or better; **: significant at 5% or better; *: significant at 10% or better

[10] In the Appendix log returns are indicated as "_r" whereas arithmetic returns with "_R". If not specified, all calculations have used log returns.

As expected, all banks show a positive and statistically significant Euro Stoxx Beta, whereas the intercept is always not significant. More importantly, 9 banks out of 10 also have a climate Beta that is both positive and statistically significant at the 95% level: only DBK appears to have a negligible and not significative sensitivity to the climate factor. Further details are shown in the Appendix. In the case of DBK, the reason might be related to its business model and its global exposure, more skewed towards OTC derivatives, level 3 assets (mark-to-model) and trading[11] than the other banks included in the sample, thus characterizing Deutsche Bank more as an investment bank than a lending-focused institution. Consequently, DBK is comparatively less sensitive to climate-related risks, albeit the size of its balance sheet still induces large exposures during a crisis.

Table 2: GARCH-GJR Univariate Parameters

	const	B_M	B_C	Alpha	Beta	Gamma
BNP	0.00000	1.31807***	0.16923***	0.03231	0.94310	0.02817
ACA	0.00009	1.33611***	0.18687***	0.00334	0.97830	0.02484
GLE	0.00038	1.49230***	0.18007***	0.08065	0.85514	0.05434
SAN	0.00009	1.28613***	0.27373***	0.02498	0.95429	0.01559
BBVA	0.00002	1.24666***	0.18072***	0.04168	0.94299	0.01580
INGA	0.00000	1.37610***	0.09995***	0.01277	0.94966	0.05082
DBK	-0.00022	1.44024***	0.00701^{-}	0.02368	0.97236	-0.00025
CBK	0.00002	1.41373***	0.06146^{-}	0.01303	0.97085	0.02398
UCG	0.00031	1.52631***	0.24048***	0.05400	0.88480	0.05668
ISP	0.00016	1.31643***	0.21640***	0.05188	0.92410	0.03353

***: significant at 1% or better; **: significant at 5% or better; *: significant at 10% or better

[11] Source: EBA, G-SII 2019 exercise, page 2: https://app.powerbi.com/view?r=eyJrIjoiZTUyODBjZDktNGQyMy00NmU3LTgyZjQtNzJlMTVkMTVhYzU5IiwidCI6IjNiYWNiNGZmLWYxYTItNGM5Mi1iOTZjLWU5OWZlYzgyNmI2OCIsImMiOjl9 .

We move forward by employing the Engle and Sheppard (2001) test to determine whether correlations are static or dynamic to choose between a Bollerslev (1990) Constant Conditional Correlations (CCC) model or a DCC framework: since correlations are found to be dynamic[12], we proceed adopting a 2-step dynamic approach employing SXXE and CFE as regressors. The first step involves the quantification of univariate GARCH-GJR parameters for each bank, as presented in Table 2. All parameters are substantially in line with the previous findings related to the fixed Betas, except for CBK, whose climate Beta becomes non-significant. In the second step we estimate the multivariate process parameters[13] α and β, as shown in Table 3, all significant at the 95% level, with correlation targeting results (DCC-A/DCC) in the Appendix.

Table 3: Multivariate Parameters

	α	β
DCC	0.00635^{***}	0.98125^{***}
DCC-A	0.00645^{***}	0.98136^{***}
DCC-TT	0.00458^{***}	0.98822^{***}

***: significant at 1% or better; **: significant at 5% or better; *: significant at 10% or better

We then compare[14] CCC, DCC (Engle), DCC-A (Aielli cDCC) and DCC-TT (Tse and Tsui) across the entire period considered, obtaining the results shown in Table 4.

Table 4: Conditional Correlation Models Comparison

Model	**T**	**p**	**log-likelihood**	**SC**	**HQ**	**AIC**
CCC	2735	0	82672.133	-60.455	-60.455	-60.455
DCC	2735	2	82807.478	-60.548	-60.551	-60.552
DCC-A	2735	2	82811.072	-60.551	-60.554	-60.555
DCC-TT	2735	2	82792.799	-60.537	-60.540	-60.542

[12] See the Appendix for the results.

[13] See Eq. (16).

[14] Using OxMetrics 8.2 G@RCH module.

As expected, given the results of the Engle-Sheppard test, CCC is outperformed by all the dynamic correlation models. DCC-A shows better results in terms of log-likelihood, Schwarz (SC), Hannan-Quinn (HQ) and Akaike (AIC) criteria, with DCC as second best and DCC-TT third. Since both DCC-A and DCC return very close outputs, if a dynamic approach is warranted, we recommend using either of them to estimate any enlarged, EU-focused, multi-factor model developed along the lines of the Fama-French (2015) framework that takes into consideration climate risk exposure and is built including CFE (or its equivalent) among the regressors.

3.3 CRISK estimation

We then move to the next phase, employing two different statistical packages[15] and using the Dynamic Conditional Correlation (DCC) and Dynamic Conditional Beta (DCB) framework developed by Engle (2002) and Engle (2009) to estimate the dynamic parameters for the banks included in the sample with respect to the climate factor[16] alone. By combining the results generated by DCC/DCB, balance sheet data and the banks' market capitalization on a given date, it is possible to compute specific and aggregated CRISK estimates that can be then used to assess climate riskiness. This has been done with a simulation that follows the procedure proposed by Brownlees and Engle (2017):

1) Generate the standardized shock series;
2) Execute a coarse sampling with replacement of the shocks;

[15] OxMetrics 8.2 and Matlab R2021b, integrated with the MFE Toolbox by K. Sheppard.

[16] See Engle, Jondeau and Rockinger (2015) and Brownlees and Engle (2017) for DCB implementation.

3) Create the desired number of runs S for a simulated time window w to obtain a series of conditional log returns using the parameters generated by the DCC for the last day as a starting set;

4) Convert the log returns to an arithmetic return for each run;

5) Compute CRISK for the given date as the Monte Carlo average capital shortfall conditional on the climate factor dropping more than the crisis threshold *thresh*.

The simulation is conducted separately for each bank, with batches of demeaned returns used as DCC input. In our study we have used a simulated time window w with w=63 and w=125 (3 and 6 months), five thousand iterations S per each reference date and a crisis threshold *thresh*=-30%. In the period from July 2011 to April 2022, this value corresponds approximately to the first percentile in terms of cumulative arithmetic return (loss) registered by SXXE and SXET over both the 3-month and 6-month windows; for CFE it represents the fourth worst performance for a 3-month period and the eleventh for a 6-month window[17].

Computationally, Brownlees and Engle[18] use a recursive estimation scheme: from the start date this method gradually expands the amount of data used as input for the each DCC calculation and ends up including the entire time sample for the last output. Despite the pros of the expanding sample, we have opted to implement a rolling window approach since we consider it to be closer to an actual risk management set-up. It is also nimbler and faster to compute, albeit its output is somewhat more volatile and less robust by construction due to the reduced

[17] Jung, Engle et al. (2021) use a 50% drop of the climate factor as crisis threshold.

[18] See Brownlees and Engle (2017).

sample size. To assess sensitivity, DCC calculations have been carried out employing different methods (rolling and expanding time windows), showing significant overall stability at an aggregate level. We show the results generated by using a 250-day and a 500-day rolling window, both with a 5-day interval between each sampling, for a total of 498 and 448 datapoints respectively, using w=63 days and S=5 thousand iterations. Figures 5 and 6 display the actual output for both CRISK 250 and CRISK 500, remarkably similar even using the two different time spans. As expected, CRISK500 shows higher persistency than CRISK250.

Figure 5: Combined CRISK250, 8/2012–2/2022

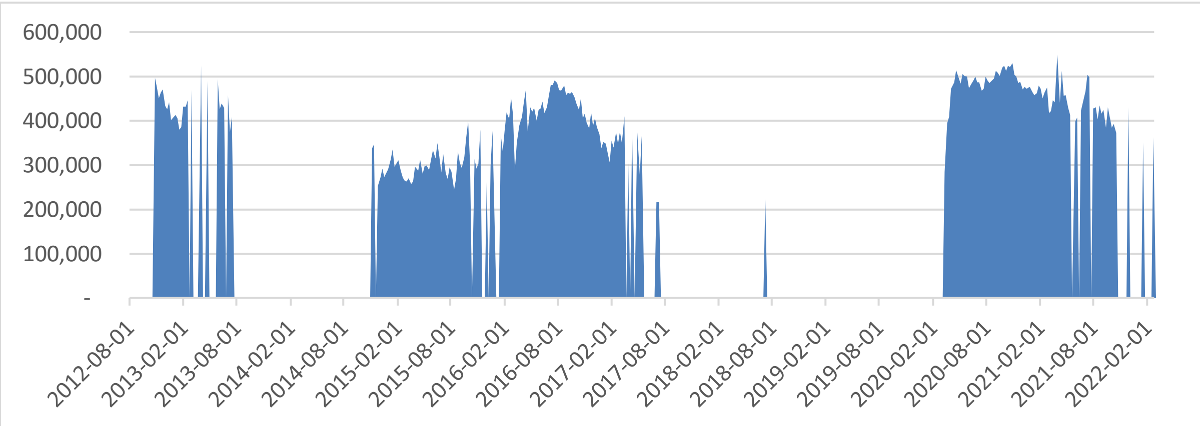
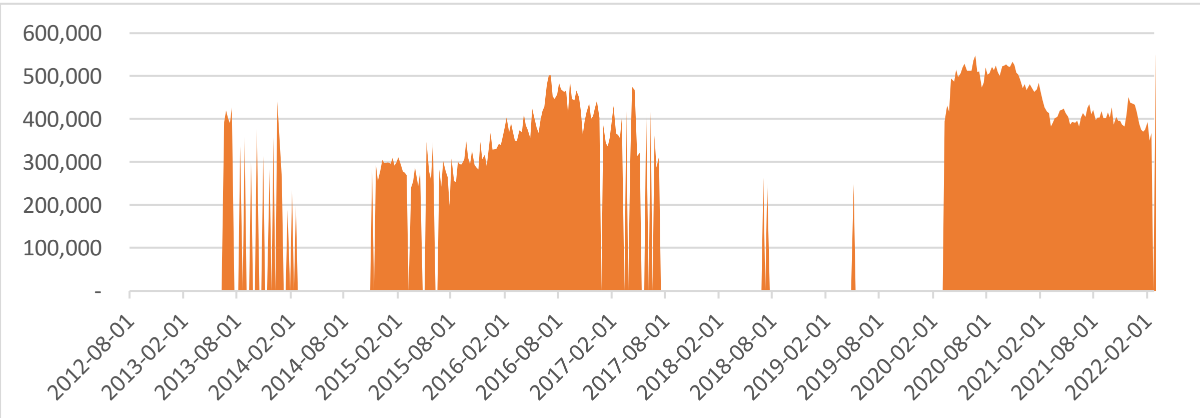


Figure 6: Combined CRISK500, 8/2012–2/2022

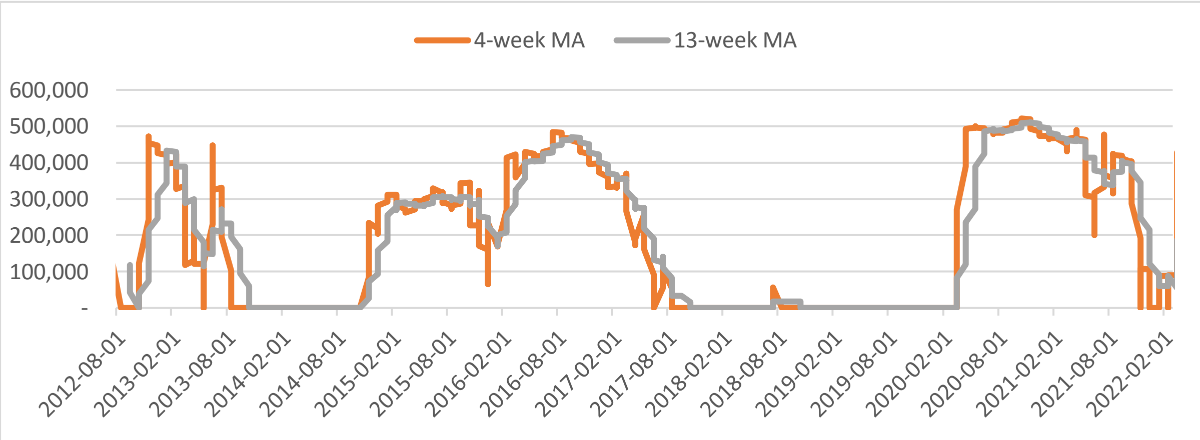


3.4 Results

We found three periods that show considerable aggregate CRISK for our sample of banks, as shown by the 4-week and 13-week CRISK250 moving averages in Figure 7: 2011-12, 2015-

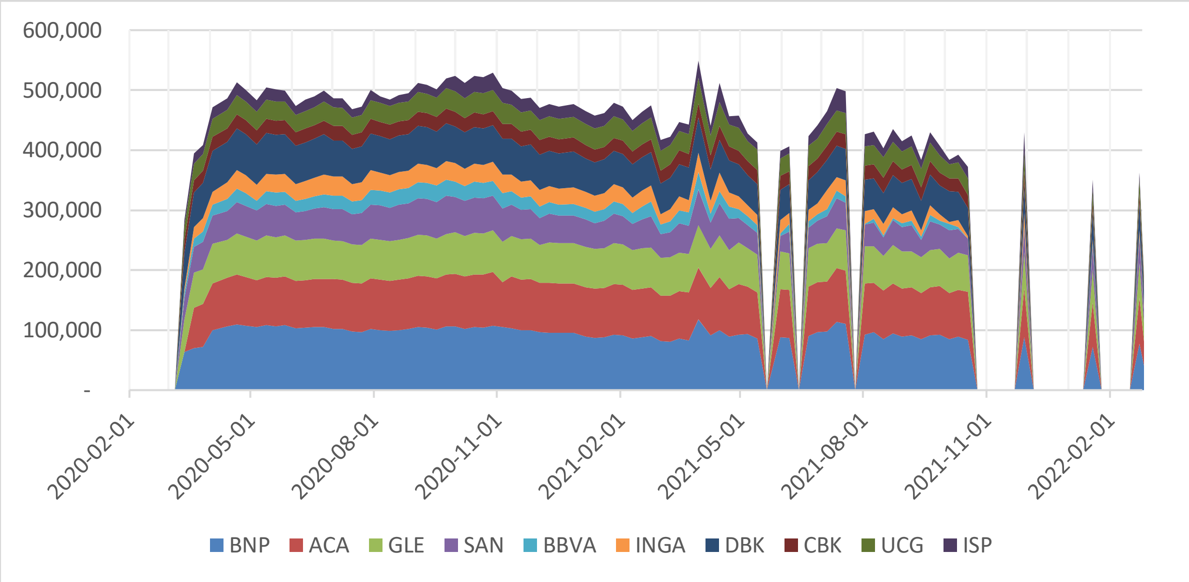
16 and 2020-22. The first two happen to be also times of financial distress, coinciding with the EU sovereign debt crisis and Brexit, both with no clear links to climate issues. The 2020-2022 window, however, represents an ideal benchmark to assess how CRISK can be used to measure transition risk.

Figure 7: Combined CRISK250, 4-week and 13-week Moving Averages, 8/2012-2/2022



In 2020 after the COVID outbreak CRISK climbs from zero to elevated levels that persist even after markets react to the fiscal and monetary stimulus emergency response, eventually moving to new highs. This phase has all the markings of an energy sector crisis generated by a fall in global demand that puts the market out of balance, creating a widespread excess of fossil fuels supply that in turn depresses their prices. CPRS1 firms experience a sudden and sharp contraction in revenues, income, and loss in the value of their reserves: debt spreads soar and equity valuations collapse. In this situation, the sector-specific risks of insolvency go up substantially and banks exposed to energy companies experience a severe increase of transition risk, causing a de-rating of the lenders' equity metrics. Figure 8 shows the contribution of all selected banks to the aggregate CRISK jump from zero to levels exceeding 500 billion euros. The synchronicity in the increase underlines the systematic nature of climate risk with respect to the potentially material capital shortfall hitting the entire banking industry at the same time.

Figure 8: CRISK250 Contribution, 02/2020-02/2022

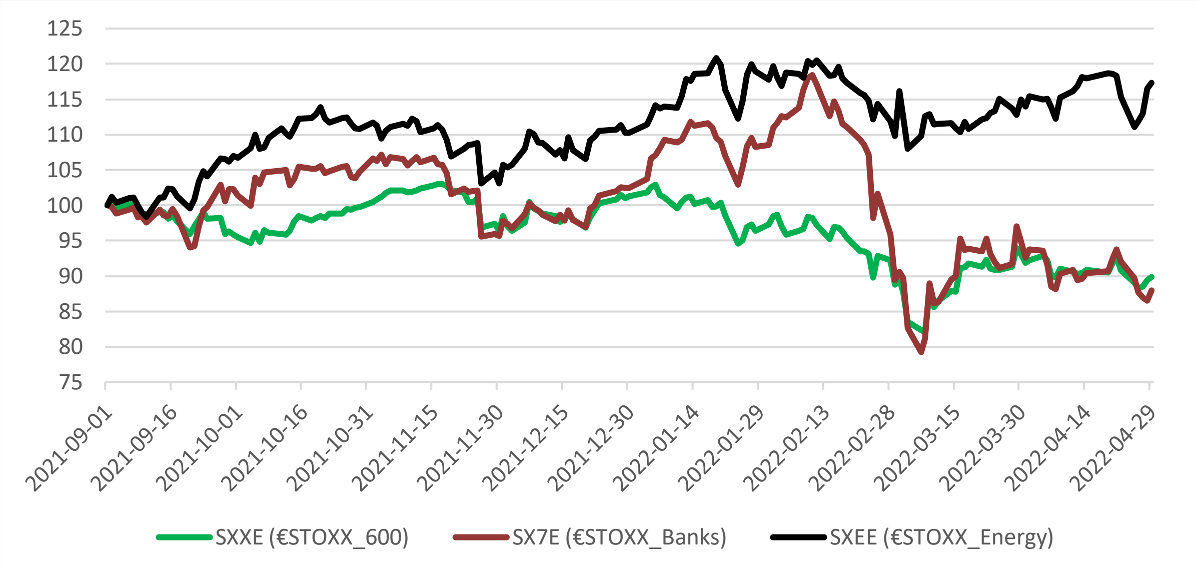


During 2021 CRISK250 starts to decrease, returning to zero in autumn. As seen in Figure 6, the less reactive CRISK500 shows a contraction only at the end of February 2022, a period that coincides with the start of the Russo-Ukrainian conflict. The break-out of a war involving a major oil and gas producer provokes the opposite effect than the pandemic outbreak: supply reductions and sanctions put the global energy markets out of balance once again, causing hydrocarbon prices to increase and energy companies to record windfall profits. This situation strengthens the outlook for CPRS1 companies and reduces risks for lenders: aggregate CRISK250 drops, reflecting a reduced credit risk for banks exposed to the sector and, at least temporarily, a less severe quantification of transition risk.

We now move on to analyze the factors determining CRISK, which are both sectoral and company specific. After years of poor relative returns, likely related to an ever-growing ESG awareness within the investment industry, energy equities start to outperform markedly in the autumn of 2021, somewhat anticipating the effects of future geopolitical events and the improving position of the sector: from September 2021 to April 2022 EURO STOXX Energy

SXEE overperforms both the EURO STOXX SXXE and the EURO STOXX SX7E bank index by more than 27%, as shown in Figure 9.

Figure 9: SXXE vs SX7E vs SXEE, 09/2021-04/2022



During this period CFE returns are particularly strong, influencing CRISK estimates: a robust energy sector relative momentum is likely to lower CRISK, whereas underperformance pushes CRISK up, as occurred in 2020. The effects are, as expected, more visible on CRISK250, that reacts more quickly than CRISK500. Figure 10 shows graphically the existence of positive correlation between SXEE and SXE7 until the start of the war: both energy and banks are fundamentally cyclical sectors which, barring specific issues, tend to show similarly trending relative returns vis-à-vis the market benchmark. The move up from September 2021 to April 2022, shared by both SXEE and SXE7, could also indicate overperformance of value-based investing strategies with respect to growth-based alternatives. This structural co-dependence of energy and bank stocks on cyclical is likely to be the main cause of the spurious results registered during the EU sovereign debt crisis and Brexit, leading to elevated and prolonged aggregated CRISK values in absence of any specific climate trigger and cautioning against the use of CRISK if taken out of context. In terms of estimation, the marked positive correlation between energy and bank stocks experienced in the September 2021 to January 2022 time frame (0.866 vs 0.301 from September 2021 to April 2022) is likely to be captured by the simulation algorithm and prolong the persistency of elevated CRISK500 values going forward.

With respect to the attribution of transition risk to individual companies, the most important idiosyncratic factors that affect CRISK are balance sheet size, P/BV, leverage (QLev), and DCC climate Beta: CRISK increases given a larger pool of asset, a higher leverage ratio and a more pronounced climate Beta, whereas it decreases given a better price to book ratio.

Table 5 shows these metrics and the DCC Beta 13-week moving average at the end of 2020, that is at the height of the energy sector crisis, together with the absolute value of CRISK250 and its relative share among lenders.

Table 5: 2020Q4 Bank Metrics

Bank	TA	P/BV	QLev	DCC β	β 13W	CRISK250	CRISK250%
BNP	2,595,498	0.48	46.89	1.160	0.915	95,486	20.0%
ACA	1,969,300	0.47	64.00	1.094	0.919	82,207	17.3%
GLE	1,472,337	0.24	98.42	1.370	1.128	67,315	14.1%
DBK	1,387,791	0.31	72.76	0.970	0.750	59,492	12.5%
SAN	1,514,242	0.54	33.36	1.537	1.083	46,359	9.7%
UCG	903,353	0.28	50.25	1.009	0.902	34,389	7.2%
INGA	956,481	0.56	30.99	1.411	0.993	27,796	5.8%
CBK	544,330	0.21	78.87	1.191	1.056	23,428	4.9%
ISP	996,848	0.54	25.98	0.789	0.672	20,580	4.3%
BBVA	727,014	0.62	26.51	1.163	1.019	19,296	4.1%

The corresponding CRISK500 results, which are very similar, are shown in the Appendix. The three French banks BNP, ACA and GLE account for more than half of total CRISK250 (and CRISK500), followed by DBK and SAN. BNP is by far the largest bank by total assets: despite its average climate Beta, price to book discount and leverage, the sheer size of its balance sheet pushes CRISK higher. ACA, the second riskiest bank of the sample, manages to register only a modestly higher CRISK than GLE despite a 34% larger balance sheet due to better metrics across the board, whereas GLE is affected by the combination of the highest discount in terms of price to book and the highest leverage coupled with a high climate beta. DBK comes fourth, with a worse CRISK with respect to SAN (fifth) despite a lower asset base: the main cause is the leverage ratio, which is 2.2 times higher. The remaining banks show declining CRISK values: UCG and CBK are characterized by relatively low climate betas but also high discounts to book, whereas INGA's CRISK (7th highest), thanks to a balanced set of metrics but the Beta, is only 18% above CBK's measure despite a much larger balance sheet. ISP and BBVA, with the lowest CRISK of the lot, benefit from a relatively better equity valuation and moderate leverage compared to their peers. The climate betas are all positive with a mean of 1.17 and trending higher than their respective trailing averages: this dynamic is anticipating that aggregate CRISK is not going to decrease any time soon, as effectively measured in the following weeks.

Table 6 presents the results of the same exercise at the end of March 2022, describing a very different situation:

Table 6: 2022Q1 Bank Metrics

Bank	TA	P/BV	QLev	DCC β	β 13W	CRISK250	CRISK250%
ACA	2,073,955	0.49	60.52	-0.579	0.171	74,521	19.9%
BNP	2,634,444	0.56	39.41	-0.895	0.257	73,832	19.8%
GLE	1,464,449	0.33	66.90	-0.832	0.219	59,749	16.0%
DBK	1,323,993	0.36	53.30	-0.260	0.226	47,441	12.7%
SAN	1,595,835	0.63	28.69	-0.391	0.340	36,257	9.7%
UCG	916,671	0.36	39.60	0.161	0.385	27,749	7.4%
INGA	951,290	0.71	24.51	-0.387	0.354	20,223	5.4%
ISP	1,069,003	0.65	25.24	-0.560	0.131	19,115	5.1%
CBK	473,044	0.32	49.39	-0.863	0.330	14,750	3.9%
BBVA	662,885	0.82	18.22	-0.299	0.220	-	0.0%

Individual and aggregate CRISK250 levels are more contained, driven down by improved equity metrics. ACA is now the bank with the largest CRISK, and BBVA is still the lowest, reporting a zero value. The most striking difference, however, is that all climate Betas are now trending well below the trailing average and are negative: the projection is for CRISK to drop and stay lower for longer, possibly at or near zero. CRISK500 developments, shown in the Appendix, are similar, with all DCC Betas in negative territory.

To assess the climate riskiness of a bank, though, absolute levels of CRISK might not be appropriate: the use of the sole climate factor CFE to compute CRISK is arbitrary and suitable only if applied to very specific cases, precisely when transition risk becomes the single most important cause of market volatility and systemic instability. In other instances, the effect of climate change as measured by a broader and carefully selected multi-factor model that includes CFE among the determinants of stock returns is probably a better choice. However, at any given time, it is our opinion that relative climate sensitivity of listed banks can be estimated using the ratio of absolute CRISK over market capitalization. This dimensionless measure, that has zero as its lower bound and an unconstrained upper limit, allows the regulator or the portfolio manager to rank lenders according to their absolute sensitivity to climate issues weighted by the market value of their equity, which is the ultimate reserve of value against the creditors' claims and the quintessential equity metric.

Tables 7 to 10 show the rankings of the banks in our sample with respect to CRISK250 and CRISK500 at the previously considered dates (December 28th, 2020, and March 30th, 2022). On December 28th, 2020, using the CRISK to MV ratio, GLE is the riskiest bank, whereas BNP ranks only 6th, preceded by CBK, DBK, ACA and UCG. ISP is at the bottom of the ranking, with BBVA, INGA and SAN immediately above.

Table 7: Rankings by CRISK250 to MV Ratio, 2020Q4

Bank	MV	CRISK250	CRISK250/MV
GLE	14,654	67,315	4.59
CBK	6,713	23,428	3.49
DBK	19,052	59,492	3.12
ACA	30,479	82,207	2.70
UCG	17,225	34,389	2.00
BNP	54,529	95,486	1.75
SAN	44,535	46,359	1.04
INGA	30,667	27,796	0.91
BBVA	26,833	19,296	0.72
ISP	37,353	20,580	0.55

Table 8: Rankings by CRISK500 to MV Ratio, 2020Q4

Bank	MV	CRISK500	CRISK500/MV
GLE	14,654	66,817	4.56
CBK	6,713	23,075	3.44
DBK	19,052	58,315	3.06
ACA	30,479	81,857	2.69
UCG	17,225	35,945	2.09
BNP	54,529	100,964	1.85
SAN	44,535	46,480	1.04
INGA	30,667	25,594	0.83
BBVA	26,833	19,553	0.73
ISP	37,353	22,616	0.61

Interestingly, the rankings are the same using both CRISK250 and CRISK500.

Table 9: Rankings by CRISK250 to MV Ratio, 2022Q1

Bank	MV	CRISK250	CRISK250/MV
GLE	21,234	59,749	2.81
ACA	33,696	74,521	2.21
DBK	24,045	47,441	1.97
CBK	9,179	14,750	1.61
UCG	22,150	27,749	1.25
BNP	65,518	73,832	1.13
SAN	54,493	36,257	0.67
INGA	38,166	20,223	0.53
ISP	41,465	19,115	0.46
BBVA	35,940	-	0.00

The rankings on March 30th, 2022, are different: ACA jumps at the second place above the German banks, followed by UCG in the case of CRISK250 and BNP for CRISK500. BBVA is always the less risky, preceded either by ISP or INGA. GLE is always top of the list and SAN is a6th, exactly as at the end of 2020.

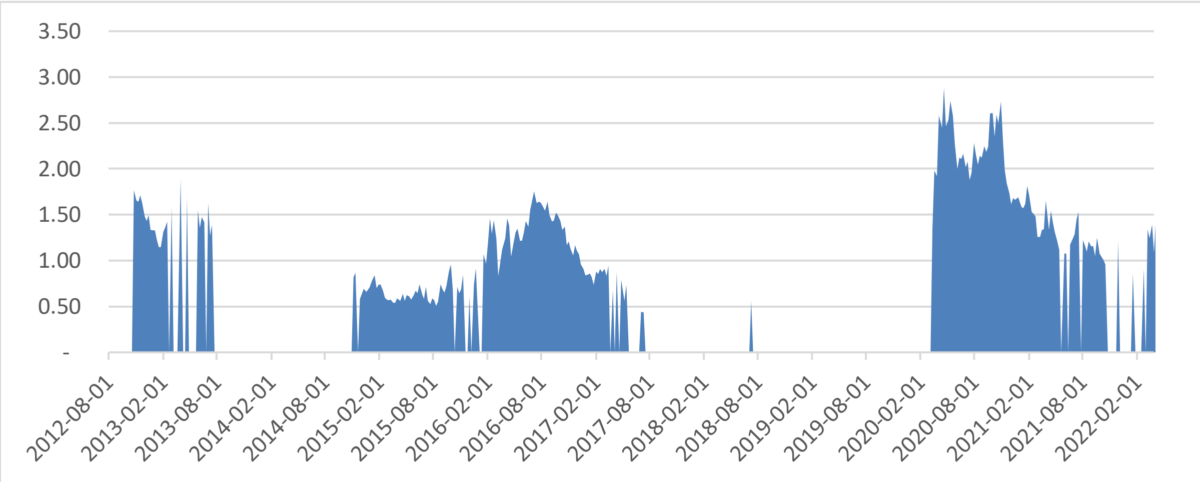
Table 10: Rankings by CRISK500 to MV Ratio, 2022Q1

Bank	MV	CRISK500	CRISK500/MV
GLE	21,234	64,379	3.03
ACA	33,696	90,102	2.67
DBK	24,045	51,077	2.12
CBK	9,179	18,241	1.99
BNP	65,518	101,187	1.54
UCG	22,150	29,908	1.35
SAN	54,493	45,281	0.83
ISP	41,465	26,953	0.65
INGA	38,166	23,088	0.60
BBVA	35,940	6,597	0.18

It is our opinion that these rankings are more useful, especially because even banks with large balance sheets, such as BNP or SAN, can be relatively less risky than peers that show a higher climate Beta, are more leveraged or trade at lower P/BV multiples. Furthermore, they complement standard ESG Environmental Pillar ratings which, by design, are mostly geared towards the assessment of banks' efforts to tackle climate change rather than focusing on their loan portfolio exposure. As discussed by Brandon et al. (2021), ESG rating disagreements are common and influence stocks risk premia: CRISK rankings would be unambiguous, sorting out banks according to their sensitivity towards climate-induced systemic risks. The evolution of the rankings and the Betas could also give strong hints about which bank is taking the necessary steps to become less affected by transition risk: dropping towards the bottom of the table is a de facto synthetic indicator of commitment to take the appropriate steps to manage transition risk and, more broadly, climate change. This type of behavior is likely to result in a premium valuation over the peers.

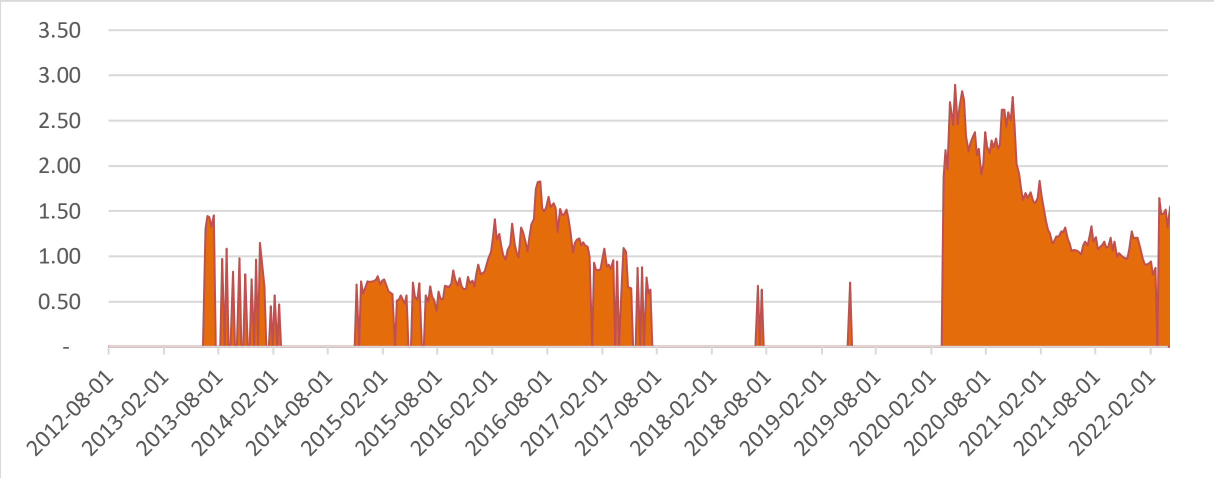
This ratio can also be used with aggregate values, that is total CRISK over total market cap, to assess the riskiness of the entire banking sector. In this role, the indicator could be seen as a sort of "climate thermometer" for EU lenders and could play the role of a leading indicator to signal an incoming shock.

Figure 10: CRISK250/MV_AGG Ratio, 6/2012-3/2022



As shown by Figures 10 and 11, given the historical precedent in 2020, regulators and markets should consider the financial sector climate exposure a rising systemic risk factor when both aggregate CRISK250/MV_AGG and CRISK500/MV_AGG ratios climb above 2.50 for a few weeks.

Figure 11: CRISK500/MV_AGG Ratio, 6/2012-3/2022



4. Conclusions

In a decade dominated by ESG investing and marked by the push towards a greener EU economy at the detriment of carbon producers, the achievement of a satisfactory and accurate measurement of the greenness of a bank loan portfolio is still far from being accomplished. While the effort to harmonize reporting standards and carbon disclosures is ongoing, ECB climate risk stress tests could be effectively complemented by alternative measures of transition risks that are nimbler and easier to implement. In this framework, indicators based on relative CRISK could play an important role: even if they involve complex calculations, they have the advantage of requiring only publicly available market data and produce dynamic rankings that are easy to follow and study. Therefore, it is reasonable to expect an increase in the number of independent studies and research that use CRISK to determine either the relative climate riskiness of a lender or assess the level of aggregate systemic stress in the European financial sector generated by climate risk: CRISK is likely to become a common tool for the investment community.

Individual companies can also use CRISK effectively to check their progress in tackling climate risk. Banks that limit excess capital allocations to potentially stranded assets, control their leverage and improve their equity base, eventually will experience low or near-zero climate betas, and consequently a lower CRISK. It is our opinion that this approach will be rewarded by the market with premium valuations for the banks that achieve better climate risk management results by showing a lower relative CRISK measure than the competitors. Similarly, ESG portfolio allocations could also employ relative CRISK to tilt their exposure in the sector towards the less risky lenders.

Lastly, the identification of a proper EU climate factor is important towards the formulation of an EU multi-factor model that explicitly includes climate risk among the determinants of equity returns. A most interesting result would be the quantification and the decomposition of systemic risk among its various components, with a focus on the evolution of the share taken by climate risk.

Chapter 2: Multifactor Risk Attribution applied to Systemic, Climate and Geopolitical Tail Risks for the Eurozone Banking Sector

Abstract

The aim of this work is to introduce an innovative methodology to perform risk attribution within a multifactor risk framework. We apply this analysis to the assessment of systemic, climate and geopolitical risks relative to a representative sample of Eurozone banks between 2011 and 2022. Comparing the results to the output of a bivariate approach, we find that contemporaneous tail crises generate combined equity losses exceeding partial analysis estimates. We then attribute the combined risk to each factor and to the effect of their interaction by employing our proposed frequency-based approach. For our computations we use multivariate GARCH, Monte Carlo simulations and a suite of Eurozone-specific factors. Our results show that total combined risk is on average 18% higher than traditional systemic risk estimates, that climate risk more than doubled in our period of analysis, and that geopolitical risk surged to over 5% of total combined risk. Our climate risk estimate is in line with the results of the 2022 European Central Bank climate stress test and our geopolitical risk measure shows positive correlation with the Threats index by Caldara and Iacoviello (2022), American Economic Review, 112(4), 1194-1225.

Keywords: Risk Attribution; Climate Risk; Geopolitical Risk; Systemic risk; Multifactor Models; Risk Management; Eurozone Banks.

1. Introduction

Three major macro risk factors mostly threaten bank solvency: systemic, climate and geopolitical risks. Our work presents an innovative methodology that allows simultaneous risk assessment and attribution for these three combined factors based exclusively on publicly available data.

Allen and Carletti (2013) identify four major sources of systemic risk: panics, asset price dislocations, contagions, and foreign exchange mismatches. When such events occur, the failure of one or more banks has the potential to impair other financial institutions, thus provoking economic damages much greater than the nominal gross exposure, possibly severe enough to put overall financial stability into question. Regulators constantly monitor the health of the banking system and conduct regular stress-test exercises to keep systemic risk at a minimum, whereas scholars have devised different approaches to quantify combined losses. We identify three consolidated approaches to estimate capital shortfalls: CoVar, network-based analyses and SRISK. Introduced by Adrian and Brunnermeier (2016), CoVar concentrates on the tail dependency between the banking system and a particular lender in distress to measure the aggregate value at risk (VaR) for the financial sector. Network based models explore cross exposures to capture the interdependencies that spread contagion within the system: Battiston et al. (2012) show how banks can be treated as interconnected nodes whose solvency depends on the strength of their counterparts. SRISK, developed by Engle et al. (2015) and Brownlees and Engle (2017) on the concept of Marginal Expected Shortfall pioneered by Acharya et al. (2017), estimates negative equity by using the output of a bivariate MGARCH analysis on index and banks' returns to perform a Monte Carlo simulation which projects the potential capital shortfall in the event of a dislocation in the equity market. Our contribution is closely related to the latter, as we introduce a multifactor assessment and attribution framework applied to an SRISK-type approach.

Climate change is a further risk factor that could impair banks' assets. It manifests itself in two ways: physical risk, linked to the occurrence of natural disasters due to changing climatic conditions that destroy economic capital, and transition risk, that affects carbon-emitting companies whose business model might be disrupted by sudden economic, market or regulatory shifts related to the transition towards a low-carbon economy. In the EU the sector these activities belong to are identified as Climate Policy Relevant Sectors (CPRS). Lenders have committed plenty of capital to these companies: according to the European Central Bank (ECB, 2021), the total Eurozone credit sector exposure vis-à-vis CPRS was approximately €1.9 trillion. These assets might sooner or later transform into "stranded assets", due to their perceived long-term loss of value in a fully decarbonized world. Currently, the methodology to assess climate risk properly is in its early stages of development and its quantification is therefore difficult. The ECB, building on the methodology proposed by Battiston et al. (2017)[19], carried out its first climate stress test exercise[20] (CST) in 2022, and estimated potential losses linked to climate change at €70 billion, with the caveat that this figure may materially understate transition risk due to the lack of accurate carbon emission data. However, there exists a complementary, market-based methodology[21] to assess transition risk: CRISK,

[19] The work by Battiston et al. (2017) laid the basis to include the evolution of carbon emissions and temperatures in a comprehensive climate stress test effort, whereas Roncoroni et al. (2021) proposed to combine the stress test approach with network evaluation analysis to investigate higher-round effects of a climate crisis on the financial sector.

[20] European Central Bank (ECB-ESBR) (2022), "2022 climate risk stress test", July.

[21] For an alternative, network-based approach, see Roncoroni et al. (2021).

introduced by Jung et al. (2021). CRISK adopts the same bivariate approach designed to compute SRISK applied to a different climate factor tracking the relative performance of stranded assets vis-à-vis the main stock market index.

Geopolitical risk is doubtless the third major macro risk factor menacing bank solvency. It can be broadly defined as risk caused by war, terrorism and political tensions or actions that might undermine banks' balance sheet: some of the costliest capital write-downs of either assets or goodwill can be traced back to the effects of political events, such as Brexit, or to the consequences of a conflict, as the war in Ukraine. There is no straightforward way to quantify geopolitical risk: current approaches rely on indices that track global or regional risk levels based on relative frequencies of non-financial data, such as news articles related to such events, as the GPRD by Caldara and Iacoviello (2022)[22], or on custom-made composite indicators published by universities[23], large institutions[24] and organizations. To the best of our knowledge, no specific methodology exists to quantify the effect of geopolitical risk on banks' assets based on publicly available data only.

Since each bank has only one balance sheet and mandatory capital requirements are designed to prevent bankruptcies regardless of the nature of the crisis, we think that these three macro risks should be assessed simultaneously. However, both SRISK and CRISK compute the amount of negative equity independently by using a bivariate, partial analysis. Why is this the case? We suspect that the lack of well-established methods to attribute risk in a multifactor

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[22] See Caldara, D., Iacoviello, M., (2022). "Measuring Geopolitical Risk," American Economic Review, April, 112(4), pp.1194-1225 with freely accessible data at https://www.matteoiacoviello.com/gpr.htm and section A1

[23] See for example https://vlab.stern.nyu.edu/georisk published by the NYU.

[24] For example, the Blackrock Investment Institute Geo-political risk dashboard.

framework might be at the root of the problem: a bivariate approach relies only on one dynamic correlation between factor and bank returns, whereas a multifactor framework depends on $\frac{n(n-1)}{2}$ unique pairwise correlations, with n indicating the number of factors. Additionally, the number of possible factor combinations is 2^n, or (2^n-1) if only non-zero occurrences are considered. Therefore, a multifactor analysis needs to take into consideration all the possible outcomes and attribute risk accordingly. Our work aims to provide a solution to this issue by proposing an innovative methodology to perform risk attribution within a multifactor risk framework. We apply this analysis to the assessment of systemic, climate and geopolitical risks on a representative sample of Eurozone banks between 2011 and 2022 and when comparing our results to the output of a bivariate approach, we find that contemporaneous tail crises generate combined equity losses that exceed partial analysis estimates. We then attribute the combined risk to each factor and to the effect of their interaction by employing our proposed frequency-based approach. Computations are based on multivariate GARCH, Monte Carlo simulations and a suite of Eurozone-specific factors. The paper is organized as follows. In Section 2 we present our methodology, whereas in Section 3 we show how to apply it simultaneously to systemic, climate and geopolitical risk factors on our sample of Eurozone banks. We present our results, by also including a sensitivity analysis, in Section 4. Section 5 concludes.

2. Methodology

2.1 Expected capital shortfall

If a bank fails, the most important step is to identify the capital shortfall, defined as the losses that exceed its equity. The magnitude of this equity deficit represents the haircut imposed on creditors or the amount of the potential bailout to be borne by the taxpayers. The expected capital shortfall CS_t estimated at time *t* is computed following the methodology adopted by Brownlees and Engle (2017) up to the definition of Long Run Marginal Expected Shortfall (LRMES). Hereafter, we introduce the notation adopted in this paper by showing the bivariate process in six equations, whereas multifactor risk attribution is discussed in Section 2.2.

At time *t*, by indicating with TL_t the book value of the bank's liabilities, with MV_t the market capitalization of the company, and with *k* the minimum proportion of assets to be held as equity, we define CS_t as:

$$CS_t = k\, TL_t - (1-k)MV_t\,, \tag{1}$$

where k is a prudential capital buffer expressed as a percentage of the bank's liabilities.

A positive value for CS_t indicates a potential capital shortfall. In other words, $CS_t > 0$ signals the possibility of recording losses exceeding the market value of the bank. The parameter k varies depending on the jurisdiction: Engle et al. (2015) recommend setting k=8% when dealing with balance sheets that follow the US GAAP accounting standard, whereas k=5.5% is preferable in the case of banks reporting using IFRS rules[25].

[25] For a comprehensive discussion on this matter see Admati and Hellwig, (2013).

Indicating with w ($w > 0$) the time span used in our projection window, CS_t can be expressed as the expected capital shortfall at time t conditional to the outburst of a crisis:

$$CS_t = E_t(k\,TL_{t+w} + k\,MV_{t+w} - MV_{t+w} \mid crisis) \ . \tag{2}$$

Assuming no bail-in, the market value of TL_{t+w} is supposed to remain close to par and, consequently, the expected value of the bank's debt is equal to its nominal value[26]. By expanding and substituting we get to Eq. (3):

$$CS_t = kTL_t - (1-k)E_t(MV_{t+w} \mid crisis) \ . \tag{3}$$

kTL_t represents the capital buffer expressed in terms of the reporting currency that needs to be covered by the expected market capitalization of the bank which, during the breakout of a crisis, is projected to fall by the multiperiod arithmetic return R_b. Since the occurrence of an event is signaled by a factor return R_f breaking a critical level *thresh*, the magnitude of the fall given a crisis is defined as $LRMES_t$ (Long Run Marginal Expected Shortfall at time t), and it is expressed as shown in Eq. (4):

$$LRMES_t = -E_t(R_{b,t+1:t+w} \mid R_{f,t+1:t+w} < thresh) \, . \tag{4}$$

In a dynamic bivariate context, with $I_{\{R_{f,t+1:t+w} < thresh\}}$ being the indicator function signaling a factor drop below the crisis threshold, $LRMES_t^{dynamic}$ is computed as the Monte Carlo average for S runs of a series of simulated bank arithmetic returns R_b over the projected time span w:

[26] During times of crisis the total amount of bank debt tends to have small absolute fluctuations, even if its composition might vary: a reduction in deposits might be compensated by an increase in other types of funding, often provided by central banks. The no bail-in assumption implies that bank bonds are set to be reimbursed without haircuts.

$$LRMES_t^{dynamic} = -\frac{\sum_{s=1}^{S} R_{b,t+1:t+w}^{s} \; I_{\{R_{f,t+1:t+w}^{s}<thresh\}}}{\sum_{s=1}^{S} I_{\left\{R_{f,t+1:t+w}^{s}<thresh\right\}}} \quad . \tag{5}$$

Rearranging Eq. (3) we get the expression for the expected capital shortfall CS_t:

$$CS_t = kTL_t - (1-k)\, MV_t \left(1 - LRMES_t^{dynamic}\right). \tag{6}$$

2.2 Multifactor risk attribution

Bivariate approaches use Eq. (6) to compute the magnitude of the equity deficit at time *t*, but to calculate CS_t within a multifactor framework we need to apply MGARCH analysis to *n* factors and to the bank, that is to *n*+1 variables. In our case study we estimate the capital shortfall using a quartet of variables which includes the three macro factors (systemic or market: MKT; climate: CFE; geopolitical: GFE) and the bank. Factors MKT and CFE perform a break of the threshold when their return is lower than *thresh*, whereas the geopolitical factor GFE behaves in reverse[27] and the threshold is broken when the return of GFE is higher than (-*thresh)*. The MGARCH output is then elaborated in a simulation window of length *w*. By indicating the simulated returns with:

1) $R_{f=m,t+1:t+w}$ for the return of the market factor *MKT*
2) $R_{f=c,t+1:t+w}$ for the return of the climate factor *CFE*
3) $R_{f=g,t+1:t+w}$ for the return of the geopolitical factor *GFE*
4) $R_{b,t+1:t+w}$ for the return of the bank

[27] A geopolitical event causing flight-to-quality flows is likely to produce an increase, and not a fall, in GFE.

we analyze each one of the (2^3-1) possible, non-zero, combinations of events ($EVENT = G, C, CG, S, SG, SC, SCG$) occurring with frequencies *f(EVENT)*, summarized in Table 1.

Table 1: Simulation Occurrences

EVENT	MKT<thresh	CFE<thresh	GFE>(-thresh)	FREQ
G			X	f(G)
C		X		f(C)
CG		X	X	f(CG)
S	X			f(S)
SG	X		X	f(SG)
SC	X	X		f(SC)
SCG	X	X	X	f(SCG)

We then derive an expression for $LRMES^{dynamic}_{EVENT,t}$ which varies with each of the (2^3-1) outcomes:

a. G: only GFE above (- *thresh*), with frequency f(G)

$$LRMES^{dynamic}_{G,t} = -\frac{\sum_{s=1}^{S} R^{s}_{b,t+1:t+w} \ I_{\{R_{f=g,t+1:t+w} > -thresh\}}}{\sum_{s=1}^{S} I_{\{R_{f=g,t+1:t+w} > -thresh\}}} ;$$

b. C: only CFE below *thresh*, with frequency f(C)

$$LRMES^{dynamic}_{C,t} = -\frac{\sum_{s=1}^{S} R^{s}_{b,t+1:t+w} \ I_{\{R_{f=c,t+1:t+w} < thresh\}}}{\sum_{s=1}^{S} I_{\{R_{f=c,t+1:t+w} < thresh\}}} ;$$

c. CG: only CFE below *thresh* and GFE above (- *thresh*), with frequency f(CG)

$$LRMES^{dynamic}_{CG,t} = -\frac{\sum_{s=1}^{S} R^{s}_{b,t+1:t+w} \ I_{\{R_{f=c,t+1:t+w} < thresh \wedge R_{f=g,t+1:t+w} > -thresh\}}}{\sum_{s=1}^{S} I_{\{R_{f=c,t+1:t+w} < thresh \wedge R_{f=g,t+1:t+w} > -thresh\}}} ;$$

d. S: only MKT below *thresh*, with frequency f(S)

$$LRMES^{dynamic}_{S,t} = -\frac{\sum_{s=1}^{S} R^{s}_{b,t+1:t+w} \ I_{\{R_{f=m,t+1:t+w} < thresh\}}}{\sum_{s=1}^{S} I_{\{R_{f=m,t+1:t+w} < thresh\}}} ;$$

e. SG: only MKT below *thresh* and GFE above (- *thresh*), with frequency f(SG)

$$LRMES_{SG,t}^{dynamic} = -\frac{\sum_{s=1}^{S} R_{b,t+1:t+w}^{s} \; I_{\left\{R_{f=m,t+1:t+w}<thresh \,\wedge\, R_{f=g,t+1:t+w}>-thresh\right\}}}{\sum_{s=1}^{S} I_{\left\{R_{f=m,t+1:t+w}<thresh \,\wedge\, R_{f=g,t+1:t+w}>-thresh\right\}}};$$

f. SC: only MKT below *thresh* and CFE below *thresh*, with frequency f(SC)

$$LRMES_{SC,t}^{dynamic} = -\frac{\sum_{s=1}^{S} R_{b,t+1:t+w}^{s} \; I_{\{R_{f=m,t+1:t+w}<thresh \,\wedge\, R_{f=c,t+1:t+w}<thresh\}}}{\sum_{s=1}^{S} I_{\{R_{f=m,t+1:t+w}<thresh \,\wedge\, R_{f=c,t+1:t+w}<thresh\}}};$$

g. SCG: MKT below *thresh*, CFE below *thresh* and GFE above (- *thresh*), with frequency f(SCG)

$$LRMES_{SCG,t}^{dynamic} = -\frac{\sum_{s=1}^{S} R_{b,t+1:t+w}^{s} \; I_{\{R_{f=m,t+1:t+w}<thresh \,\wedge\, R_{f=c,t+1:t+w}<thresh \,\wedge\, R_{f=g,t+1:t+w}>-thresh\}}}{\sum_{s=1}^{S} I_{\{R_{f=m,t+1:t+w}<thresh \,\wedge\, R_{f=c,t+1:t+w}<thresh \,\wedge\, R_{f=g,t+1:t+w}>-thresh\}}}$$

Each case generates a specific capital shortfall $CS_{EVENT,t}$, computed as a Monte Carlo average. Hence, at time *t* there is an array of (2^n-1) different equity deficit estimates to be analyzed. Of these, *n* depend on single factor outcomes, (2^n-*n*-2) on a combination of more than one factor and only one on the occurrence of all the events at once.

By ranking the *n* single factor occurrences by the magnitude of the respective capital shortfall it is possible to determine whether there exists a dominant type of risk: this assessment should give the same result as the comparison operated using bivariate shortfall estimates. In our case, the expectation is for the systemic (market) shortfall $CS_{S,t}$ to be consistently higher than the one generated by either a climate ($CS_{C,t}$) or geopolitical ($CS_{S,t}$) isolated events:

$$(CS_{S,t} > CS_{C,t}) \wedge (CS_{S,t} > CS_{G,t})$$

This expectation is confirmed by the results.

Furthermore, by ranking all the outcomes, it is possible to identify the major source of aggregate risk, which we define as MAX_RISK_t. The expectation is for MAX_RISK_t to correspond to the negative equity generated by the simultaneous outbreak of all the crises at once: specifically, in our case across the entire period we expect $CS_{SCG,t}$ to be the largest shortfall compared to all composite occurrences in addition to the ones related to the single dominant factor:

$$(CS_{SCG,t} > CS_{SG,t}) \wedge (CS_{SCG,t} > CS_{SC,t}) \wedge (CS_{SCG,t} > CS_{CG,t}) \wedge (CS_{SCG,t} > CS_{S,t})$$

We find that $MAX\_RISK_t = CS_{SCG,t}$ holds 99.7% of the times[28].

Once a dominant risk factor has been identified and the maximum combined risk quantified, we use relative frequencies to attribute excess tail risk. We define excess tail risk $MAX\_RISK\_NET_t$ as the difference between MAX_RISK_t and the shortfall generated by the dominant risk. In our example, the attribution of tail risk is necessary when a systemic incident occurs in conjunction with either a geopolitical or a climate crisis, or both (SG, SC, and SCG types of events). Hence, $MAX\_RISK\_NET_t$ is the difference between MAX_RISK_t and systemic risk estimate $CS_{S,t}$:

$$MAX\_RISK\_NET_t = CS_{SCG,t} - CS_{S,t} \, .$$

$MAX\_RISK\_NET_t$ measures the potential losses exceeding the dominant systemic risk caused by the simultaneous occurrence of systemic, climate and geopolitical events or combinations

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[28] See Section 4.3 for the details.

thereof. We then proceed by attributing $MAX\_RISK\_NET_t$ to either climate, geopolitical, or interaction risk using the relative frequencies $f(EVENT_t)$ of each single occurrence at time t.

Indicating with D_t the denominator, computed as the sum of all frequencies, or $D_t = f(SC_t) + f(SG_t) + f(SCG_t)$, the climate tail risk relative share $MCRISK\text{-}X_t$ is given by $f(SC_t)/D_t$, the geopolitical tail risk part $MGRISK\text{-}X_t$ as $f(SG_t)/D_t$ and the portion of the interaction effect INT_t among factors as $f(SCG_t)/D_t$. Summing up:

a) $MCRISK\text{-}X_t$ is the deficit exceeding $CS_{S,t}$ attributed to climate risk, computed as:

$$MCRISK\text{-}X_t = \left(CS_{SCG,t} - CS_{S,t}\right) \frac{f(SC_t)}{f(SC_t) + f(SG_t) + f(SCG_t)} ;$$

b) $MGRISK\text{-}X_t$ is the excess shortfall over $CS_{S,t}$ resulting from geopolitical risk, quantified as:

$$MGRISK\text{-}X_t = \left(CS_{SCG,t} - CS_{S,t}\right) \frac{f(SG_t)}{f(SC_t) + f(SG_t) + f(SCG_t)} ;$$

c) INT_t is the negative equity surpassing $CS_{S,t}$ attributable to the interaction of all factors calculated as:

$$INT_t = \left(CS_{SCG,t} - CS_{S,t}\right) \frac{f(SCG_t)}{f(SC_t) + f(SG_t) + f(SCG_t)} .$$

Risk assessment and attribution is now complete.

This methodology is applicable also if there is no dominant single risk factor: in these instances, once that MAX_RISK_t has been determined, risk attribution is carried out based on relative frequencies calculated with respect to all composite occurrences that exceed the single risk factor that produces the highest shortfall at time *t*.

2.3 Conditional correlation models (CCC and DCC)

The proposed approach employs conditional correlations modelling to analyze data and generate simulation parameters. Over any given period, correlations between factors can be either constant or dynamic: after checking the specific sample properties, we apply either Constant Conditional Correlation (CCC) introduced by Bollerslev (1990) or Dynamic Conditional Correlation (DCC) by Engle (2002; 2009).

CCC is a multivariate GARCH model used when correlation is constant. It allows individual variables to follow idiosyncratic variance processes but forces correlation to be time invariant. As such, CCC estimation is carried out in two, computationally efficient, steps:

4) Univariate volatility and standardized residuals estimation using an appropriate GARCH model;

5) constant correlations estimation using the standardized residuals.

DCC is a multivariate GARCH method that allows for dynamic correlation. It is based on a combination of time-varying conditional correlations and volatility adjusted returns, using standardized residuals with mean zero and both conditional and unconditional variance equal to 1 to estimate the correlation matrix directly. DCC calculations, as outlined by Engle (2009), are carried out in 3 steps, with the first one being in common with CCC:

1) "DE-GARCHING" - univariate volatility and standardized residuals estimation using the selected GARCH model;

2) Dynamic quasi-correlations estimation using the standardized residuals;

3) Rescaling of the quasi-correlations to produce a correlation matrix.

We adhere to the standard financial practice of estimating each series variance v_t using the univariate asymmetric GJR-GARCH introduced by Glosten, Jagannathan and Runkle (1993), which is modeled as a function of the unconditional variance ω, the lagged squared shock y_{t-1}^2, the lagged variance v_{t-1} and an indicator function $I_{\{y_{t-1}<0\}}$:

$$v_t = \omega + \varphi y_{t-1}^2 + \gamma y_{t-1}^2 I_{\{y_{t-1}<0\}} + \lambda v_{t-1} . \tag{7}$$

This asymmetric GARCH specification[29] is most useful in financial econometrics since it takes into consideration the greater impact of negative shocks on volatility[30]. In our case it produces the standardized residuals used to generate the quasi-correlation matrix Q_t.

We use an Engle (2002; 2009) DCC mean reverting process: indicating with ε_t the residual vector, with ε_t^T its transpose and by using correlation targeting with $\underline{Q}$ being the unconditional variance-covariance matrix, Q_t can be expressed as:

$$Q_t = (1 - \alpha - \beta)\underline{Q} + \alpha \varepsilon_t \varepsilon_t^T + \beta Q_{t-1} . \tag{8}$$

under the constraint $(\alpha + \beta < 1)$ applied to the mean-reverting parameters α and β. Eq. (8) represents the dynamic conditional correlation equation. Finally, Q_t needs to be rescaled to generate the proper correlation matrix R_t:

$$R_t = diag(Q)_t^{-0.5}\, Q_t\, diag(Q)_t^{-0.5} . \tag{9}$$

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[29] Under the constraint $\varphi+\lambda+\gamma/2<1$ for a Gaussian distribution,

[30] See Rabemananjara and Zakoian (1993).

with $diag(Q)_t^{-0.5}$ being the inverse of a matrix formed by the volatilities on the main diagonal and zeros elsewhere.

DCC calculations are executed maximizing the joint log likelihood with respect to all volatility and correlation parameters and can be computationally demanding, especially in the case of large multifactor frameworks.

In our study, $LRMES_{EVENT,t}^{dynamic}$ estimates are based on the DCC output whenever the data shows that correlations are dynamic; otherwise, we use CCC.

3. Multifactor risk attribution applied to the Eurozone banking sector

3.1 Sample selection

We apply our multifactor risk framework to a sample comprising large Eurozone banks in the period July 2011 - April 2022. To our best knowledge, this is the first attempt to analyze simultaneously the effect of the three macro risks of interest (systemic, climate and geopolitical) with the aim to quantify and attribute tail risk. Given the multivariate nature of this context, we now identify systemic risk as MSRISK (corresponding to the shortfall $CS_{S,t}$), climate risk as MCRISK ($CS_{C,t}$), and geopolitical risk as MGRISK ($CS_{G,t}$) to differentiate these estimates from their bivariate specifications, whereas MCRISK-X, MGRISK-X and INT define, respectively, the part of tail risk attributable to climate, geopolitical and interaction risk.

The sample includes BNP, Credit Agricole (ACA) and Société Générale (GLE) for France, Deutsche Bank (DBK) and Commerzbank (CBK) for Germany, Santander (SAN) and BBVA for Spain, Unicredit (UCG) and Intesa (ISP) for Italy, ING (INGA) for the Netherlands. We believe that this sample represents a good proxy for the Eurozone banking industry, mainly for two reasons.

Firstly, it includes all the Eurozone-based institutions that contribute the most to systemic risk, both in terms of TA and of Risk-Weighted Assets (RWA). These are key metrics used by EU and international regulators to identify Global Systematically Important Institutions (G-SII): in 2019, net of UK lenders, the European Banking Authority (EBA) determined that large French banks tended to carry the most in terms of TA and RWA, followed by a group of German, Dutch, Spanish and Italian lenders. Country-wise, the situation was similar, with France, Spain, Germany, Italy, and the Netherlands contributing the most to the Eurozone total bank assets. Following the release of the 2021 exercise by EBA, these data were confirmed.

Secondly, during the period considered, the combined market cap of these 10 banks represented more than 70% of the total value of the Eurozone bank index STOXX SX7E. Zhang et al. (2021) select a sample of large lenders comprising about 70% of total assets to analyze the relationship between liquidity creation and systemic risk for Chinese banks. Measures of risk such as MSRISK, MCRISK, and MGRISK (or their bivariate specifications) rely on market capitalization to evaluate the potential equity shortfall attributable to a specific entity: by including in our study over 70% of the combined market valuation of the top Eurozone lenders we consider this group of banks as a representative sample of listed equities contributing the most to systemic risk. In terms of balance sheet aggregates, from January 2011 to April 2022, total assets TA for the basket increased 15.4%, from €11.99 trillion to €13.84 trillion, whereas risk-weighted assets RWA decreased 0.6%, from €3.95 to €3.92 trillion, with standard deviations of 5.7% and 2.8% respectively[31].

3.2 Systemic Risk Factor

To compute MSRISK we have taken as reference the Euro STOXX 600 market index. The EURO STOXX 600 index (SXXE) comprises only the euro-denominated securities included in the wider STOXX 600 index, thus representing a smaller, currency-homogeneous subset of equities. At the beginning of 2022 SXXE included 291 stocks[32].

SXXE returns are considered net of the Eurozone overnight (O/N) risk-free rate returns. The choice of which rate is used in the computations, being it a money market rate, such as the overnight or the 3-month interbank rate, as opposed to a benchmark derived from the capital markets like bond or interest rate swap returns, might influence the results of the analysis, especially in the presence of persistently steep yield curves. This is not our case. ECB's monetary policy in the Eurozone has been remarkably stable across the entire period considered: the three key rates (deposit, repo, and marginal lending) have been kept around zero percent (or slightly below in the case of the deposit rate) from 2012 until mid-2022. Consequently, money market rates as measured by the overnight EONIA rate, replaced by €STR at the end of 2021, have remained close to 0% (or below) since 2012. Similarly, yields on 10-year Bunds, the German government bonds considered as the long-term risk-free rate

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[31] Gehrig and Iannino (2021) show that the attempts by the successive rounds of Basel regulations have failed to reduce systemic risk for large banks: given this dichotomy between TA and RWA showed by the aggregate sample, we should not assume a decrease in total risk, since trends in regulatory measures of exposure, such as RWA, might not be very good indicators of the overall financial sector systemic risk.

[32] See index provider Qontigo - https://www.stoxx.com/index-details?symbol=sxxe.

benchmark for the Eurozone, during the period considered have dropped from being above 2.5% in 2011 to close to 0% in 2015, hovering around this level until April 2022 (see Appendix Section A7 for more details). Therefore, given the characteristics of the time-series considered, it would have been equally appropriate to use a risk-free rate of 0% for the Eurozone during the entire period: the results would have been the same.

Hence, we define the Market Factor for the Eurozone MKT as a long position in the Euro Stoxx SXXE net of the overnight risk-free return i_t:

$$MKT = SXXE_t - i_t \, .$$

3.3 Climate Risk Factor

In this work we include climate risk within our multifactor framework using a Eurozone-specific climate factor CFE. As a proxy for the world markets[33] we use a liquid ETF listed in Europe that tracks the S&P500 index but hedges the EURUSD currency risk regularly and is marked-to-market at the close of European bourses: our choice is Blackrock's iShares IUSE[34]. Listed on 11 European exchanges under different tickers, IUSE[35] is an accumulation fund whose net asset value in November 2021 was close to €5 billion.

[33] During the period considered the S&P500 index represented more than of 60% of the MSCI World Index.

[34] There are valid alternatives to IUSE, such as Lyxor's SP5H/SPXH, but not with a price history encompassing the entire period considered.

[35] IUSE was launched in the fall of 2010 and since then has tracked the dollar-denominated SPX very well: in the period considered the iShare ETF cumulated daily and yearly log returns show a 99.9% correlation with the corresponding SPX USD return statistics. Given the currency hedge and that the price of IUSE is arbitraged until the close of European business, it is our opinion that the characteristics of this ETF eliminate the need to account for lagged returns in this type of analysis.

With respect to the stranded assets portfolio, it is not easy to identify a proper coal tracker for the Eurozone: most of the European coal and lignite production is concentrated in Germany and Poland, with most of the mines operated by utilities (CPRS 2) like RWE (Germany) or PGE (Poland). The biggest mining companies in terms of market capitalization are diversified multinational entities listed in the UK, with the largest share of the extraction activity, mostly non-coal focused, taking place outside the continent. Therefore, we think that the best option is to use only the EURO STOXX Energy index SXET, which represents the net return plus dividends of the SXEE Euro Energy index: it comprises companies whose main legacy business is fossil fuels exploration and production (E&P, a good proxy for CPRS 1) and does not include any renewable energy pure plays. In 2020 all sectors were heavily affected by the outbreak of the COVID pandemic, but oil and gas equities were also hit by the temporary collapse of fossil fuel prices that depressed sector returns long after the broader market recovered.

For the reasons discussed, we define the Climate Factor for the Eurozone CFE as the combined return of a long position in the Energy index SXET and a short position in the IUSE euro-hedged SPX ETF:

$$CFE = SXET - IUSE \,.$$

This definition of the climate factor makes a bank with a higher exposure vis-à-vis energy companies more inclined to experience a sharper drop in its market capitalization when transition risk rises.

3.4 Geopolitical Risk Factor

Geopolitical risk is the third risk factor included in our multivariate framework. Typically, global tensions cause “flight-to-quality” dynamics that are likely to boost the prices of perceived safe assets, such as Treasury bonds, gold or stocks of companies operating in the defense sector and depress equities most geared towards economic expansion and international trade, including the banking sector. We introduce a metric constructed as the combined return of a long position in a basket comprised 50% by gold and 50% by European equities operating in the defense sector and a short position in the IUSE ETF as Geopolitical factor for the Eurozone GFE. We have not included any fixed income instrument return in our analysis due to the rate dynamics described in Section 3.2, but such an addition would likely benefit the accuracy of a geopolitical factor meant to be used for a different macro area and/or timeframe.

Gold returns are computed using the PHAU physical gold ETF issued by Wisdom Tree, that tracks closely the price of gold expressed in US dollars both in London and Tokyo but trades in euros on 3 European exchanges. Given that the US Dollar itself is often perceived to be a safe-haven, the choice of using PHAU euro-denominated returns accounts for the effect of the appreciation or depreciation of the euro vis-à-vis the US currency as well, with an increase in geopolitical risk usually causing PHAU returns in euros to be higher, and vice versa. PHAU ETF NAV at the beginning of 2022 was close to €5 billion and consisted entirely of registered gold bullion stored in London safes. Being PHAU entirely bullion-based, the ETF does not offer any form of distribution.

The defense industry return is calculated using the STOXX SXRARO Defense and Aerospace index, which represents the return including net dividends of the European stocks included in the SXPARO index. It comprises all major European companies involved in the defense sector, which is positively correlated with an increase in the perceived geopolitical risk.

Hence, the long component of GFE is computed as the average daily return of a position 50% in PHAU and 50% in SXRARO against a short position 100% in the IUSE ETF:

$$GFE = 0.5\,PHAU + 0.5\,SXRARO - IUSE\,.$$

Banks with a higher sensitivity with respect to the geopolitical factor GFE experience sharper market capitalization declines when geopolitical-driven flight-to-safety flows take place.

4. Results

4.1 Data

The computation of systemic, climate, geopolitical risk, and combinations thereof requires the collection of balance sheet data. We used Datastream to gather all reported quarterly results for our sample of banks starting from Q2-2011 to Q1-2022. Adjusted price data for the 10 securities start on June 30th, 2011, and log returns are computed from the following day, July 1st, 2011, up to and including April 29th, 2022. To ensure synchronicity, only days when all the components of the basket traded have been included[36], for a total of 2735 observations per each security, index or factor and an average trading year consisting of 252 sessions. Given that all the banks operate in the same time zone and adopt the euro as both operating and reporting currency, there has been no need to implement any lag or forex adjustment to complete our study, making the whole estimation process much simpler and faster.

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[36] See the Appendix, Section A10, for a full list of excluded dates.

4.2 Simulation procedure

We start by applying either Bollerslev (1990) Constant Conditional Correlation (CCC) or Engle (2009) Dynamic Conditional Correlation (DCC), as warranted by the characteristics of each sub-sample[37], to estimate the parameters for the factors and the banks that serve as input for the simulation. The results are cross-checked using two different statistical packages[38]. We then combine these parameters to the balance sheet and market capitalization data recorded on a given date to compute specific and aggregated conditional shortfall estimates and assess simultaneously systemic, climate, geopolitical risk, and combinations thereof. This simulation, inspired by Brownlees and Engle (2017) and Engle (2017), is structured to reflect the multivariate framework employed. It is coded using Matlab and runs separately for each bank, with batches of demeaned returns used as DCC (or CCC) input. In our study we have used a simulated time window *w* with w=63 (3 trading months), 75,000 iterations S per each date and a crisis threshold vector *thresh*=(-30%, -35%, -40%). During the observation period the first percentile for the cumulative arithmetic return (loss) registered over any 3-month window is represented by a fall of approximately 30% for the market factor MKT and by a 20% drop for the climate factor CFE[39]; with respect to the geopolitical factor, which works in reverse, the GFE 3-month return (gain) that corresponds to the 99% percentile of the sample is 18.5%.

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[37] A preliminary analysis on the full sample has been conducted using the Tse (2000) and the Engle and Sheppard (2001) tests. See Appendix A8.1 and A8.2 for details.

[38] OxMetrics 8.2 and Matlab R2021b, integrated with the MFE Toolbox by K. Sheppard and the Parallel Computing module.

[39] Jung et al. (2021) use a 50% climate factor drop in 6 months as crisis threshold. Considering the distributions of realized returns in our sample, we deem such a steep fall unrealistic for our specific purpose.

Computationally, Brownlees and Engle (2017) use a recursive estimation scheme: from the start date this method gradually expands the period and the amount of data used as input for the each multivariate GARCH calculation, ending up including the entire time sample. The loglikelihood of the estimates grows with the sample size. We have adopted both this method and a rolling window approach, which is closer to an actual risk management set-up. It is also nimbler and faster to compute, albeit its output is somewhat more volatile and less robust by construction due to the fewer datapoints. Hereafter we present the results generated using the expanding (recursive) method, a -30% threshold for all the factors and a 5-day interval between each sampling, for a total of 498 datapoints and over 2 billion simulated returns per bank, whereas the rolling window results are employed to assess relative riskiness among banks in a different work[40].

For each window, either expanding or rolling, the multivariate simulation consists of the following steps:

1. Generate a quartet of data composed by the standardized shocks - 3 factors and one bank;
2. Select the best fitting multivariate GARCH model (CCC or DCC) based on likelihood;
3. Generate the parameters to be used in the simulation;
4. Perform a coarse sampling with replacement of the shocks;
5. Simulate for the selected number of runs conditional log returns over a time window *w* using, as a starting set, the last parameters generated by the multivariate GARCH;
6. Convert log returns to arithmetic returns;

[40] "Identifying green banks", forthcoming.

7. Compute the Monte Carlo average capital shortfall conditional on either factor, or combination thereof, breaking the crisis threshold *thresh* (MKT and CFE below *thresh*, GFE above minus *thresh*). Taking into consideration all seven non-zero breaks possible occurrences, we record both the size of the deficit and the frequency of each specific type of event resulting from the simulation.

4.3 Tail risk estimation and attribution

As explained in Section 2.2 and Section 3.1, we define systemic risk $MSRISK_t$ as the capital shortfall $CS_{S,t}$, climate risk $MCRISK_t$[41] as $CS_{C,t}$, and geopolitical risk $MGRISK_t$ as $CS_{G,t}$. Each risk measure is computed as the Monte Carlo average of the equity deficit recorded during the simulation runs when only the return of their respective market factor breaks its threshold: *MKT<thresh* for $CS_{S,t}$, *CFE<thresh* for $CS_{C,t}$, and *GFE>(-thresh)* for $CS_{G,t}$.

Risk estimation is carried out as follows. We first check how $MSRISK_t$, generated by type-S occurrences, compares with $MCRISK_t$ or $MGRISK_t$, originated from type-C or type-G events respectively. Since $MSRISK_t$ is consistently larger than $MCRISK_t$ and $MGRISK_t$, the simulation results confirm that systemic (market) risk is the dominant risk factor: neither climate nor geo-political risk seem to be capable to provoke losses exceeding the effects of a Eurozone financial crisis.

This result is expected, since the €1.9 trillion total exposure of Eurozone banks to CPRS relevant sectors is only a fraction of the approximately €14 trillion combined assets comprised in our sample; similarly, it is reasonable to assume that the level of losses caused by a

[41] In their VLAB website the NYU publishes the bivariate CRISK estimate. See https://vlab.stern.nyu.edu/climate

widespread financial crisis would surpass the impact of a severe geopolitical event barring an apocalyptic incident that most likely would also provoke a market dislocation (comprised in type-SG events). Moreover, type-CG events, which estimate the effect of simultaneous climate and geopolitical events that do not trigger a wider systemic crisis, rarely produce a corresponding equity shortfall CS_{CG} which surpasses CS_S and, when this is the case, the two estimates are close[42]. Therefore, we deduce that $MSRISK_t$ represents the maximum loss that can be reasonably expected following the occurrence of either type-S, type-C, type-G, or type-CG events. In other words, the capital shortfall provoked by a systemic event is likely to comprise the maximum losses caused by separate financial, climate or geopolitical crises, or even by a concurrent climate and geopolitical event: $MSRISK_t$ can be used as the reference risk to calculate and allocate tail risk.

This step is necessary when a systemic incident occurs in conjunction with either a geopolitical or a climate crisis, or both. As described in Section 2.2, these are the events SC, SG and SCG. In our work we verified that the condition

$$(CS_{SCG,t} > CS_{SG,t}) \land (CS_{SCG,t} > CS_{SC,t}) \land (CS_{SCG,t} > CS_{CG,t}) \land (CS_{SCG,t} > CS_{S,t})$$

holds in 4966 out of 4980 cases, that is 99.7% of all the single bank instances considered, whereas in terms of aggregate risk the condition is always verified.

These results show that MAX_RISK_t always surpasses $MSRISK_t$: across the 498 dates considered MAX_RISK_t is higher than $MSRISK_t$ by a minimum of +4.1% and a maximum of +56.4%, registering a +18.1% average increase and a median gain of 17.1%. These results

[42] In the cases when $CS_{C,G}$ does exceed CS_S, we find that $CS_{C,G}$ is on average larger than CS_S by 2.8%.

quantify potential losses exceeding systemic risk caused by the occurrence of contemporaneous crises of different nature: this is tail risk, which would be unaccounted for without this type of multifactor analysis due to the way bivariate risk measures such as SRISK are constructed. Therefore, we conclude that bivariate systemic risk measures appear to underestimate maximum capital shortfall because they ignore the effects of climate, geopolitical and interaction risks.

Hereafter we present the results[43] of our analysis based on an expanding window. MAX_RISK_NET is attributed to MCRISK-X, MGRISK-X and INT using relative frequencies recorded at the end of each run.

Figure 1 shows aggregate risk MAX_RISK increasing from €573 billion to €649 billion (+13.2%) during the whole period: after bottoming below €400 billion in 2014Q3, it reaches its peak right at the beginning of 2022Q1. Figure 2 decomposes MAX_RISK in MSRISK, MCRISK-X, MGRISK-X, and INT values.

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[43] As explained in Section 4.2, the observation period goes from the beginning of July 2011 to the end of April 2022 using a 5-day interval between measurements, for a total of 498 dates. The threshold *thresh* is set at -30% whereas the Monte Carlo simulation is conducted with 75,000 runs over a 63-day period (3 months) per date, per bank.

Figure 1: MAX_RISK

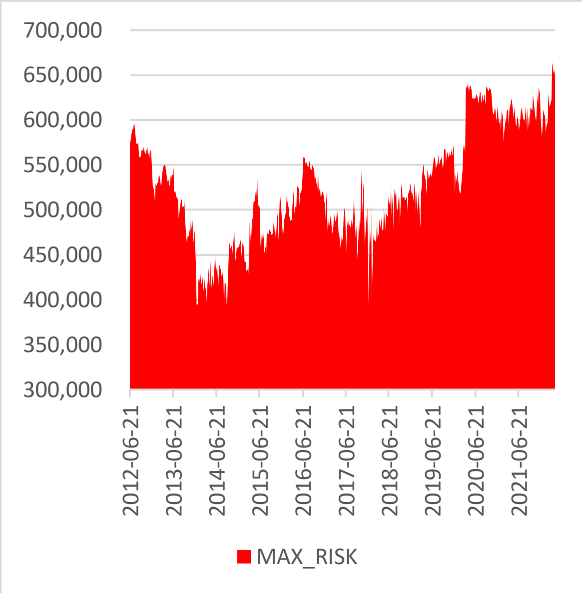
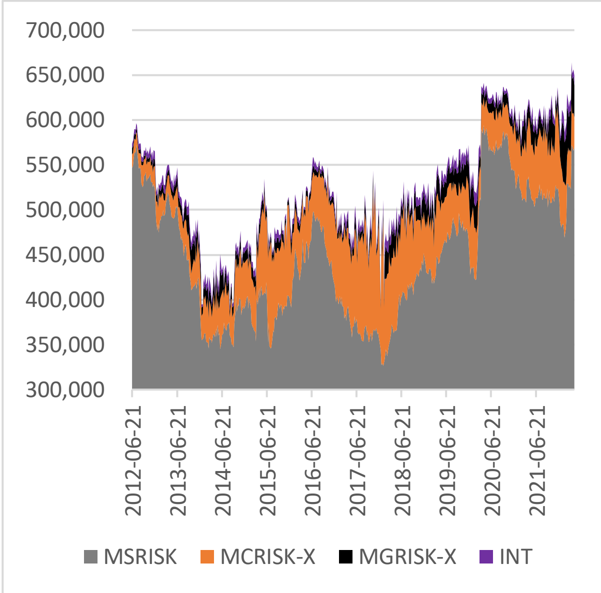


Figure 2: MSRISK, MCRISK-X, MGRISK-X, INT



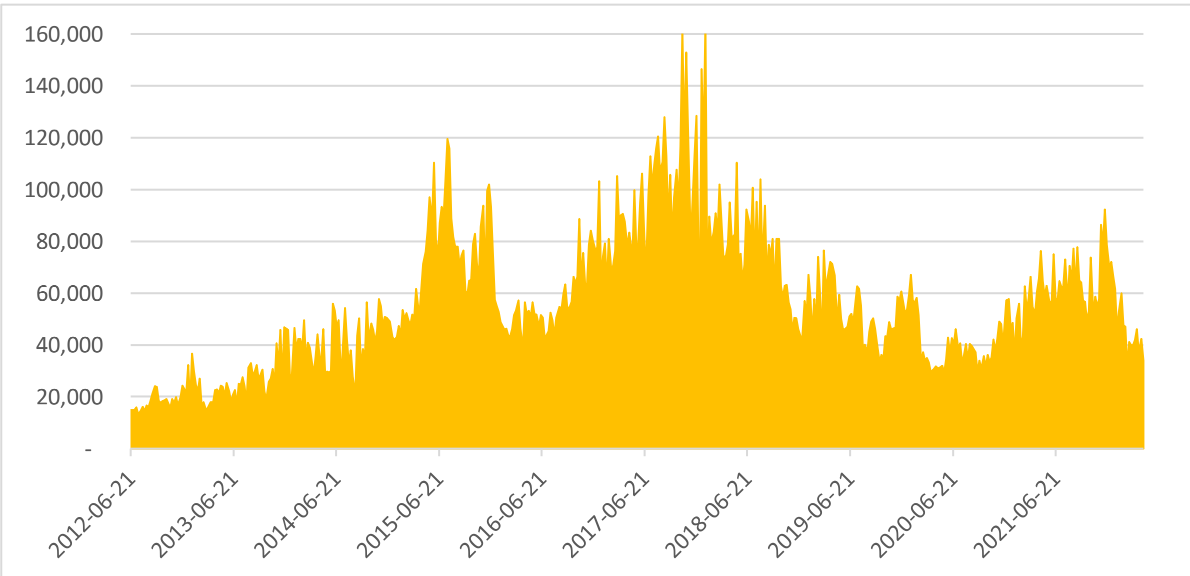
MSRISK moves from €547 billion to €569 billion (+4.0%), increasing less than MAX_RISK and staying closer to being unchanged, as suggested by the static value in RWA. In line with Gehrig and Iannino (2021), our study finds that the modest fall in the regulatory exposure fails to capture the increase in the aggregate systemic risk, especially considering climate and geopolitical tail risks as measured by MCRISK-X and MGRISK-X.

From July 2011 to April 2022 our proposed climate risk measure MCRISK-X more than doubles, increasing from approximately €15 billion to over €34 billion, after surpassing €160 billion following the ratification of the Paris Climate Agreement. On average, MCRISK-X increases MAX_RISK by 13.2% with respect to MSRISK estimates (median hike: 11.5%). As presented in Figure 3, MCRISK-X rises sharply during the 2015 and 2020 energy bear markets[44] due to the related surge in transition risk. Conversely, MCRISK-X recent fall is likely

[44] In both instances Brent crude prices dropped more than 50%.

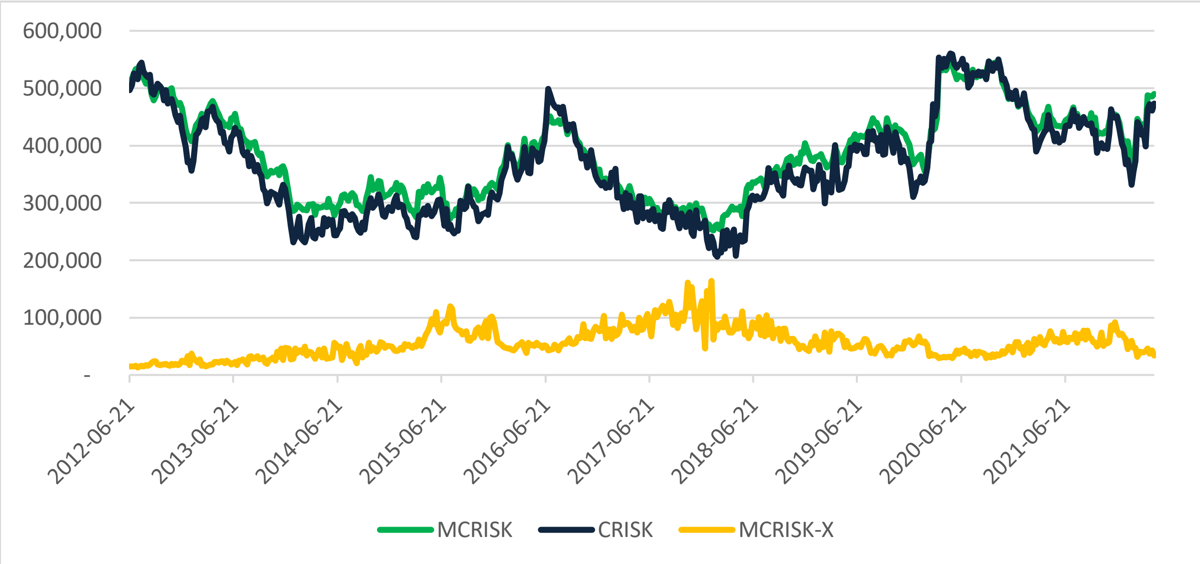
caused by a temporary reduction of transition risk, likely attributable to the sharp rise in the price of fossil fuels provoked by the breakout of the Russo-Ukrainian war. Given the attention reserved to climate by Eurozone governments and regulators, this situation appears to be transitory: in its 2022 CST exercise the ECB quantifies the potential climate losses for Eurozone financial institutions in approximately €70 billion, of which €53 billion due to disorderly transition. It also cautions that this estimate might significantly understate the extent of the problem. Our aggregate MCRISK-X measure in the first months of 2022 is above €47 billion for a sample of listed banks that represents approximately 70% of the EUROSTOXX sectoral market cap. Therefore, we concur with the central bank and conclude that the actual climate risk hanging over the Eurozone financial sector is likely to be somewhat higher than this appraisal.

Figure 3 – tail risk attributable to climate risk MCRISK-X



A bivariate approach would produce results way apart from the CST output. Figure 4 compares climate tail risk MCRISK-X with MCRISK and its bivariate equivalent CRISK. MCRISK, represented in our analysis by the event C and the shortfall CS_C, that is when only the climate factor CFE breaks the threshold, tracks closely CRISK. Climate risk estimates based on either metric would be, on average, more than 9 times MCRISK-X[45], which exhibits also a markedly different trend. This finding shows the limits of bivariate risk analysis and validates the adoption of a multifactor risk framework in conjunction with the proposed risk attribution methodology.

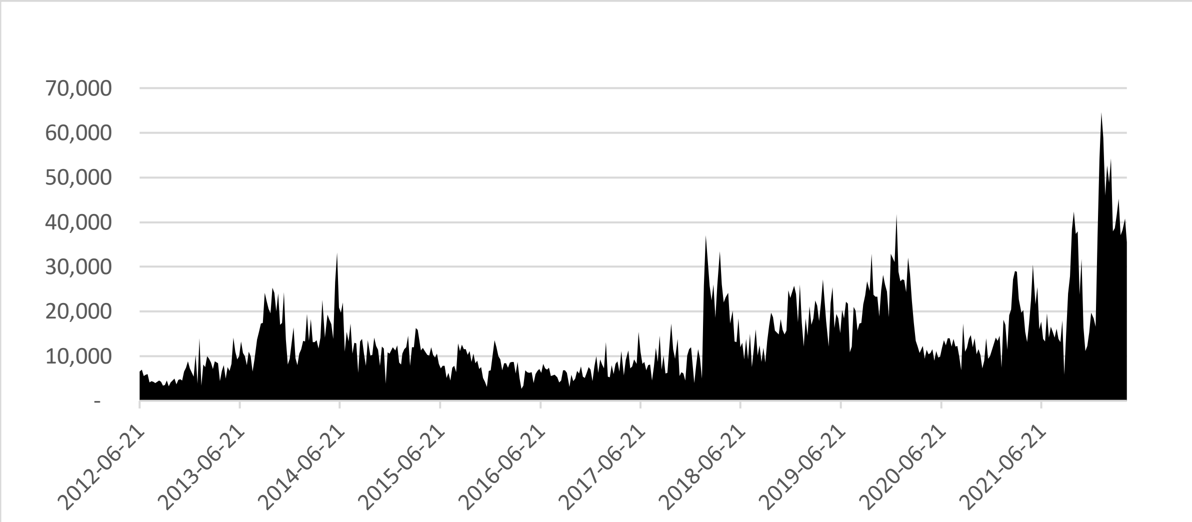
Figure 4: MCRISK vs CRISK vs MCRISK-X



MGRISK-X estimates are presented in Figure 5. By its nature, MGRISK-X is very volatile, influenced by high-impact but low-persistency shocks provoked by events, actions, threats, or news that influence markets for a limited period except for prolonged wars.

[45] These findings are in line with the NYU V-Lab output: for the selected sample the C event generates a multivariate MCRISK estimate on April 29th, 2022, of €490 billion, versus a bivariate V-LAB measure of $469 billion: considering the prevailing FX rate at the time of €/$=1.05, this equates to a €446 billion bivariate CRISK, or 91.1% of our MCRISK estimate produced in a multivariate context using a different climate factor.

Figure 5 – tail risk attributable to geopolitical risk MGRISK-X



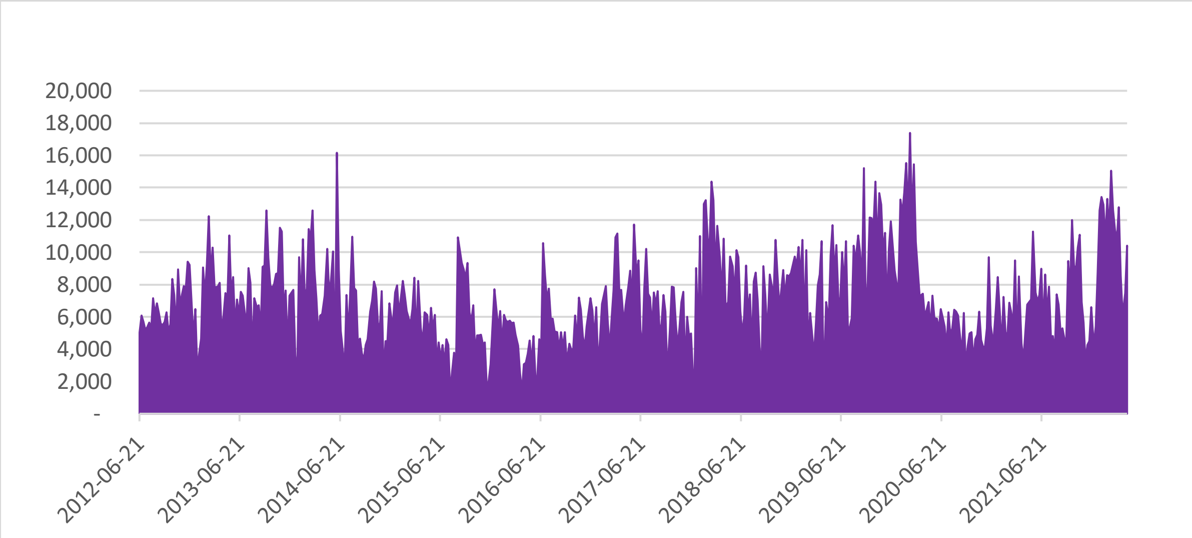
MGRISK-X shows significant correlation with the Caldara and Iacoviello (2022) GPRD (0.30***) and GPRD Threats (0.46***) indices, built using Anglo-Saxon news sources. Caldara and Iacoviello do publish single country indices but, to our best knowledge, not an aggregate Eurozone geopolitical risk index.

As expected, given the composition of the geopolitical factor GFE, MGRISK-X reacts more noticeably to conflicts[46] than to terrorist activity affecting Eurozone member states. From a low of €2 billion in early 2016, MGRISK-X has been propelled to above €64 billion by the break-out of the war in Eastern Europe in early 2022, reaching the highest level recorded during the whole period. On average, MGRISK-X contributes to MAX_RISK 3.2% of MSRISK measures, with a median increase of 2.8%. Worryingly, since 2018, the floor for MGRISK-X seems to have moved higher.

[46] Such as the annexation of Crimea in 2014, the fall of the ISIS Caliphate in late 2017-2018 and the North Korean crisis in 2018-2019.

The interaction effect INT is presented in Figure 6.

Figure 6: tail risk attributable to interaction risk INT



Contrary to MCRISK-X and MGRISK-X, this measure of extra risk provoked by the simultaneous occurrence of a systemic, climate and geopolitical crisis does not show a particular trend, reaching its peak of approximately €17 billion at the breakout of the pandemic. INT adds, on average, 1.6% of MSRISK estimates to MAX_RISK (median addition: +1.5%).

4.4. Sensitivity Analysis

To assess sensitivity, in addition to using the vector (-30%, -35%, -40%) of threshold values, shortfall estimates have been carried out employing different rolling 250-day and 500-day time windows. Generally, shorter time frames and higher absolute value thresholds tend to generate larger risks, and with rolling windows there are some cases of CCC outperforming DCC. However, despite using 75,000 runs per date, the higher the absolute value of the threshold, the higher the number of instances that require data interpolation for both 250 and 500-day rolling windows to estimate certain risk measures continuously. Therefore, the results presented are obtained using the expanding method.

Both MAX_RISK and MSRISK estimates tend to grow with the absolute value of the threshold, whereas the dispersion tends to contract (Table 2), as shown by the ratio of the respective measures calculated with different thresholds.

Table 2: MAX_RISK and MSRISK threshold ratios

	MAX_RISK threshold ratios			MSRISK threshold ratios		
	Ratio_35/30	Ratio_40/35	Ratio_40/30	Ratio_35/30	Ratio_40/35	Ratio_40/30
Mean:	103.7%	102.9%	106.7%	104.8%	104.3%	109.3%
Std. Dev.:	2.5%	2.5%	3.9%	1.8%	1.7%	3.4%
Min:	91.9%	92.8%	85.3%	101.6%	101.1%	103.0%
Max:	122.0%	119.3%	125.8%	110.0%	109.7%	119.4%

In Tables 2, 3, 4 and 5, Ratio_x/y indicates the ratio of the estimates computed respectively with threshold x% and threshold y%.

Even with *thresh* set at -40%, only one date (2013-01-25) requires data interpolation to obtain MSRISK, proving the reliability of the expanding (recursive) window method.

In terms of stability, MCRISK-X estimates are not very sensitive to changes to the absolute value of the threshold, which tends to increase the dispersion rather than affecting the magnitude of the climate risk estimate, as reported in Table 3.

Table 3 – MCRISK-X threshold ratios

	Ratio_35/30	Ratio_40/35	Ratio_40/30
Mean:	97.0%	93.3%	90.5%
Std. Dev.:	14.8%	19.9%	23.2%
Min:	38.3%	18.5%	17.1%
Max:	164.0%	205.9%	195.7%

As mentioned, we have calculated MCRISK-X using also rolling windows: in both instances the resulting metric values show wider swings, signaling very well the transition risk spikes occurred in 2015 and 2020. In both instances the surges are followed by a sharp decline.

As presented in Table 4, in terms of MGRISK-X the choice of the threshold appears to affect more the dispersion than its value:

Table 4: MGRISK-X threshold ratios

	Ratio_35/30	Ratio_40/35	Ratio_40/30
Mean:	100.8%	100.3%	100.7%
Std. Dev.:	25.0%	33.9%	39.3%
Min:	23.0%	0.0%	0.0%
Max:	281.8%	330.4%	401.0%

Using 250-day and 500-day rolling windows, MGRISK-X shows prolonged periods of zero or near zero geopolitical risk, followed by spikes before the Crimean crisis in 2014, the breakout of the pandemic and of the Russo-Ukrainian war.

Table 5: INT threshold ratios

	Ratio_35/30	Ratio_40/35	Ratio_40/30
Mean:	94.7%	93.9%	90.5%
Std. Dev.:	20.4%	28.8%	37.2%
Min:	0.0%	0.0%	0.0%
Max:	186.8%	233.8%	253.0%

Interaction estimates are not very sensitive to threshold changes, as shown in Table 5.

5. Conclusions

Our work develops a multifactor framework that allows for tail risk assessment and attribution. This approach manages to identify a dominant risk factor, if present, and uses it as a reference to quantify and allocate tail risk to other concurrent sources when events of different nature occur at once.

The application of this methodology to the sample of large Eurozone lenders produces several interesting findings that are robust to changes in factor thresholds:

1) Systemic risk is identified as the dominant risk factor for Eurozone banks. Furthermore, our analysis indicates that, on average, current systemic risk estimates obtained using a bivariate approach underestimate potential aggregate losses by €77.1 billion (median: €75.6 billion), or 18.1% (median: 17.1%). The undershooting is caused by the effects of the interaction between the different types of risk that can be captured only by a multivariate analysis.
2) The proposed climate tail risk attribution model produces a result which is comparable with the ECB climate stress test appraisal, even though their €53 billion transition risk assessment is likely to be moderately optimistic (lower than the actual risk). Conversely, bivariate approaches overestimate climate risk by almost one order of magnitude. This overshooting is provoked by the overlapping of capital shortfall estimates that fails to consider the dominant risk, that is systemic risk, as the major source of potential negative equity comprising the losses of isolated events of different nature. However, climate risk does constitute a dangerous source or tail risk if combined with systemic and geopolitical issues. Its mean addition to systemic risk is, on average, €55.7 billion (median: €51.6 billion), representing 10.8% of the maximum potential aggregate shortfall (median: 9.9%). It can account for up to 32.1% of maximum combined losses during energy bear markets. In the period considered, despite its late drop, climate tail risk has more than doubled.
3) Geopolitical risk adds €14.3 billion (median: €11.9 billion) to mean systemic risk, representing on average 2.7% (median: 2.3%) of aggregate maximum risk if combined with systemic and climate events. During the dramatic period leading to the breakout of the war in Ukraine tail risk linked to the geopolitical factor surged to €64.7 billion, or 10.6% of maximum aggregate losses, thereby reaching the maximum incidence

across the entire period analyzed. Further refinements in the geopolitical factor GFE would certainly improve the accuracy and timeliness of the results, which are significantly correlated with the Caldara and Iacoviello (2022) Threats index.

4) Interaction risk is a by-product of the simultaneous occurrence of multiple crises which can be measured only within this type of multivariate framework. It does not show any specific trend and represents on average 1.4% (median: 1.3%) of total risk. However, it never drops to zero and can reach 3.6% of combined aggregate losses, thereby indicating latent potential excess shortfall.
5) Our results are in line with Gehrig and Iannino (2021) in suggesting that the relative stability of risk weighted exposure reported by Eurozone banks does not reflect the actual trajectory of their aggregate risk, which is higher in 2022 than in 2011.
6) These findings could be used to develop portfolio construction techniques robust to multiple shocks. Lin et al. (2023) have introduced a suite of metrics based on bivariate $LRMES_t^{dynamic}$ designed to identify portfolios of banks able to overperform during systemic crises, whereas MCRISK-X and MGRISK_X could be utilized to perform sectoral stock selection to minimize the impact of climate and geopolitical shocks on portfolio returns. We are currently in the process of investigating this subject further with the forthcoming "Identifying green banks" paper.

Regulators could use this approach to explore the effects of simultaneous, manifold risk occurrences on Eurozone capital buffers. As shown by Gouriéroux et al. (2022), the identification of optimal capital requirements becomes extremely difficult when long-term challenges, such as the transition to a carbon neutral economy, have to be matched with short-term micro-prudential considerations. Regulation needs to ensure systemic integrity while preserving Eurozone banks' capability to produce earnings and strengthening their capital base, because a well-supervised and successful banking sector is necessary to achieve long-term financial stability. Hopefully, the methodology proposed in this work will contribute to achieving such a goal.

Chapter 3: Identifying Green Bank Stocks

Abstract

We investigate the effectiveness of three different climate metrics in identifying green banks within a sample of large Eurozone and US lenders in the February 2019 – April 2022 period. We compute weight modifiers determined by relative exposure to stranded assets, environmental ratings and Scope 2 emissions and apply them to create sectoral portfolios robust to climate events. The adjusted portfolios' risk-return performance is compared against a market capitalization benchmark and an optimized portfolio. The results show that the selected climate loss proxy overperforms in the Eurozone, succeeding in creating an effective climate tilt while containing active risk. Both emission-adjusted and rating-modified portfolios work as well, albeit less effectively. Conversely, the results with respect to US banks are inconclusive, with no metric consistently overperforming, likely due to accounting practices that tend to inflate total assets and the absence of a homogeneous Scope 3 indirect emissions reporting standard.

Keywords: bank stocks; stock selection; portfolio management; ESG; Environmental ratings; climate risk, Scope 2 emissions, Scope 3 emissions.

1. Introduction

Despite coordinated efforts by international regulators like the Basel Committee for Banking Supervision (BCBS, 2021) and organizations such as the Network for Greening the Financial System (NGFS)[47], the Task Force on Climate-related Financial Disclosures (TCFD, 2020), and the Net Zero Banking Alliance (NZBA)[48] to improve the transparency of the financial system with respect to climate change disclosures, the assessment of the greenness of a lender is still a subjective exercise that depends considerably on the relevant jurisdiction. If Eurozone banks have to comply with the Corporate Sustainability Reporting Directive (CSRD), US lenders must follow the US Security and Exchange Commission Climate Disclosure Rule (CDR), and banks domiciliated in other constituencies need to adopt different climate disclosure standards yet (APRA, 2021). Consequently, any metric designed to reflect the greenness of a lender depends on a very specific set of rules: for example, the EU Green Asset Ratio (GAR), mandatory from 2024, compares the proportion of climate-friendly green assets, as defined by the EU taxonomy (Alessi et al., 2019), with the total size of the balance sheet, formulated used International Financial Reporting Standards (IFRS). Hence, GAR cannot be directly applied to banks adopting a different framework, or reporting using another accounting method, such as the US Generally Accepted Accounting Principles (GAAP). Furthermore, emission reporting is prepared following multiple standards, making comparisons hard.

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[47] The NGFS is an international organization formed in late 2017 to facilitate the cooperation among governments and regulators on the matter of climate risk (NGFS, 2020). It comprises all major central banks and international institutions, such as the Bank for International Settlements (BIS).

[48] The United Nations-sponsored NZBA fosters the implementation of a path towards a carbon neutral global financial system by 2050, as suggested by the IEA (IEA, 2021). NZBA membership is strictly voluntary.

Within this fragmented context, investors pursuing specific sustainability goals are prone to screen assets employing ratings (Lesser et al., 2016) issued, autonomously or on request, by private agencies, which combine environmental (E), social (S) and governance (G) pillars into an ESG score. These ESG ratings tend to have a controversial influence on funds' performance (Alda, 2020; Bofinger et al., 2022), asset returns (Shanaev and Ghimire, 2022; Teti et al., 2023), equity risk premia (Brandon et al., 2021) and cost of capital (Rojo-Suárez and Alonso-Conde, 2023). By construction all ESG ratings are low frequency, lagging data: bank ESG ratings are usually updated only once a year[49], in the calendar quarter[50] following the publication of corporate sustainability reports referring to the previous accounting period. ESG ratings are assigned on the basis of a combined score, obtained by blending the three pillars and the controversies assessment together: when they diverge, it is due to differences in measurements, scope, or weights (Berg, Kolbel and Rigobon, 2022). Weights assigned to the environmental, social and governance pillars vary depending on the industry classification of any given company. Since the financial sector is perceived as being a light GHG emitter, in the case of lenders the E-pillar usually represents the least relevant contributor to the ESG rating: Standard and Poors Global (S&P) and Morgan Stanley Capital (MSCI) give the environmental score for banks only a 13% overall weight, articulated in three sub-scores. Refinitiv, which is the rating provider chosen for this work, follows a similar approach, assigning the E-pillar 14.4% of the rated banks' ESG evaluation. Environmental E scores are assigned taking into consideration

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[49] If regulatory actions or litigations emerge in between, some providers react to these events refreshing ratings earlier to track the development of open controversies.

[50] It is best practice to update ESG ratings by April: for example, a 2021 E rating should have been refreshed by April 2022. Consequently, our test considers applicable changes to the rating for portfolio choices occurring from late April of each year. Sometimes ratings are delayed, but the market is likely to discount new corporate sustainability information soon after dissemination.

several qualitative and quantitative factors, ranging from the depth of climate-related initiatives promoted by the company to the amount of green assets under management, and they include also actual metrics related to a lender's footprint, such as the consumption of natural resources, waste, and greenhouse gas (GHG) emissions. Refinitiv's environmental rating is decomposed in 3 parts: resource usage (2.4% of total), carbon emissions (again 2.4%) and innovation (9.6%). Consequently, emissions influence only 17% of the environmental score and carry a very marginal effect on the combined ESG rating. The key metric determining the emission component of the E score, identified by Refinitiv as @AnalyticCO2, is built around the sum of the reported Scope 1 and Scope 2 emissions, that is GHG generated directly by the lenders (Scope 1) or related to the indirect emissions linked to their energy consumption (Scope 2). @AnalyticCO2 is calculated as the ratio of total Scope 1 and Scope 2 emissions (in metric tons) with respect to Total Revenues (in currency millions) for each bank: the lower the metric, the greener the bank. Unfortunately, Scope 1 and Scope 2 reporting is still not fully harmonized, even within the same region. Hereafter we present Table 1, showing @AnalyticCO2 for the Eurozone sample.

Table 2:Reported GHG (Scope2) over Revenues - Eurozone 10 largest banks by assets.

	BNP	**ACA**	**GLE**	**SAN**	**BBVA**	**INGA**	**DBK**	**CBK**	**UCG**	**ISP**
2010	8.04	0.31	3.50	6.47	10.11	21.76	15.17	5.15	11.76	3.25
2011	8.14	1.29	3.42	5.67	10.62	7.96	13.14	6.27	11.80	8.17
2012	4.42	0.71	2.82	5.23	8.36	5.12	12.04	4.87	11.76	3.15
2013	4.34	0.66	2.05	4.61	7.76	3.92	4.84	3.49	11.31	2.42
2014	4.46	0.50	2.66	4.38	8.87	3.24	5.29	4.54	10.26	5.06
2015	4.35	0.59	4.66	4.79	8.65	2.77	4.25	14.18	10.70	5.71
2016	4.50	1.49	4.15	7.73	10.44	1.73	5.05	13.81	12.91	6.23
2017	5.09	1.14	3.20	5.99	9.37	1.15	4.50	11.82	13.05	5.77
2018	5.19	1.20	4.13	6.02	9.46	0.93	4.71	12.31	9.77	6.20
2019	4.54	0.99	3.97	5.25	11.04	0.90	5.33	12.39	9.80	5.04
2020	3.96	1.08	3.29	4.74	8.28	0.68	3.70	8.92	7.69	3.36
2021	3.50	1.05	2.92	4.80	8.14	0.57	2.50	7.67	7.84	4.28

It includes the ten largest Eurozone listed banks by assets in the July 2011-April 2022 period: Credit Agricole (ACA), Banco Bilbao Vizcaya and Argentaria (BBVA), Banque National de Paris (BNP), Commerzbank (CBK), Deutsche Bank (DBK), Société Générale (GLE), ING Group (INGA), Banca Intesa (ISP), Banco Santander (SAN) and Unicredit (UCG). Certain names appear to be materially greener than others, but this contrast is mostly caused by different criteria used to compute total emissions. Table 2 illustrates the ratio for a US sample which comprises the ten largest North American banks listed in the United States by assets in the 2011-2022 period, excluding financial companies classified as investment banks, asset gatherers or broker-dealers. The US lenders included in the analysis are Bank of America (BAC), Citigroup (C), JP Morgan Chase (JPM), Wells Fargo (WFC), US Bancorp (USB), Truist Financial Corporation (TFC), PNC Bank (PNC), Capital One Financial (COF), Bank of New York Mellon (BK), and MTB Bank (MTB). For the US sample the differences in the approach to emission reporting are striking, with some lenders not publishing climate disclosures for prolonged periods of time.

Table 3: Reported GHG (Scope2) over Revenues - US 10 largest banks by assets.

	BAC	C	JPM	WFC	USB	TFC	PNC	COF	BK	MTB
2010	16.44	11.99	12.85	18.81	22.93	18.55	24.36	13.06	16.96	--
2011	18.16	12.81	13.61	19.78	22.85	--	29.97	12.03	16.26	--
2012	18.49	13.65	13.43	16.58	20.37	--	28.75	9.77	14.95	--
2013	16.33	11.59	12.10	16.28	--	--	26.49	10.05	14.38	--
2014	15.55	10.99	10.55	15.73	--	--	25.72	9.43	10.77	--
2015	13.47	10.67	11.35	13.77	--	--	22.52	8.98	0.94	--
2016	12.64	10.89	10.21	12.02	--	--	22.14	8.38	0.81	--
2017	10.32	9.64	8.43	10.57	--	--	18.46	5.58	9.97	8.53
2018	9.36	8.85	7.56	10.75	--	--	15.40	6.08	9.16	8.40
2019	8.60	7.97	6.71	9.94	--	17.60	12.60	5.81	8.40	7.77
2020	8.23	6.97	6.11	10.45	10.94	8.99	10.09	4.15	7.20	6.84
2021	7.39	7.07	6.91	8.21	10.27	11.31	8.41	3.37	6.02	6.35

The lack of homogeneous data is even more pronounced for @AnalyticCO2IndirectScope3, a similarly constructed metric which is supposed to consider indirect GHG generated upstream by the supply chain and downstream by lending, that is the primary business of any bank. Table 3 presents @AnalyticCO2IndirectScope3, computed as the ratio of indirect Scope 3 GHG in metric tons to revenue (in euro millions) for the European banks considered:

Table 4: Reported indirect GHG (Scope3) over Revenues - Eurozone 10 largest banks by assets.

	BNP	ACA	GLE	SAN	BBVA	INGA	DBK	CBK	UCG	ISP
2010	2.53	0.31	1.20	1.84	1.08	4.04	3.06	1.98	0.49	0.50
2011	2.71	0.00	1.48	2.08	0.99	1.77	2.34	2.47	0.55	0.34
2012	1.42	0.50	1.09	2.19	1.17	4.88	1.84	2.31	0.62	0.41
2013	1.28	0.41	0.79	2.15	1.23	2.20	1.97	4.78	0.37	0.58
2014	1.48	0.20	1.13	2.10	1.27	1.35	1.95	6.20	0.35	0.55
2015	1.64	0.36	2.22	2.30	1.41	1.49	1.81	6.83	0.38	0.74
2016	1.61	0.67	2.05	2.43	1.36	1.48	1.75	6.88	0.52	0.91
2017	1.84	1,619.72	1.59	1.62	1.54	1.32	1.71	6.33	0.45	2.30
2018	2.45	1,568.96	2.84	1.90	1.90	1.33	1.76	6.40	0.32	2.57
2019	1.84	1,537.06	2.85	1.81	1.83	1.09	2.42	6.57	0.39	0.53
2020	1.08	1,834.19	1.88	0.63	0.19	0.34	0.43	3.65	0.31	0.62
2021	0.61	1,610.55	1.21	0.58	0.30	0.26	0.09	3.04	0.10	0.54

The only bank fully reporting both upstream and downstream GHG, Credit Agricole (ACA), shows a @AnalyticCO2IndirectScope3 ratio for 2021 of 1,610.55, which is about one thousand times higher than its peers. Interestingly, in the case of ACA, indirect Scope 3 emissions (147 million metric tons) represent 153% of combined Scope 1 and Scope 2 GHG (96 million metric tons), or more than 60% of total Scope 1, Scope 2, and Scope 3 combined emissions. To put this value into context, in 2021 Total Energies SA, the largest oil and gas conglomerate headquartered in the Eurozone, reported a @AnalyticCO2IndirectScope3 of 2,118.54, only 31% higher than ACA's, with respect to a @AnalyticCO2 (Scope 1 and Scope 2) ratio of 191.59, that is 27 times higher than ACA's 7.07. The other Eurozone lenders report Scope 3 emissions below Scope 1 and Scope 2 GHG not because of a much greener business model, but simply due to the choice of a different emission reporting methodology.

Noticeable differences in GHG reporting standards emerge also in the US sample. The @AnalyticCO2IndirectScope3 metric for the North American banks is shown in Table 4.

Table 5: Reported indirect GHG (Scope3) over Revenues - US 10 largest banks by assets.

	BAC	**C**	**JPM**	**WFC**	**USB**	**TFC**	**PNC**	**COF**	**BK**	**MTB**
2010	11.89	1.17	1.34	1.39	1.35	--	7.56	--	1.93	--
2011	41.83	1.54	1.56	1.40	1.31	--	11.92	1.42	1.66	--
2012	57.86	1.78	1.55	1.56	9.47	--	10.58	1.21	3.21	--
2013	49.44	2.04	1.67	1.76	--	--	10.08	1.43	1.58	--
2014	53.88	2.40	1.64	1.39	--	--	10.47	1.33	--	--
2015	49.53	1.46	1.57	1.13	--	--	10.50	1.37	1.34	--
2016	65.99	1.95	1.44	1.24	--	--	10.27	8.22	1.29	--
2017	59.60	2.09	1.86	44.57	--	--	9.45	1.85	1.15	0.59
2018	43.87	2.06	1.62	43.77	--	--	6.58	5.00	1.05	1.17
2019	46.60	1.70	1.57	41.50	--	0.56	4.05	13.34	0.89	1.15
2020	38.90	0.29	0.30	33.08	3.59	6.46	0.97	7.81	0.14	0.32
2021	32.95	0.15	0.32	27.21	3.64	4.54	0.33	7.24	0.08	0.22

BAC and WFC seem to produce indirect Scope 3 GHG which are a multiple of the competitors, but this is just another instance of different emission reporting standards that cause a marked misalignment in the data. This serious issue hinders a proper relative evaluation of the greenness of a lender based on indirect emissions and leads us to conclude that at this stage

Scope 3 data cannot be used to identify green banks, even if they are probably the most important metric to track the progress of the drive towards a greener financial system.

This problem is coupled with the way E pillar scores are attributed: banks receive a total numerical score obtained as the sum of their performance in Resource Usage (weight: one sixth), Emissions (weight: one sixth) and Innovation (weight: two thirds). Therefore, E-ratings give more weight to internal practices and broad initiatives to confront climate change rather than focusing on lending policies with respect to brown assets, incentivizing bank managers to concentrate on boosting their performance in the Innovation category (9.6% of total ESG score) rather than reducing downstream emissions. Table 5 presents the evolution of the Environmental pillar ratings for the Eurozone sample.

Table 6: Environmental Pillar Score for the EU sample, 2010-2021 (Weight 14.4% on TOTAL ESG SCORE).

	BNP	ACA	GLE	SAN	BBVA	INGA	DBK	CBK	UCG	ISP
2010	**A+**	**A+**	**A+**	**A**	**A+**	**A**	**A**	**A+**	**A**	**A+**
2011	**A+**	**A**	**A+**	**A**	**A+**	**A**	**A+**	**A+**	**A**	**A+**
2012	**A+**	**A**	**A+**	**A**	**A**	**A**	**A**	**A**	**A**	**A+**
2013	**A+**	**A**	**A+**	**A**	**A+**	**A**	**A+**	**A**	**A**	**A+**
2014	**A+**	**A**	**A+**	**A+**	**A+**	**A**	**A+**	**A**	**A**	**A+**
2015	**A+**	**A+**	**A+**	**A+**	**A+**	**A**	**A+**	**A**	**A**	**A+**
2016	**A+**	**A+**	**A+**	**A+**	**A+**	**A+**	**A+**	**A**	**A**	**A+**
2017	**A+**	**A+**	**A**	**A**	**A**	**A**	**A+**	**A**	**A**	**A**
2018	**A+**	**A+**	**A+**	**A**	**A**	**A**	**A+**	**A-**	**A-**	**A**
2019	**A+**	**A+**	**A+**	**A**	**A-**	**A**	**A+**	**A**	**A**	**A**
2020	**A+**	**A+**	**A+**	**A**	**A+**	**A**	**A+**	**A**	**A**	**A+**
2021	**A+**	**A+**	**A+**	**A**	**A+**	**A**	**A+**	**A+**	**A**	**A+**

Total scores are sorted and put into classes spaced by 0.083 points: A+ is the highest rating, assigned for scores comprised between 0.9166 and 1.0000, while D- is the worst, issued for scores between 0.0000 and 0.0833. E pillar ratings are then issued depending on the class, without distinction between different intra-class scores: a bank obtaining 0.9167 gets A+, and so does a bank with a perfect score of 1. Table 6 illustrates the environmental ratings assigned by Refinitiv to the banks included in the US sample.

Table 7: Environmental Pillar Score for the US sample, 2010-2021 (Weight 14.4% on TOTAL ESG SCORE).

	BAC	C	JPM	WFC	USB	TFC	PNC	COF	BK	MTB
2010	**A**	**A+**	**A**	**A-**	**B+**	**D+**	**A-**	**C**	**A-**	**D+**
2011	**A**	**A+**	**A-**	**B**	**B**	**D+**	**B+**	**C**	**A-**	**D+**
2012	**A**	**A+**	**A-**	**B**	**B**	**D**	**B+**	**C**	**A**	**D+**
2013	**A**	**A+**	**A-**	**B**	**B**	**D**	**B+**	**C**	**A**	**D+**
2014	**A+**	**A**	**B+**	**B**	**B**	**D**	**B+**	**B+**	**A+**	**D+**
2015	**A+**	**A**	**A-**	**A**	**B+**	**D+**	**A-**	**B+**	**A+**	**C-**
2016	**A+**	**A**	**A-**	**A**	**B+**	**D+**	**A-**	**B+**	**A+**	**C-**
2017	**A**	**A+**	**B**	**A**	**B-**	**D-**	**B**	**C**	**A**	**D**
2018	**A**	**A+**	**B-**	**A**	**B-**	**D**	**B**	**B**	**A**	**D**
2019	**A**	**A**	**A-**	**A-**	**B-**	**D**	**B**	**B**	**A**	**D**
2020	**A-**	**A**	**A-**	**A-**	**B-**	**D+**	**B-**	**B**	**A**	**B**
2021	**A**	**A**	**A**	**A-**	**A**	**D+**	**C+**	**B**	**A**	**B+**

The exhibits show two very different pictures: Eurozone lenders tend to get high and stable environmental ratings, whereas US banks show more volatility. This dichotomy reflects both the different regulatory path towards carbon neutrality adopted in the two macro areas as well as idiosyncratic issues affecting the ratings of some US banks. The uniformly positive European results likely make E-ratings unsuitable to assess relative greenness within the Eurozone financial sector; conversely, given the more differentiated outcomes, potentially they could be used if applied to the US sample.

Academic literature on portfolio selection and ESG factors recognizes the problem of downstream Scope 3 emissions reporting. Pedersen, Gibbons, and Pomorski (2021) use a ratio of Scope 1 and Scope 2 emissions to revenues (equivalent to Refinitiv's @AnalyticCO2) as an environmental rating proxy to construct an ESG-modified efficient frontier, citing the noisiness and inconsistency of Scope 3 estimates as the reason to neglect them. We concur: Scope 3 emissions are difficult to track and are systematically under reported by most of the companies; however, to manage portfolios mandated to identify and invest only in the greenest stocks, brown asset exposure should probably represent one of the main factors determining which names to hold. In the case of banks, more capital allocated to borrowers involved in heavy carbon-emitting activities leads to increased sensitivity to volatility affecting stranded assets: rather than ignoring indirect emissions, there might be ways to use proxies and perform portfolio selection accordingly. Specifically, we propose the ratio of climate-induced losses to the size of the balance sheet as a natural way to assess greenness: the smaller the incidence, the more robust is the lender.

But can a portfolio manager rely on any, or all, of these metrics to adopt a sectoral exposure robust to climate risk? This work investigates their effectiveness in identifying the greenest banks during a climate event by applying weight modifiers based on the three criteria (loss-to-asset ratios, E-ratings, and Scope 2 emissions) to model portfolios comprising both samples in the 2019-2022 period and check whether they are successful in improving the portfolio risk-return profile with respect to a cap-weighted benchmark. The window between January 2019 and April 2022 includes the run-up to the breakout of COVID-19, the severe 2020-21 energy bear market, its aftershock, and the early stages of the Russo-Ukrainian war. In 2020 the consequences of the pandemic depressed global hydrocarbons demand and provoked severe dislocations in the energy markets, affecting stranded assets and creating the same conditions that can be reasonably expected in the aftermath of a climate event. By mid-2021 the supply-demand unbalances were mostly cleared and, in 2022, following the international reaction to the war in Eastern Europe, abruptly reversed by an opposite shock provoking a temporary surge in price due to restrictions to the supply of fossil fuels. Therefore, we can conclude that, in the period considered, stranded assets experienced a complete reverse boom-bust cycle, which might serve as a guide for the unfolding of climate events and represents an ideal test period to confront different climate robustness measures.

2. Assessing the greenness of a bank: methodology

To perform such a task, we first have to design metrics that allow to identify banks characterized by a) higher environmental ratings than their peers; b) lower exposure to losses related to stranded assets; c) lower Scope 2 emissions to revenues ratio than the competitors. The portfolio weight of these "green" banks is going to be higher than the benchmark, whereas the opposite is true for "brown" lenders.

2.1 Environmental Rating Weight Modifier RWM

We start with the environmental rating modifier related to E pillar ratings. As stated before, we assume they are refreshed once a year in April, using data published in the corporate and social responsibility reports referring to the previous fiscal year. Since both Eurozone and US banks tend to report annual results early in the first quarter, this assumption is realistic. Given that E ratings do not differentiate among companies bearing the same classification, we assign to the bank *i* at time *t* the relevant top score $SCORE_{i,t}$ reflecting its E-rating: 1.000 for A+, 0.9167 for A, and so on, down to 0.0833 for D-. We then obtain the reverse score $REVSCORE_{i,t}$ by subtracting $SCORE_{i,t}$ from 1 (an A+ rating gets 0, an A 0.083, and a D- gets a 0.9166) and carry on by computing the difference between the average reverse score $\overline{REVSCORE_t}$ and each individual reverse score: this value, divided by 100 to be expressed in percentage terms, represents the rating weight modifier $RWM_{i,t}$, which can be either positive or negative:

$$RWM_{i,t} = \frac{\overline{REVSCORE_t} - REVSCORE_{i,t}}{100}\ . \quad (1)$$

Banks with an E-pillar rating better than the average would show a positive $RWM_{i,t}$, and vice versa: we will be employing rating weight modifiers to determine the extent of the overweight, or underweight, to apply to each name during a climate crisis. Tables 7 and 8 present the relevant Eurozone and US RWM metrics for the period considered.

Table 8: Eurozone Rating Weight Modifiers RWM and Mean Reverse Score REVSCORE (2018-2022).

	BNP	ACA	GLE	SAN	BBVA	INGA	DBK	CBK	UCG	ISP	MEAN
2017	0.058%	0.058%	-0.025%	-0.025%	-0.025%	-0.025%	0.058%	-0.025%	-0.025%	-0.025%	0.058%
2018	0.067%	0.067%	0.067%	-0.017%	-0.017%	-0.017%	0.067%	-0.100%	-0.100%	-0.017%	0.067%
2019	0.058%	0.058%	0.058%	-0.025%	-0.108%	-0.025%	0.058%	-0.025%	-0.025%	-0.025%	0.058%
2020	0.033%	0.033%	0.033%	-0.050%	0.033%	-0.050%	0.033%	-0.050%	-0.050%	0.033%	0.033%
2021	0.025%	0.025%	0.025%	-0.058%	0.025%	-0.058%	0.025%	0.025%	-0.058%	0.025%	0.025%

Table 9: US Rating Weight Modifiers RWM and Mean Reverse Score REVSCORE (2018-2022).

	BAC	C	JPM	WFC	USB	TFC	PNC	COF	BK	MTB	MEAN
2017	0.283%	0.367%	0.033%	0.283%	-0.050%	-0.550%	0.033%	-0.217%	0.283%	-0.467%	0.367%
2018	0.258%	0.342%	-0.075%	0.258%	-0.075%	-0.492%	0.008%	0.008%	0.258%	-0.492%	0.342%
2019	0.250%	0.250%	0.167%	0.167%	-0.083%	-0.500%	0.000%	0.000%	0.250%	-0.500%	0.333%
2020	0.125%	0.208%	0.125%	0.125%	-0.125%	-0.458%	-0.125%	-0.042%	0.208%	-0.042%	0.292%
2021	0.158%	0.158%	0.158%	0.075%	0.158%	-0.508%	-0.258%	-0.092%	0.158%	-0.008%	0.242%

2.2 Climate Loss Weight Modifier LWM

Following a climate event, an assessment of the loss $CLIMATE\_LOSS_t$ at time t caused by the exposure to the k brown assets in the loan book can be conducted using Loss Given Default LGD_t and probability of default POD_t estimates, updated given the occurrence of such a crisis:

$$CLIMATE\_LOSS_t = \sum_{i=1}^{k} \left(LGD_{t,i} \mid crisis\right) \left(POD_{t,i} \mid crisis\right). \qquad (2)$$

This calculation requires granular information related to the loan and investment books of the bank, usually accessible for the regulator but unavailable to the public, thus prompting the need to choose a proxy for climate risk losses. Climate risk includes both physical risk and transition risk (Battiston et al., 2017): while physical risk is represented by the loss of capital directly provoked by climate events, for lenders transition risk depends on the exposure to stranded assets. In its 2022 Climate Stress Test (CST) the European Central Bank (ECB) concludes that transition risk represents approximately 76% of the Eurozone banking sector exposure to total climate risk (ECB, 2021; ECB, 2022). In our previous work (Bettin, Mensi and Recchioni; 2023) we estimated Eurozone bank losses attributable to transition risk using only market data, and yet obtaining aggregate values compatible with the ECB 2022 CST results.

Hence, we proceed by employing our proposed climate tail risk measure as a proxy for $CLIMATE\_LOSS_{i,t}$ to identify the banks less exposed to climate risk, noting that any other realistic estimate of losses induced by climate risk exposure would serve the same purpose and could be used to replace it: the more accurate the indicator, the better the results. Climate loss estimate $MCRISKX_{i,t}$ for bank *i* at time *t* is calculated following a multi-step process described in detail in Chapter 2. Firstly, it is necessary to assess each lender's sensitivity to its specific regional climate factor that tracks the relative performance of stranded assets using market returns and multivariate MGARCH analysis (Engle, 2002; Bauwens et al., 2006; Engle, 2009, Brownlees and Engle, 2016; Engle, 2017; Jung et al., 2021) in a multifactor framework. These parameters are then deployed to conduct a simulation and compute the climate loss estimate $MCRISKX_{i,t}$ as a Monte Carlo average of the expected tail losses at time *t* given the occurrence of a crisis, which is defined as a 30% fall in 3 months for the respective factor: $MCRISKX_{i,t}$ represents an appraisal of total tail risk for a given bank attributable to climate risk.

$MCRISKX\text{-}R_{i,t}$ is computed by dividing $MCRISKX_{i,t}$ by the Total Assets $TA_{i,t}$ of the bank, obtaining a dynamic, high-frequency, coincident and dimensionless metric expressed as a percentage of the balance sheet size: the lenders with the lowest loss estimate are the greenest.

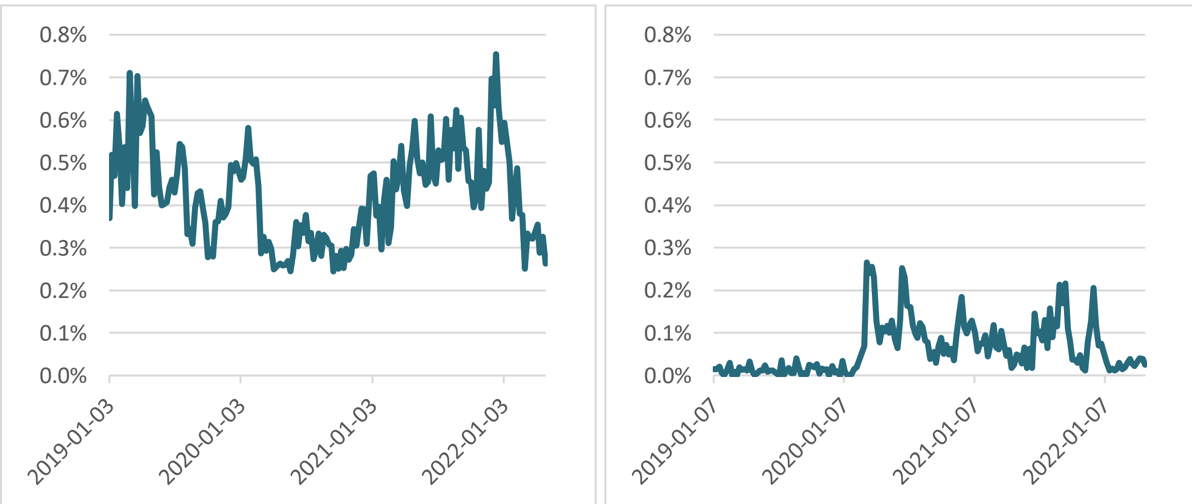
$$MCRISKX\text{-}R_{i,t} \cong \frac{CLIMATE_{LOSS\,i,t}}{TA_{i,t}}\,. \tag{3}$$

We apply this methodology to investigate transition risk for the two samples in the period considered to represent a proxy of a possible climate event. As for E ratings, we are to use the difference between the average value at time *t*, indicated as $\overline{MCRISKX\text{-}R_t}$, and $MCRISKX\text{-}R_{i,t}$, to penalize lenders with exposure to climate losses greater than the average and increase allocation to banks that are greener, that is less sensitive to stranded assets volatility as indicated by a value for $MCRISKX\text{-}R_{i,t}$ lower than the average. The Climate Loss Weight Modifier $LWM_{i,t}$ is defined as:

$$LWM_{i,t} = \overline{MCRISKX\text{-}R_t} - MCRISKX\text{-}R_{i,t}\,. \tag{4}$$

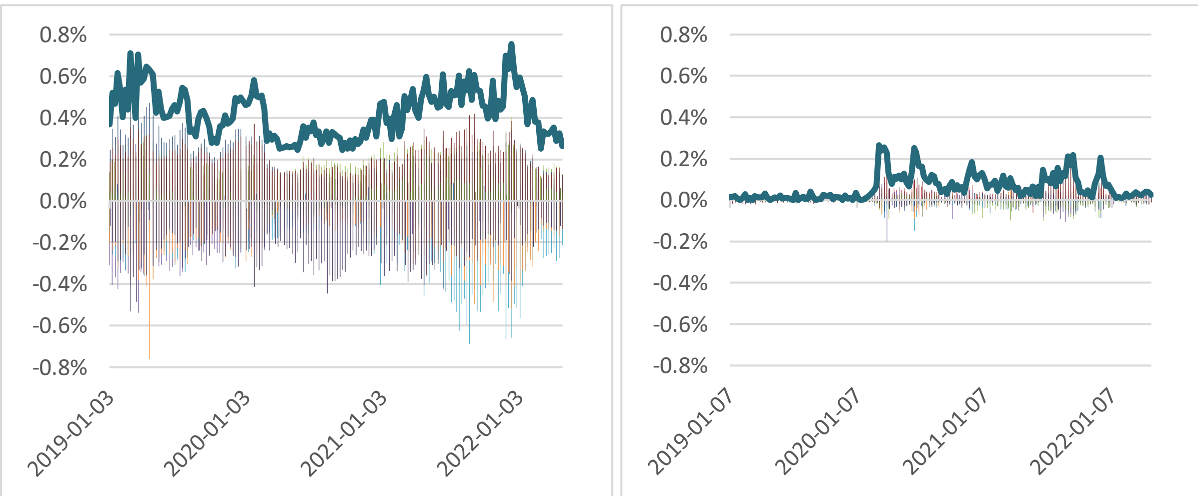
Figure 1 presents the average $\overline{MCRISKX\text{-}R_t}$ for the Eurozone and the US sample respectively.

Figure 2: Average MCRISKX-R, Eurozone and US samples (2019-2022).



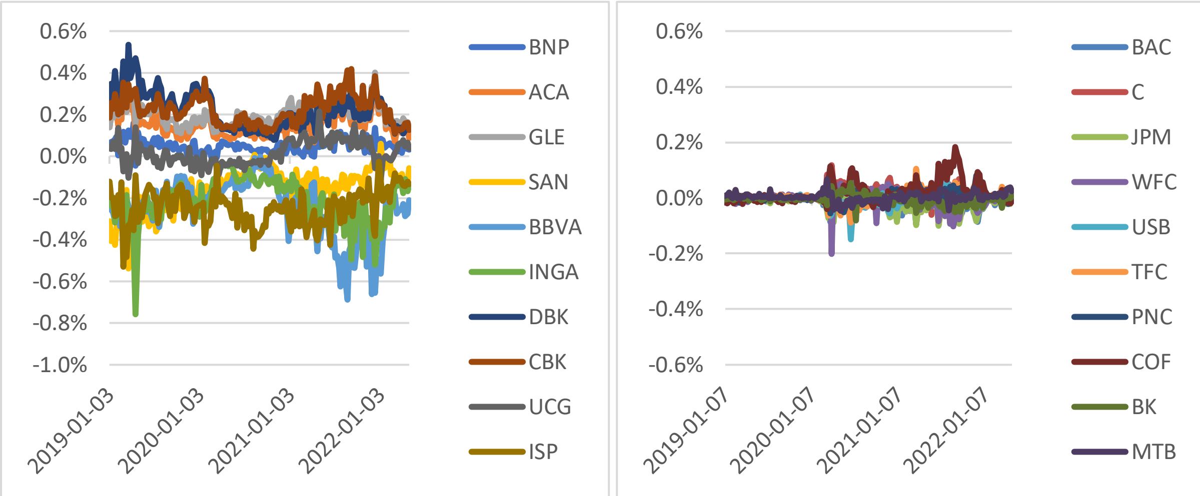
In the Eurozone, climate risk as measured by average $\overline{MCRISKX\text{-}R_t}$ remains elevated throughout 2021, showing consistently higher values than the USA during the entire period. In both regions, average risk drops considerably following the military escalation in Eastern Europe in early 2022. For the EU bank sample, mean transition risk estimates calculated with $\overline{MCRISKX\text{-}R_t}$ are neither stable nor static. The same can be said for the dispersion of individual metrics with respect to mean risk. As shown by Figure 2 and Figure 3, banks display idiosyncratic sensitivities to the climate factor which, in contrast with the rather homogeneous picture given by E pillar ratings, are markedly diverse. This heterogeneity can be used to identify the greenest banks and complement indicators such as GAR or any other metric based on taxonomy.

Figure 2: Average MCRISKX-R vs idiosyncratic dispersion with respect to mean, Eurozone and US samples (2019-2022).



The US sample shows a diametrically opposite behavior: exposure to climate risk losses, as measured by MCRISKX-R, appears to be consistently lower and the average dispersion is much more contained. Interestingly, this is the exact opposite picture shown by environmental E-ratings.

Figure 3: Idiosyncratic MCRISKX-R dispersion with respect to mean, Eurozone and US samples (2019-2022).



2.3 GHG Emission Weight Modifier EWT

Finally, we apply the same methodology to determine emission weight modifiers $EWM_{i,t}$ as the difference between the average ratio of Scope 2 emissions to Revenues $\overline{SCOPE2_t}$ and the individual ratios $SCOPE2_{i,t}$ and divide by 10,000 to scale it in line with the other modifiers:

$$EWM_{i,t} = \frac{\overline{SCOPE2_t} - SCOPE2_{i,t}}{10000}. \tag{5}$$

Lenders with a reported Scope 2 GHG ratio lower than the average will obtain a positive emission weight modifier, and vice versa. Tables 9 and 10 show relevant $EWM_{i,t}$ metrics for the Eurozone and the US sample respectively.

Table 10: Eurozone Scope2 Emissions Ratio Weight Modifiers EWM (2019-2022).

	BNP	ACA	GLE	SAN	BBVA	INGA	DBK	CBK	UCG	ISP	MEAN
2017	0.010%	0.050%	0.029%	0.001%	-0.033%	0.050%	0.016%	-0.057%	-0.069%	0.003%	0.061%
2018	0.008%	0.048%	0.019%	0.000%	-0.035%	0.051%	0.013%	-0.063%	-0.038%	-0.002%	0.060%
2019	0.014%	0.049%	0.020%	0.007%	-0.051%	0.050%	0.006%	-0.065%	-0.039%	0.009%	0.059%
2020	0.006%	0.035%	0.013%	-0.002%	-0.037%	0.039%	0.009%	-0.044%	-0.031%	0.012%	0.046%
2021	0.008%	0.033%	0.014%	-0.005%	-0.038%	0.038%	0.018%	-0.033%	-0.035%	0.000%	0.043%

Table 11: US Scope2 Emissions Ratio Weight Modifiers EWM (2019-2022).

	BAC	C	JPM	WFC	USB	TFC	PNC	COF	BK	MTB	MEAN
2017	-0.022%	-0.015%	-0.003%	-0.024%	0.082%	0.082%	-0.103%	0.026%	-0.018%	-0.004%	0.082%
2018	-0.018%	-0.013%	0.000%	-0.032%	0.076%	0.076%	-0.078%	0.015%	-0.016%	-0.008%	0.076%
2019	-0.001%	0.006%	0.018%	-0.014%	0.085%	-0.091%	-0.041%	0.027%	0.001%	0.008%	0.085%
2020	-0.002%	0.010%	0.019%	-0.025%	-0.029%	-0.010%	-0.021%	0.038%	0.008%	0.012%	0.080%
2021	0.001%	0.005%	0.006%	-0.007%	-0.027%	-0.038%	-0.009%	0.042%	0.015%	0.012%	0.075%

3. Green sectoral portfolio construction

We now proceed by employing weight modifiers to create green sectoral portfolios. If the lenders showing either lower MCRISKX-R, or better environmental ratings, or lower Scope 2 GHG to revenue ratios are effectively green lenders, we should be able to use this information to construct a sectoral portfolio robust to climate shocks which is capable to outperform a benchmark while assuming moderate tracking risk. We check this hypothesis in the period ranging from February 2019 to April 2022 by comparing the risk-return profile of a capitalization weighted benchmark portfolio, denominated P_B, against the performance of three portfolios adjusted for: 1) climate losses (P_L); 2) environmental ratings (P_R); 3) Scope 2 emissions (P_E). We include in the analysis also a standard mean-variance optimized portfolio P_O which plays the role of an actively managed portfolio built ignoring climate risk. The benchmark portfolio P_B is constructed using the components' market capitalization $MV_{i,t}$ and rebalanced according to quarterly cycles. We compute the portfolios' risk-return profile for all three available calendar cycles: Cycle 1 (January, April, July, and October), Cycle 2 (February, May, August, and November) and Cycle 3 (March, June, September, and December)[51]. Given the high volatility registered both by the markets and by the banking sector in the window

[51] MSCI indices are reviewed on the close of the last day of Cycle 2 and rebalanced in May and November, whereas Cycle 3 is used by Qontigo (EUROSTOXX) and S&P for their quarterly adjustments and scheduled rebalancing that come into effect after the close on the third Friday of the cycle months.

considered, this choice reflects the widest possible spectrum of outcomes. The benchmark weights $W_{i,t}^{B}$ for each of the *n* banks at the rebalancing time *t* are determined as:

$$W_{i,t}^{B} = \frac{MV_{i,t}}{\sum_{i=1}^{n} MV_{i,t}} \,. \tag{6}$$

The loss-adjusted portfolio P_L employs tweaked weights $W_{i,t}^{L}$, obtained by adding to $W_{i,t}^{B}$ the loss weight modifier $LMW_{i,t}$, computed as the difference between the average $\overline{MCRISKX\text{-}R_t}$ and individual $MCRISKX\text{-}R_{i,t}$ values:

$$W_{i,t}^{L} = W_{i,t}^{B} + LWM_{i,t} = W_{i,t}^{B} + \left(\overline{MCRISKX\text{-}R_t} - MCRISKX\text{-}R_{i,t}\right). \tag{7}$$

The rating-adjusted version P_R is tilted towards lenders with better E-ratings using the rating weight modifiers $RWM_{i,t}$:

$$W_{i,t}^{R} = W_{i,t}^{B} + RWM_{i,t} = W_{i,t}^{B} + \left(\frac{\overline{REVSCORE_t} - REVSCORE_{i,t}}{100}\right). \tag{8}$$

The emission-adjusted version P_E is adjusted to favor lighter Scope 2 GHG emitters using the emission weight modifiers $EWM_{i,t}$:

$$W_{i,t}^{E} = W_{i,t}^{B} + EWM_{i,t} = W_{i,t}^{B} + \left(\frac{\overline{SCOPE2_t} - SCOPE2_{i,t}}{100}\right). \tag{9}$$

For P_L, P_R and P_E, this simple rule allows banks showing 1) exposure to transition risk losses lower than the average; 2) better environmental rating than the peers; 3) lower Scope 2 GHG ratios to become overweight, whereas the ones with worse attributes become underweight[52]. Modified weights add to 1 by construction: at each rebalancing date the cap weighted benchmark P_B and the modified portfolios P_L, P_R and P_E are always fully invested, with no leverage employed. Stock purchases are funded by stock sales for the same consideration, and dividends are included in the return calculation but assumed to be distributed, not reinvested. These conditions apply to the optimized portfolio P_O too.

The modified weight formulas cab be improved by multiplying the modifiers by an aggressiveness[53] multiplier A_L, A_R and A_E. In this case the three equations would become:

$$W_{i,t}^{L} = W_{i,t}^{B} + A_L \cdot LWM_{i,t} \,. \tag{10}$$

$$W_{i,t}^{R} = W_{i,t}^{B} + A_R \cdot RWM_{i,t} \,. \tag{11}$$

$$W_{i,t}^{E} = W_{i,t}^{B} + A_E \cdot EWM_{i,t} \,. \tag{12}$$

The effect of A_L, A_R and A_E is linear with respect to the portfolios' excess returns vis-à-vis the benchmark. Their default value is 1: for values greater (lower) than the default, multipliers allow to increase (decrease) the tilt towards environmental robustness at the expense of greater (lower) tracking error. Moreover, they are useful for potential scaling needs: weight modifiers could assume values which are either too large or too small with respect to the portfolio holdings standard weights, requiring a multiplier to achieve the desired positioning.

All portfolios are dynamically adjusted and rebalanced at the close on the last date of each

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[52] At time t, if MCRISKX-R, E-ratings or Scope 2 GHG ratios were the same (or equal to zero) for all banks, the respective adjusted portfolio would be identical to the benchmark PB until the following rebalancing date.

[53] See Lee (2000) for an in-depth analysis of the selection of an optimal aggressiveness factor.

cycle when values for MCRISKX-R are available (they differ slightly depending on the region) to reflect shifts in weights. Benchmark P_B weights are adjusted only if there are changes in the share count generated by corporate actions[54] and buybacks, which apply to P_L, P_R and P_E too; however, test portfolios are further adjusted at each rebalancing date to reflect changes in the respective modifiers. Given that environmental ratings and emission estimates are refreshed only once a year, the relative overweight/underweight positions generated by $RWM_{i,t}$ and $EWM_{i,t}$ remain in place for four rebalancing periods. Conversely, $LWM_{i,t}$ can change every three months. Optimized portfolio P_O weights vary according to the model output and are refreshed at every rebalancing date. Contrary to all the other portfolios, P_O weights are unrelated to the market cap of the stocks and can go to zero if required by the algorithm.

4. Results

We present the results for the 3 EU quarterly cycles in Tables 11, 12 and 13:

Table 12: QC1_EU P_B, P_O, P_L, P_R, P_E Metrics.

QC1_EU	**BENCHMARK**	**OPTIMIZED**	**LOSS**	**RATING**	**SCOPE2**
Period Return%	-7.9230	-7.2017	-7.5994	-7.8511	-7.9078
Sharpe Ratio	0.1219	0.1478	0.1246	0.1226	0.1222
Sortino Ratio	0.1780	0.2254	0.1820	0.1789	0.1783
Information Ratio		0.2255	1.1054	0.6196	0.3498
Tracking Error		0.0712	0.0010	0.0004	0.0003
Upside Ratio		1.0745	1.0016	1.0002	1.0002
Downside Ratio		1.0503	0.9981	0.9994	1.0000
Capture Ratio		1.0231	1.0035	1.0007	1.0002

[54] Such as ISP issuing sizable new stock following the closing of the acquisition of another bank in the third quarter of 2020.

Table 13: QC2_EU P_B, P_O, P_L, P_R, P_E Metrics.

QC2_EU	BENCHMARK	OPTIMIZED	LOSS	RATING	SCOPE2
Period Return%	20.3737	24.8239	20.8089	20.4309	20.3824
Sharpe Ratio	0.3354	0.3861	0.3398	0.3360	0.3355
Sortino Ratio	0.4971	0.5743	0.5044	0.4981	0.4973
Information Ratio		0.0622	0.9358	0.3424	0.0673
Tracking Error		0.0942	0.0012	0.0003	0.0002
Upside Ratio		0.8957	1.0016	0.9998	0.9999
Downside Ratio		0.8202	0.9962	0.9990	0.9997
Capture Ratio		1.0920	1.0054	1.0008	1.0001

Table 14: QC3_EU P_B, P_O, P_L, P_R, P_E Metrics.

QC3_EU	BENCHMARK	OPTIMIZED	LOSS	RATING	SCOPE2
Period Return%	10.7614	18.9633	11.2587	10.8136	10.7687
Sharpe Ratio	0.2717	0.3510	0.2754	0.2721	0.2718
Sortino Ratio	0.3981	0.5038	0.4041	0.3987	0.3983
Information Ratio		0.4316	1.2519	0.3723	0.2441
Tracking Error		0.0872	0.0011	0.0004	0.0003
Upside Ratio		1.0967	1.0038	1.0004	1.0003
Downside Ratio		1.0120	0.9986	0.9998	1.0003
Capture Ratio		1.0836	1.0052	1.0005	1.0001

Hereafter follow Tables 14, 15 and 16, with the results for the US sample.

Table 15: QC1_US P_B, P_O, P_L, P_R, P_E Metrics.

QC1_US	BENCHMARK	OPTIMIZED	LOSS	RATING	SCOPE2
Period Return%	11.2229	4.0195	11.2036	11.2004	11.2243
Sharpe Ratio	0.2393	0.1617	0.2391	0.2391	0.2393
Sortino Ratio	0.3653	0.2311	0.3650	0.3654	0.3654
Information Ratio		-0.3917	-0.4074	0.0511	0.0891
Tracking Error		0.0667	0.0001	0.0010	0.0001
Upside Ratio		0.9384	0.9997	1.0001	1.0000
Downside Ratio		1.0356	1.0000	1.0004	1.0000
Capture Ratio		0.9062	0.9998	0.9997	1.0000

Table 16: QC2_US P_B, P_O, P_L, P_R, P_E Metrics.

QC2_US	BENCHMARK	OPTIMIZED	LOSS	RATING	SCOPE2
Period Return%	37.8967	32.0837	37.8764	37.9055	37.8851
Sharpe Ratio	0.4963	0.4511	0.4960	0.4961	0.4961
Sortino Ratio	0.8853	0.8203	0.8850	0.8856	0.8850
Information Ratio		-0.4026	-0.3199	0.0483	-0.1933
Tracking Error		0.0484	0.0001	0.0013	0.0001
Upside Ratio		0.9637	0.9997	1.0015	1.0000
Downside Ratio		1.0351	0.9999	1.0023	1.0002
Capture Ratio		0.9310	0.9998	0.9993	0.9998

Table 17: QC3_US P_B, P_O, P_L, P_R, P_E Metrics.

QC3_US	BENCHMARK	OPTIMIZED	LOSS	RATING	SCOPE2
Period Return%	36.8332	17.8403	36.8844	36.7977	36.8383
Sharpe Ratio	0.4751	0.3136	0.4754	0.4748	0.4751
Sortino Ratio	0.6784	0.4607	0.6791	0.6780	0.6785
Information Ratio		-0.6252	0.3624	-0.0278	0.2651
Tracking Error		0.1013	0.0004	0.0009	0.0001
Upside Ratio		0.7436	1.0006	1.0008	1.0002
Downside Ratio		0.8745	1.0003	1.0014	1.0003
Capture Ratio		0.8503	1.0003	0.9994	1.0000

The first tables for each region (Tables 11 and 14) refer to Quarterly Cycle 1 (QC1), starting in April 2019 and ending in April 2022. These two sets of data include the full effect of the geopolitical events in Eastern Europe, spanning over a considerably more turbulent last trading quarter and generating a markedly less favorable outcome for the recorded sector performance, especially for Eurozone lenders. Tables 12 and 15 refer to Quarterly Cycle 2 (QC2) and encompass the February 2019 to February 2022 period; Tables 13 and 16 present the results of Quarterly Cycle 3 (QC3), ranging from March 2019 to March 2022. All the results are calculated using starting weights determined by April 2019, February 2019 and March 2019 market capitalizations and weight modifiers, followed by twelve quarterly rebalancing actions. Aggressiveness factors have been kept at their default value. Optimized portfolio PO weights depend exclusively on the optimization algorithm[55], are adjusted regardless of market cap or climate factors and use a set of returns which starts in July 2011 and is updated adding new information at each rebalancing date.

We include the Sharpe Ratio[56] (SHR), the Sortino Ratio (SOR), Information Ratio (IR), Tracking Error (TE), Upside Ratio (UR), Downside Ratio (DR) and Capture Ratio (CR) statistics for all runs considered but, given the rules applied, we deem the IR to be the most relevant indicator to determine the effectiveness of the three weight modifiers in constructing a climate-tilted sectoral portfolio.

The Eurozone results are clear: P_L, the portfolio adopting $LWM_{i,t}$ derived from the loss exposure proxy MCRISKX-R, markedly overperforms, showing an IR close or above 1 across the three cycles. P_L SHR and SOR are also consistently better than P_B, and CR is always above one, while the TR is very limited. Both P_E and P_R offer a better risk profile than P_B, albeit they perform less well than P_L. In particular, the tracking error TE generated by P_E is material. P_O, generates the best overall returns but at the expense of a large 7% to 9% TE penalizing its IR. Figures 4 (QC1_EU), 5 (QC2_EU) and 6 (QC3 EU) present Eurozone excess return profiles.

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[55] We used MATLAB portfolio optimization package using a constant 1% risk-free rate given that short-term rates hovered close to zero until spring 2022 in both the Eurozone and the United States.

[56] Risk free rate: 1% p.a.

Figure 4: Eurozone QC1 Excess Returns (4/2019-4/2022).

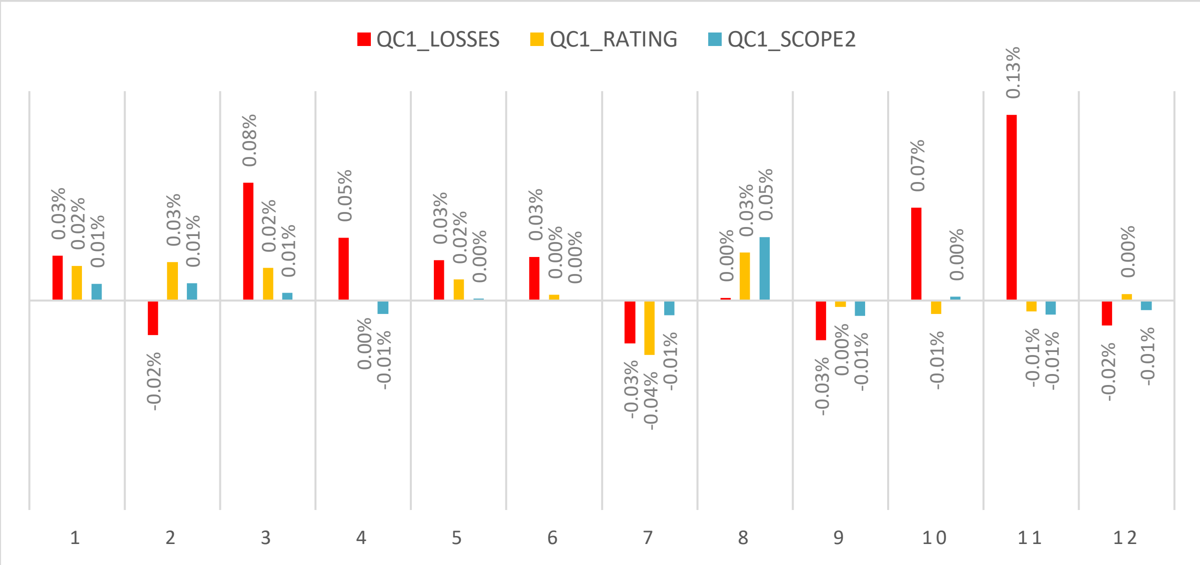


Figure 5: Eurozone QC2 Excess Returns (2/2019-2/2022).

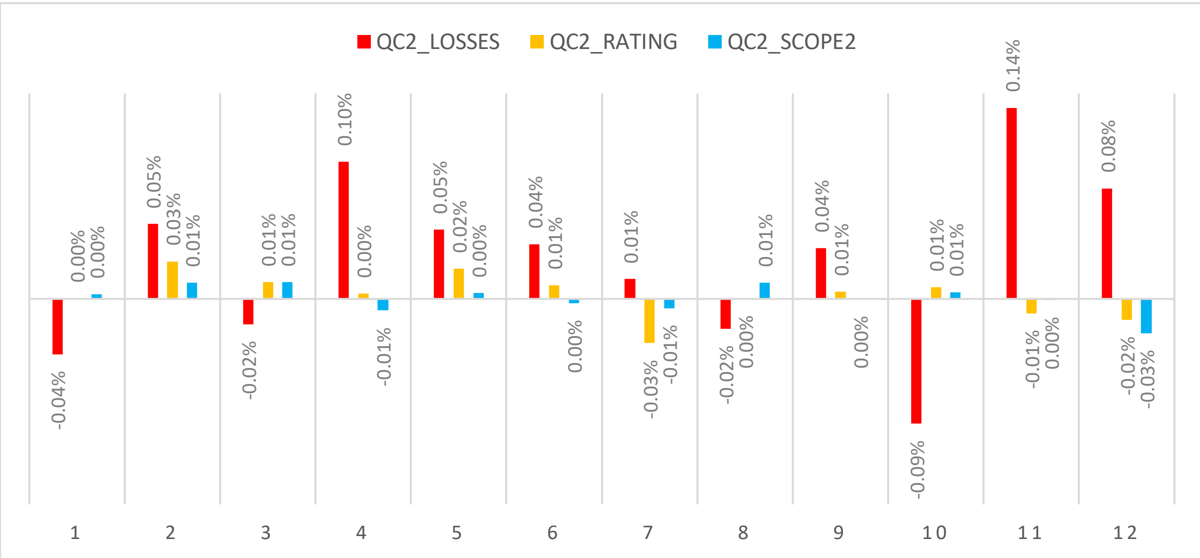
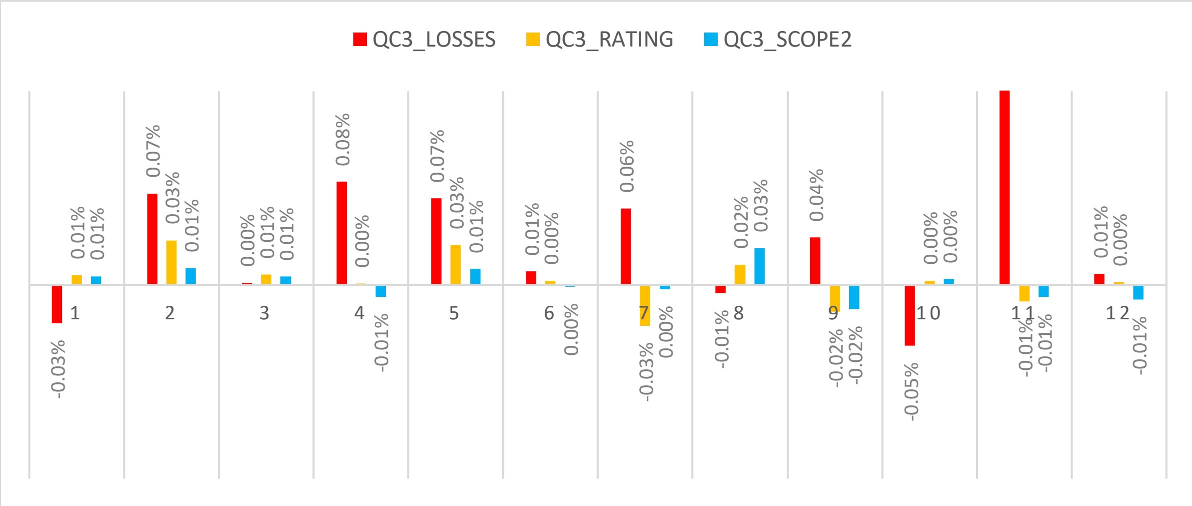


Figure 6: Eurozone QC3 Excess Returns (3/2019-3/2022).



The outcome for the North American sample is very different. None of the three metrics offers a consistent overperformance profile. PE and PR show a modestly positive IR 2 out of 3 times instead of PL's 1 out of 3. Furthermore, the same inconclusive pattern is repeated across the spectrum of indicators. Lastly, PO fails on all counts, generating consistently lower period returns coupled with the largest TE. Figures 7. 8 and 9 show US excess return profiles.

Figure 7: US QC1 Excess Returns (4/2019-4/2022).

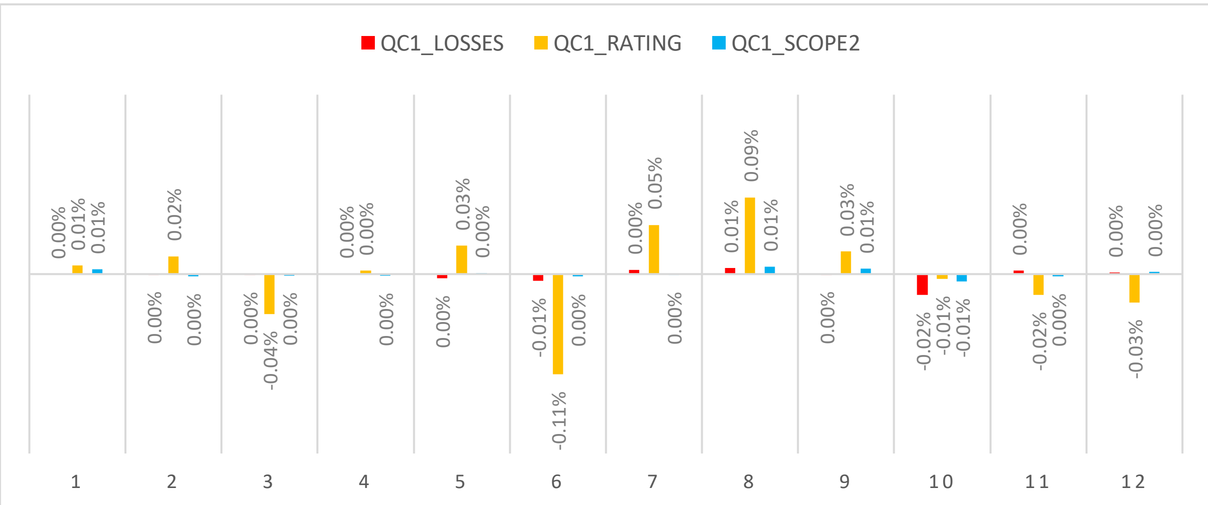


Figure 8: US QC2 Excess Returns (2/2019-2/2022).

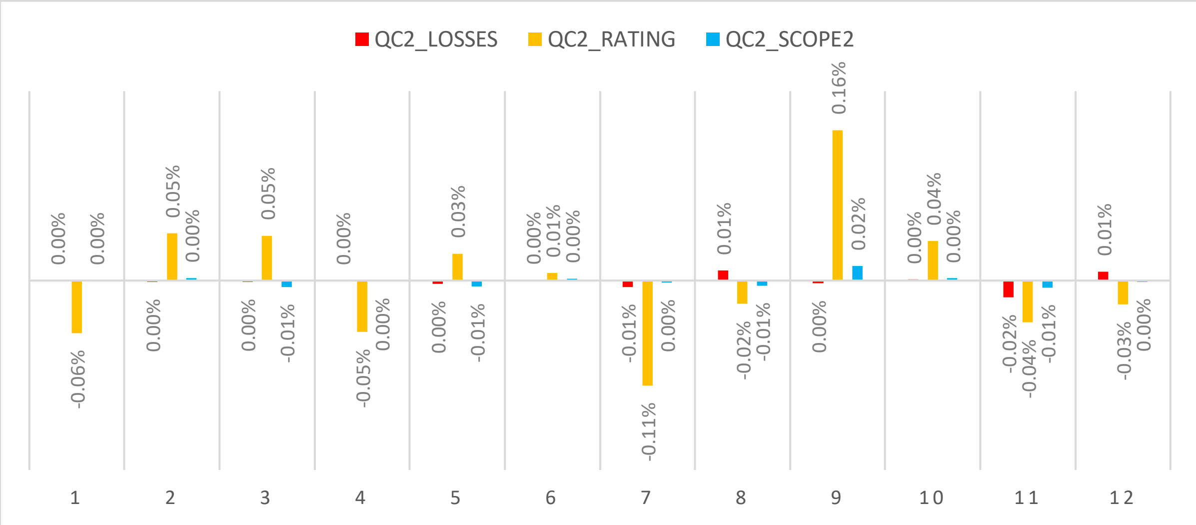
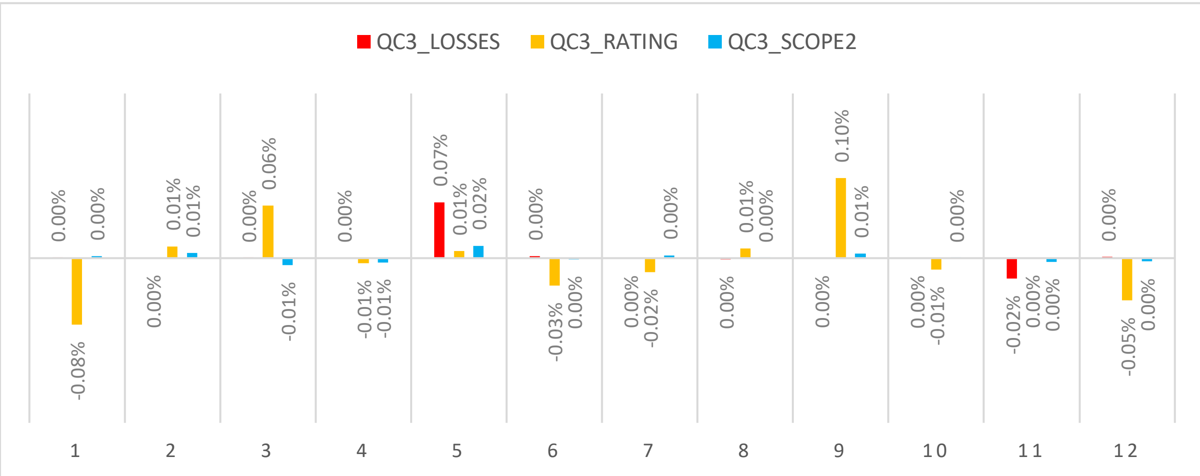


Figure 9: US QC3 Excess Returns (3/2019-3/2022).



In terms of transaction costs, we have estimated commissions for all portfolios applying current program trading rates[57] to the volume of trades exceeding the rebalancing flows required by the benchmark adjustments. We calculate a negligible impact (in few hundredths of a basis point) for the three adjusted portfolios, but a significantly higher impact for P_O.

[57] Commission rates currently range between 1 to 2 basis points (bps) on the value of the program.

5. Conclusions

Our aim was to identify green banks by comparing three climate risk metrics and testing their effectiveness in improving a financial portfolio robustness to climate shocks. We measured the greenness of a lender with respect to the average of its peers according to these parameters:

a) exposure to transition risk;

b) environmental E rating;

c) GHG footprint.

During a climate event the market should be inclined to recognize a premium for these qualities, with green lenders producing superior risk-adjusted returns. We applied this analysis to a sample of large banks operating in the Eurozone and in the USA during the 2019-2022 period, since this time window was characterized by reverse boom-bust dynamics in hydrocarbons markets which are reasonable to expect, in opposite order, given any future climate crisis. In our simulation we have analyzed the performance of three climate-tilted portfolios modified according to their respective relative climate risk metrics against a market capitalization-weighted benchmark and an optimized portfolio. For all the model portfolios we have simulated quarterly rebalancing adjustments, one for each of the three available calendar cycles.

For the Eurozone sample, our findings show that climate-tilted sectoral portfolios would have overperformed in terms of Information Ratio (IR), with minimal impact in terms of additional transaction costs. In particular, the transition risk modifier linked to climate risk losses would have consistently generated the best IR, close or above 1 for all three cycles. This result is confirmed by the Sharpe Ratio (SR) and Sortino Ratio (SOR) as well. Both the rating and the emission modifiers would have achieved modest, but positive, risk-adjusted overperformance too. The optimized portfolio would have offered the best absolute return and superior SR and SOR, but also the largest tracking error (TE) and, consequently, a poor IR.

Conversely, our findings for US banks are inconclusive: there was no modified portfolio constructed according to the abovementioned criteria able to show a constant overperformance over the benchmark across all rebalancing cycles. Rating and emission modifiers would have delivered better results just two out of three times, whereas the loss modifier, so successful with the Eurozone sample, in the US would have produced a positive IR only once. This pattern is confirmed also by disappointing SR and SOR metrics. The optimized portfolio in the US would have significantly underperformed, both in terms of absolute returns, TE and IR.

We are aware that this approach might draw criticisms: the effects of ESG criteria on portfolio construction is undoubtedly a very controversial topic. On the one hand, Horan et al. (2022) present an ESG framework that responds to the demands of investors concerned both with financial and non-financial gains, thus balancing performance and environmental (or broad ESG) considerations when performing asset allocation decisions: by construction, ESG investing is not designed to increase portfolio returns. On the other hand, Edmans (2023) suggests that ESG factors, if unanticipated, should lead to superior returns. Hence, if environmental issues are truly relevant, during an unexpected climate event green banks should outperform, leading to the possibility to construct sectoral portfolios robust to climate transition risk.

Our results show that in the Eurozone green banks stock selection is feasible: loss-exposure proxies, such as MCRISKX-R, can be used to effectively improve the performance of a sectoral portfolio with respect to a market cap benchmark. Also, E-rating and Scope 2 GHG adjusted portfolio can be used, albeit less efficiently, as alternative measures to construct a climate-robust core holding. The use of aggressiveness multipliers larger than the unit one used for the simulation would further stress the climate-robustness of portfolios, albeit at the expense of increased tracking error.

However, the findings for the North American banking sector could have been more decisive. If E-ratings and Scope 2 emissions have shown some propensity to work in identifying green lenders, their performance is not consistent. MCRISKX-R does even worse. Why is this the case? Are US banks considerably less exposed to stranded assets than their Eurozone peers? We suspect that this apparent lack of climate risk incidence on US bank returns is closely related to differences in:

a) regulatory frameworks;
b) central bank policies;
c) accounting standards.

In November 2022 the EU approved important legislation on sustainability reporting, the Corporate Sustainability Reporting Directive (CSRD), and in July 2023 the European Commission officially adopted the European Sustainability Reporting Standards (ESRS), which includes specific indicators concerning GHG emissions. Both the CSRD and the ESRS are starting to exert significant effects on the behavior of a rapidly growing number of companies and lenders alike: the European Market and Securities Authority (ESMA, 2023) estimates that by 2029 up to 50 thousand large and mid-sized enterprises, listed and not, will be required to disclose their environmental footprint in compliance with the CSRD following the ESRS. Given the scope of this effort and the need to provide detailed upstream and downstream emission data to fully comply with the normative, it is likely that most of the

European supply chain will be involved. Hence, if the current regulatory focus on climate issues persists, going forward Eurozone banks should be able to identify with greater accuracy the greenness of a borrower and deploy their capital accordingly. Conversely, in the US there exists no comparable legislation. Moreover, efforts by the Securities and Exchange Commission (SEC) to extend climate-related disclosures (SEC, 2023) are sometimes at odds with political initiatives by some individual States determined to reduce the weight of ESG parameters in formulating investment decisions.

Marked differences can also be found between the behavior of the two central banks, the ECB and the FED. In the Eurozone, the ECB has taken a proactive role in preventing climate risk, as demonstrated by the launch in 2022 of the first region-wide climate stress test. Furthermore, both the Presidency and the Supervisory Board use every chance they get to relentlessly steer banks towards a greener credit framework, with both words and actions. The FED, on the contrary, is just in the preliminary stages of arranging a pilot climate exercise with just six banks and, so far, it has avoided pushing explicitly towards greener bank lending. We think that the market has taken notice, likely downgrading the relevance of any climate-related risk signal affecting US lenders.

There are also accounting issues at work. During the Spring 2023 four mid-sized US banks had to be either resolved or liquidated in the space of a few weeks. These events exposed the risks of excessively relying on held-to-maturity (HTM) accounting: following the quick rise of interest rates, these lenders were carrying considerable losses related to their bond portfolios which, albeit not shown in their accounts, ultimately put their solvency in doubt and caused deposit runs. The application of HTM accounting to certain assets allows banks to carry them at par value regardless of their price, making balance sheet aggregates less transparent. In this instance, long fixed income positions were valued significantly higher than their mark to market (MTM) value. This scenario would not be applicable to Eurozone banks: currently they use mostly MTM, with HTM restricted to a significantly smaller portion of their assets. The 2023 mini-crisis could also suggest that SRISK, MSRISK and MCRISKX-R calculations, which normally take into account a capital buffer requirement of 8% for lenders adopting GAAP and of 5.5% for banks using IFRS, might not fully reflect the actual gap between the two accounting practices[58].

The combination of all these factors makes it hard to consistently identify the greenest US banks using the metrics selected. This situation might change if regulators and markets were to push for the development of a common, homogeneous and comparable indirect Scope 3 emissions reporting protocol, which could lead to the creation of powerful metrics to assess the greenness of a bank. This conclusion is suggested by the fact that Scope 3 emissions are the only way to fully account for the direct and indirect GHG footprint of a business and assess its impact on climate change. Unfortunately, it looks like this data won't be available for a long time. Until then, a mix of loss proxies, such as MCRISKX-R, environmental ratings, and Scope 2 emissions disclosures, might be the only viable, if imperfect, alternative to perform this type of analysis.

[58] See Engle, Jondeau and Rockinger (2015) for further analysis of this issue.

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Appendix

Appendix – Chapter 1

A1.1. Fixed Betas statistics (STATA)

Bivariate static model on the full sample.

BNP	SXXE_r	CFE_r	_cons
b	1.46099	0.15336	-0.00002
se	0.04187	0.04474	0.00028
t	34.89541	3.42788	-0.06302
p-value	0.00000	0.00062	0.94975
lower	1.37889	0.06563	-0.00056
upper	1.54308	0.24108	0.00053
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

ACA	SXXE_r	CFE_r	_cons
b	1.45905	0.16318	-0.00005
se	0.03897	0.03422	0.00030
t	37.44283	4.76922	-0.18056
p-value	0.00000	0.00000	0.85672
lower	1.38264	0.09609	-0.00064
upper	1.53546	0.23028	0.00053
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

GLE	SXXE_r	CFE_r	_cons
b	1.69900	0.20445	-0.00029
se	0.04790	0.04335	0.00033
t	35.46726	4.71654	-0.86841
p-value	0.00000	0.00000	0.38524
lower	1.60507	0.11945	-0.00093
upper	1.79293	0.28945	0.00036
Df	2732	2732	2732
Crit	1.96083	1.96083	1.96083

SAN	SXXE_r	CFE_r	_cons
b	1.27862	0.33368	-0.00022
se	0.03153	0.03690	0.00026
t	40.55546	9.04218	-0.82669
p-value	0.00000	0.00000	0.40848
lower	1.21680	0.26132	-0.00073
upper	1.34044	0.40604	0.00030
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

BBVA	SXXE_r	CFE_r	_cons
b	1.27960	0.25728	-0.00009
se	0.03046	0.04022	0.00027
t	42.00601	6.39633	-0.31934
p-value	0.00000	0.00000	0.74949
lower	1.21987	0.17841	-0.00063
upper	1.33933	0.33615	0.00045
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

INGA	SXXE_r	CFE_r	_cons
b	1.53191	0.16586	-0.00005
se	0.03467	0.03573	0.00027
t	44.18231	4.64278	-0.19894
p-value	0.00000	0.00000	0.84232
lower	1.46393	0.09581	-0.00059
upper	1.59990	0.23591	0.00048
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

DBK	SXXE_r	CFE_r	_cons
b	1.49975	0.06971	-0.00063
se	0.03624	0.03644	0.00033
t	41.38372	1.91318	-1.89078
p-value	0.00000	0.05583	0.05876
lower	1.42869	-0.00174	-0.00128
upper	1.57081	0.14115	0.00002
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

CBK	SXXE_r	CFE_r	_cons
b	1.52606	0.12928	-0.00064
se	0.04171	0.04939	0.00042
t	36.58600	2.61737	-1.54020
p-value	0.00000	0.00891	0.12363
lower	1.44427	0.03243	-0.00145
upper	1.60785	0.22613	0.00017
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

UCG	SXXE_r	CFE_r	_cons
b	1.61249	0.24483	-0.00071
se	0.05053	0.04295	0.00043
t	31.91035	5.70078	-1.66706
p-value	0.00000	0.00000	0.09562
lower	1.51341	0.16062	-0.00155
upper	1.71158	0.32905	0.00013
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

ISP	SXXE_r	CFE_r	_cons
b	1.50670	0.15618	-0.00002
se	0.04783	0.03259	0.00031
t	31.49926	4.79207	-0.05962
p-value	0.00000	0.00000	0.95246
lower	1.41291	0.09228	-0.00062
upper	1.60049	0.22009	0.00059
df	2732	2732	2732
crit	1.96083	1.96083	1.96083

A1.2. GJR-GARCH outputs (OxMetrics G@RCH)

Univariate GJR-GARCH (1,1) output for individual banks with SXXE and CFE as regressors. Robust standard errors (Sandwich). 2735 observations and 7 parameters each.

BNP	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	-0.01	0.994
SXXE_r (M)	1.318	0.042	31.11	0.000
CFE_r (M)	0.169	0.031	5.51	0.000
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.126			
Kurtosis (Y)	10.562			
Log Likelihood	8145.9			

ACA	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	0.33	0.743
SXXE_r (M)	1.336	0.036	37.22	0.000
CFE_r (M)	0.187	0.033	5.59	0.000
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.234			
Kurtosis (Y)	10.336			
Log Likelihood	7713.6			

GLE	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	1.43	0.153
SXXE_r (M)	1.492	0.050	29.74	0.000
CFE_r (M)	0.180	0.035	5.18	0.000
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.454			
Kurtosis (Y)	11.702			
Log Likelihood	7581.5			

SAN	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	0.40	0.686
SXXE_r (M)	1.286	0.038	34.24	0.000
CFE_r (M)	0.274	0.057	4.76	0.000
Mean (Y)	0.000			
Variance (Y)	0.000			
Skewness (Y)	-0.488			
Kurtosis (Y)	12.173			
Log Likelihood	8038.6			

BBVA	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	0.10	0.918
SXXE_r (M)	1.247	0.033	38.29	0.000
CFE_r (M)	0.181	0.030	5.93	0.000
Mean (Y)	0.000			
Variance (Y)	0.000			
Skewness (Y)	-0.204			
Kurtosis (Y)	-0.204			
Log Likelihood	7994.6			

INGA	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	0.01	0.994
SXXE_r (M)	1.376	0.039	35.34	0.000
CFE_r (M)	0.100	0.033	3.07	0.002
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.410			
Kurtosis (Y)	11.030			
Log Likelihood	7994.4			

DBK	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	-0.76	0.449
SXXE_r (M)	1.440	0.038	38.35	0.000
CFE_r (M)	0.007	0.035	0.20	0.841
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.234			
Kurtosis (Y)	7.894			
Log Likelihood	7382.7			

CBK	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	0.05	0.962
SXXE_r (M)	1.414	0.051	27.98	0.000
CFE_r (M)	0.061	0.047	1.30	0.195
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.205			
Kurtosis (Y)	8.121			
Log Likelihood	6809.8			

UCG	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	0.91	0.363
SXXE_r (M)	1.526	0.051	29.89	0.000
CFE_r (M)	0.240	0.043	5.63	0.000
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.490			
Kurtosis (Y)	9.277			
Log Likelihood	6915.7			

ISP	Coefficient	Std.Error	t-value	p-value
Constant(M)	0.000	0.000	0.65	0.515
SXXE_r (M)	1.316	0.041	32.30	0.000
CFE_r (M)	0.216	0.027	8.00	0.000
Mean (Y)	0.000			
Variance (Y)	0.001			
Skewness (Y)	-0.820			
Kurtosis (Y)	12.188			
Log Likelihood	7737.4			

A1.3. Dynamic Conditional Correlations model outputs (OxMetrics G@RCH)

Results on the full sample with SXXE and CFE as regressors using DCC, DCC-A (cDCC) and DCC-TT. Robust standard errors (Sandwich).

DCC	Coefficient	Std.Error	t-value	p-value
Alpha	0.006	0.002	3.43	0.001
Beta	0.981	0.008	122.70	0.000
Log Likelihood	82807.5			

DCC-A (cDCC)	Coefficient	Std.Error	t-value	p-value
Alpha	0.006	0.002	3.50	0.001
Beta	0.981	0.008	125.50	0.000
Log Likelihood	82811.1			

DCC-TT	Coefficient	Std.Error	t-value	p-value
Alpha	0.005	0.002	2.61	0.009
Beta	0.988	0.006	155.90	0.000
Log Likelihood	82792.8			

A1.4. DCC and DCC-A Correlation Targeting Matrices

Full sample correlation targeting output. 2735 observations, 117 parameters, 10 series. DCC and DCC-TT outputs are identical.

DCC	BNP	ACA	GLE	SAN	BBVA	INGA	DBK	CBK	UCG	ISP
BNP	1.000	0.604	0.684	0.487	0.490	0.516	0.463	0.458	0.477	0.471
ACA	0.604	1.000	0.629	0.418	0.435	0.485	0.422	0.457	0.441	0.432
GLE	0.684	0.629	1.000	0.459	0.473	0.514	0.477	0.497	0.487	0.465
SAN	0.487	0.418	0.459	1.000	0.690	0.352	0.365	0.373	0.430	0.396
BBVA	0.490	0.435	0.473	0.690	1.000	0.369	0.350	0.372	0.426	0.400
INGA	0.516	0.485	0.514	0.352	0.369	1.000	0.403	0.440	0.378	0.384
DBK	0.463	0.422	0.477	0.365	0.350	0.403	1.000	0.542	0.366	0.319
CBK	0.458	0.457	0.497	0.373	0.372	0.440	0.542	1.000	0.427	0.390
UCG	0.477	0.441	0.487	0.430	0.426	0.378	0.366	0.427	1.000	0.651
ISP	0.471	0.432	0.465	0.396	0.400	0.384	0.319	0.390	0.651	1.000

DCC-A	BNP	ACA	GLE	SAN	BBVA	INGA	DBK	CBK	UCG	ISP
BNP	1.000	0.611	0.689	0.490	0.491	0.519	0.462	0.460	0.479	0.471
ACA	0.611	1.000	0.636	0.417	0.434	0.485	0.422	0.458	0.442	0.434
GLE	0.689	0.636	1.000	0.464	0.473	0.519	0.477	0.498	0.490	0.466
SAN	0.490	0.417	0.464	1.000	0.690	0.353	0.367	0.374	0.431	0.394
BBVA	0.491	0.434	0.473	0.690	1.000	0.367	0.349	0.370	0.425	0.398
INGA	0.519	0.485	0.519	0.353	0.367	1.000	0.404	0.442	0.378	0.384
DBK	0.462	0.422	0.477	0.367	0.349	0.404	1.000	0.545	0.370	0.321
CBK	0.460	0.458	0.498	0.374	0.370	0.442	0.545	1.000	0.428	0.390
UCG	0.479	0.442	0.490	0.431	0.425	0.378	0.370	0.428	1.000	0.655
ISP	0.471	0.434	0.466	0.394	0.398	0.384	0.321	0.390	0.655	1.000

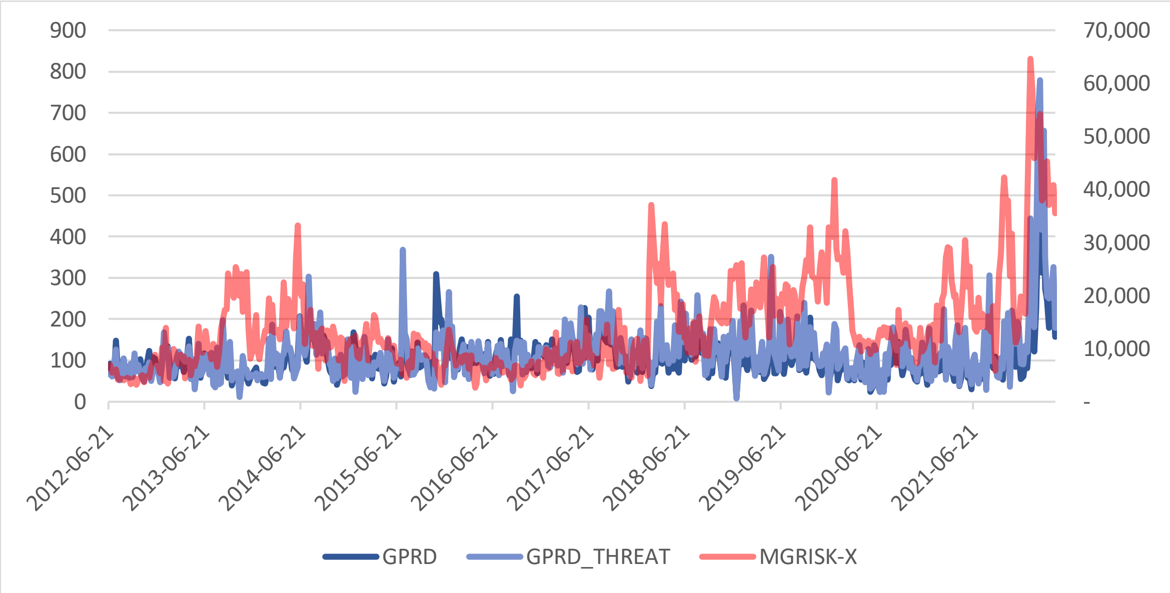
A1.5. Engle and Sheppard dynamic correlation test

Lags: 5 and 10

	E-S test	p-value
Lag: 5	60.169	0.000
Lag:10	71.584	0.000

Appendix – Chapter 2

A2.1. GPRD, THREATS indices and MGRISK-X (right scale)

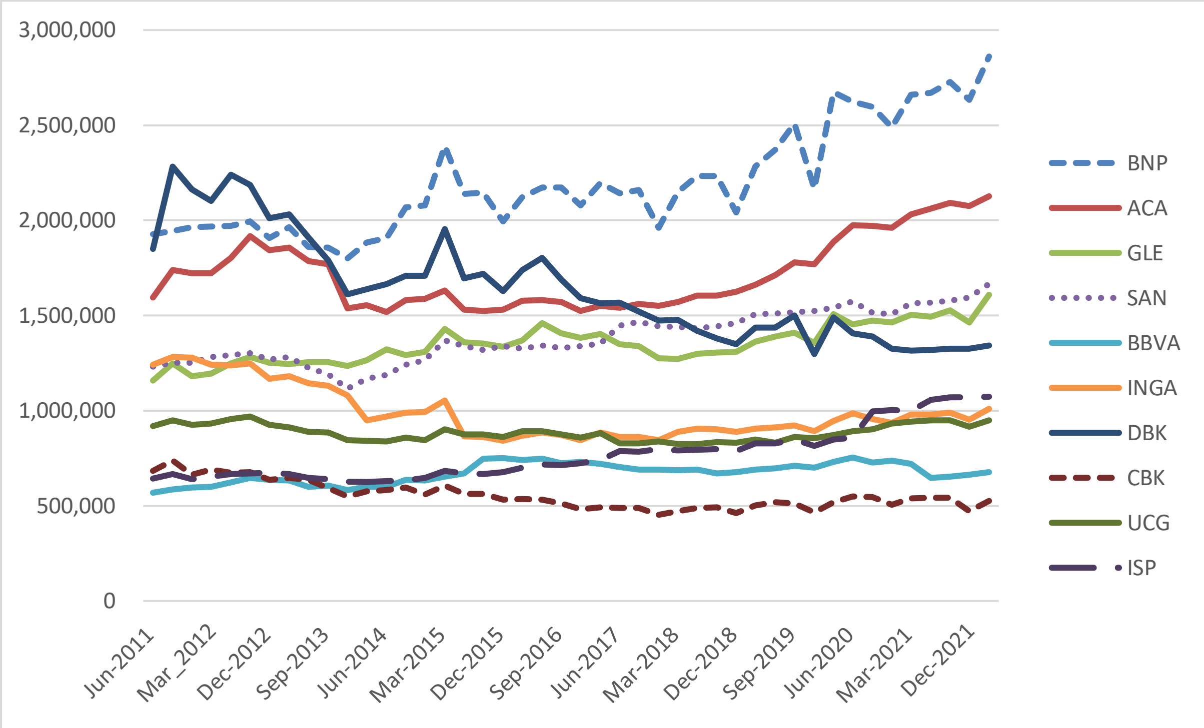


Correlation output (STATA 16.1)

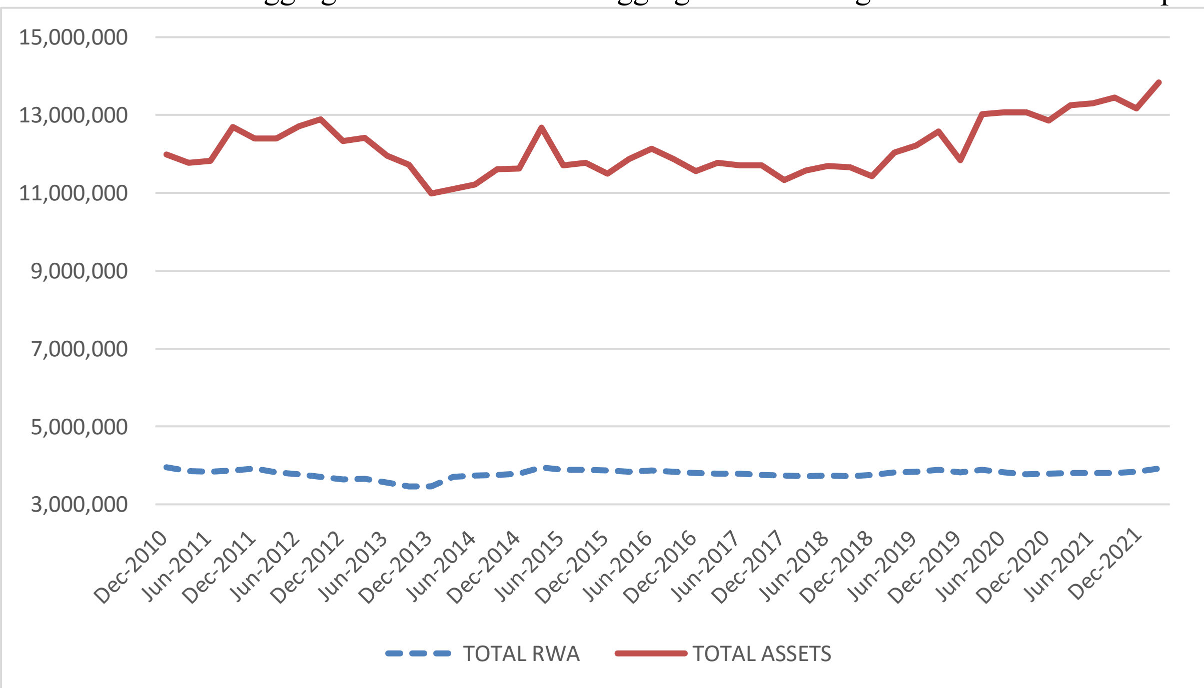
	GPRD	THREATS	MGRISK-X
GPRD	1		
THREATS	0.8980***	1	
MGRISK-X	0.3043***	0.4560***	1

Data downloaded from https://www.matteoiacoviello.com/gpr.htm on November 3, 2022.

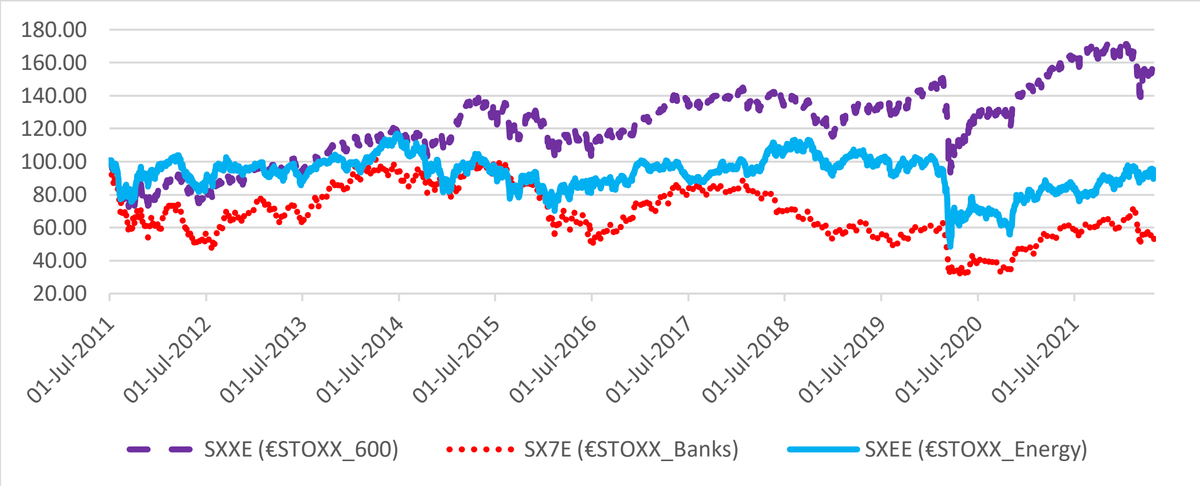
A2.2. Evolution of Total Assets (TA) for the selected sample



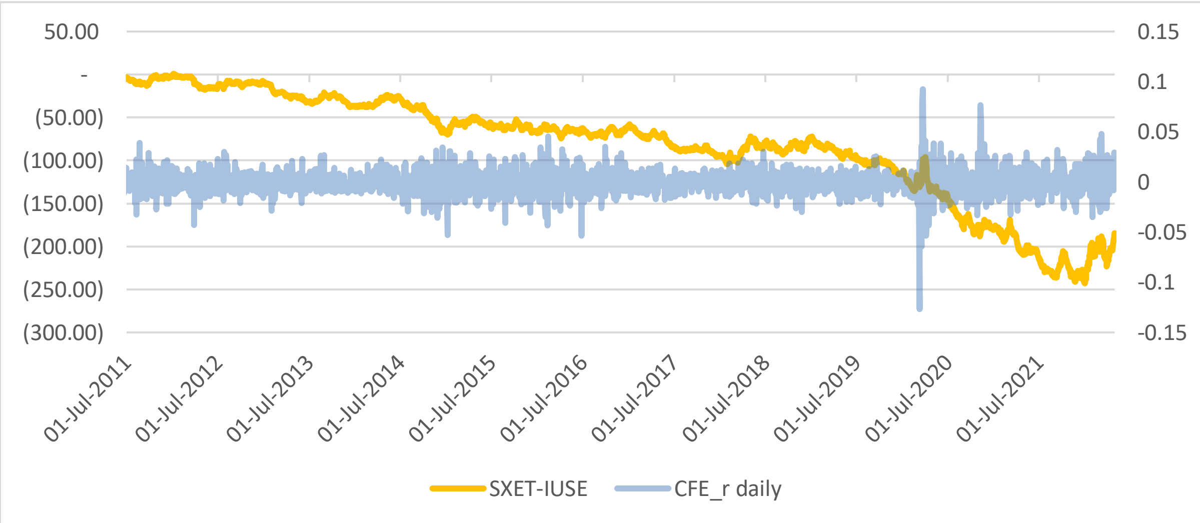
A2.3. Evolution of aggregate Total Assets and aggregate Risk Weighted assets for the sample



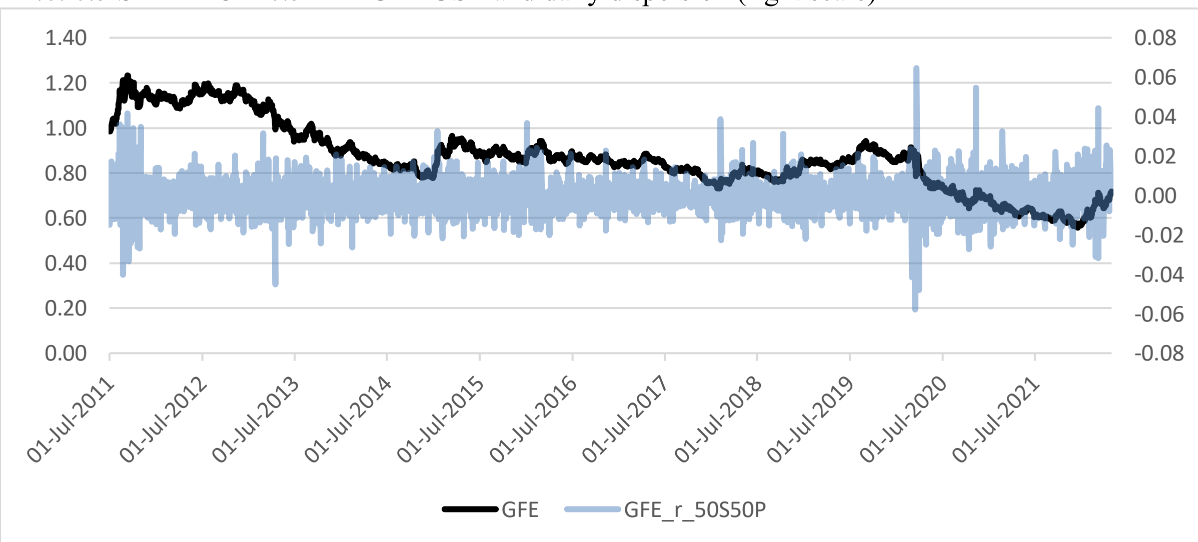
A2.4. SXXE vs SX7E vs SXEE, Q3/2021-Q2/2022



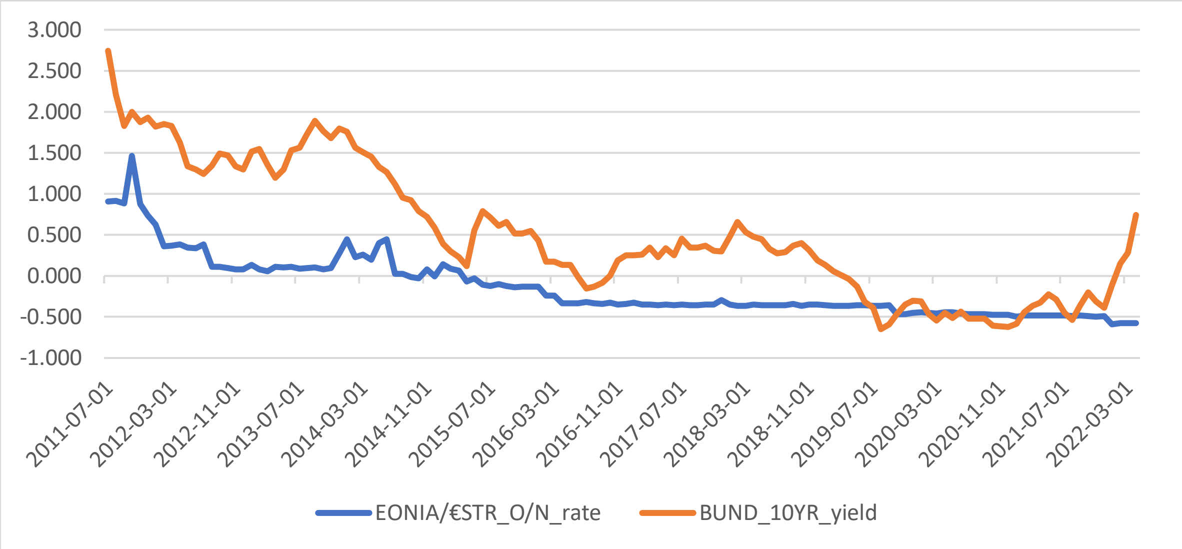
A2.5. SXET – IUSE and daily dispersion (right scale)



A2.6. 0.5 SXRARO + 0.5 PHAU – IUSE and daily dispersion (right scale)



A2.7. Eurozone interest rates, 2011Q3-2022Q1A2. Eurozone interest rates, 2011Q3-2022Q1



A2.8.1. Tse test on the entire sample (OxMetrics 8.2)

LM Test for Constant Correlation of Tse (2000)

LMC: 38.0318 [0.0000000]

P-value in brackets. LMC~X²(N*(N-1)/2)) under H0: CCC model, with N=#series

A2.8.2. Engle-Sheppard test for dynamic correlation (OxMetrics 8.2)

E-S Test(5) = 70.3061 [0.0000000]

E-S Test(10) = 116.544 [0.0000000]

P-values in brackets. E-S Test(j)~X²(j+1) under H0: CCC model

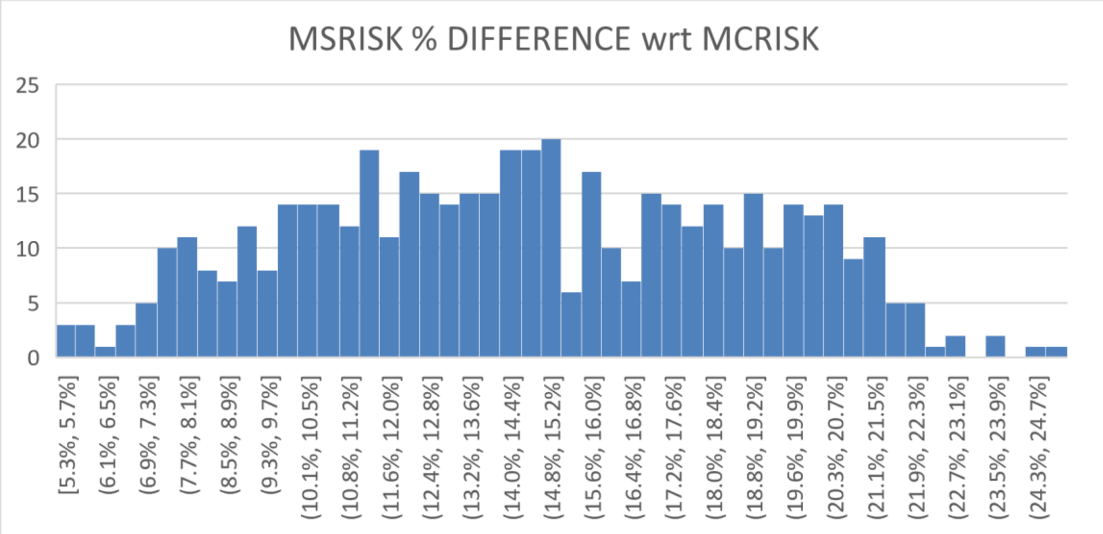
A2.9. Full-sample CCC-DCC comparison (OxMetrics 8.2)

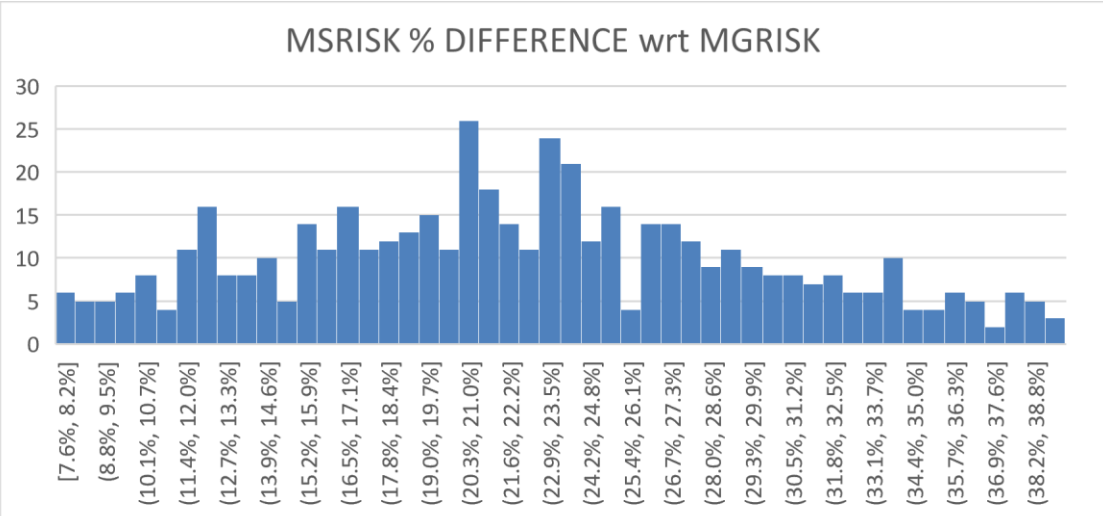
Model	T	p	log-likelihood	SC	HQ	AIC
MG@RCH(1)	2735	3	26970.570	-19.714	-19.718	-19.720
MG@RCH(2)	2735	5	27078.285	-19.787<	-19.794<	-19.798<

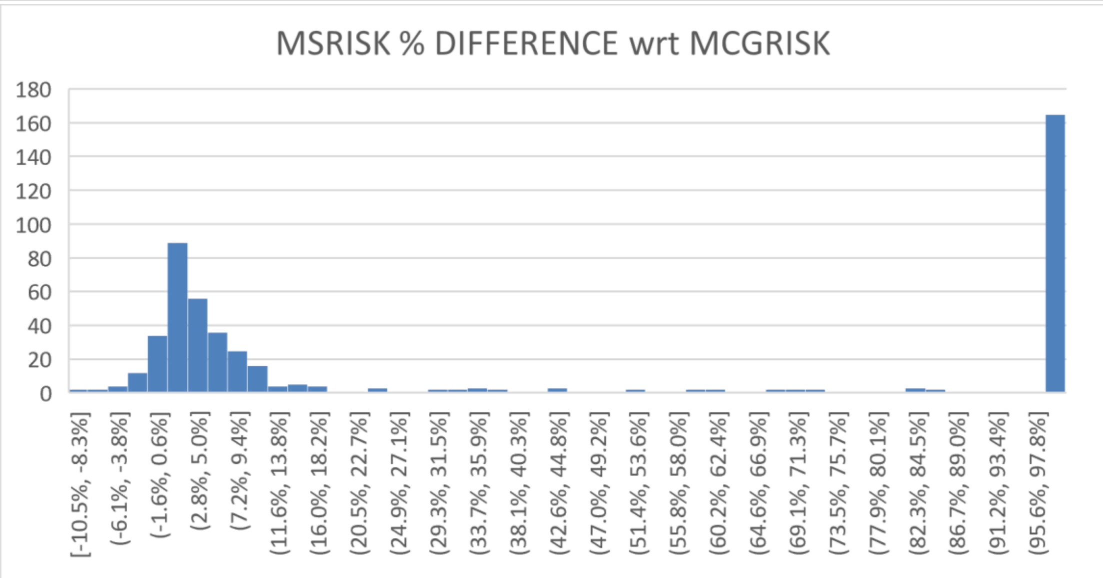
A2.10. Excluded dates (MM/DD/YYYY)

8/15/2011, 5/1/2012, 8/15/2012, 12/24/2012, 12/31/2012, 5/1/2013, 8/15/2013, 12/24/2013, 12/26/2013, 12/31/2013, 5/1/2014, 8/15/2014, 10/3/2014, 12/24/2014, 12/26/2014, 12/31/2014, 5/1/2015, 5/25/2015, 12/24/2015, 12/31/2015, 5/16/2016, 8/15/2016, 10/3/2016, 12/26/2016, 5/1/2017, 6/5/2017, 8/15/2017, 10/3/2017, 10/31/2017, 5/1/2018, 5/21/2018, 8/15/2018, 10/3/2018, 12/24/2018, 12/31/2018, 5/1/2019, 6/10/2019, 8/15/2019, 10/3/2019, 12/24/2019, 12/31/2019, 5/1/2020, 6/1/2020, 12/24/2020, 12/31/2020, 5/24/2021, 12/24/2021, 12/31/2021.

A2.11. *MSRISK$_t$* percentage difference with respect to *MCRISK$_t$*, *MGRISK$_t$*, *MCGRISK$_t$*







Appendix – Chapter 3

A3.1. EU banks ESG combined ratings – Refinitiv.

	BNP	ACA	GLE	SAN	BBVA	INGA	DBK	CBK	UCG	ISP
2010	B+	B-	B	A-	A-	A-	C+	B	B-	A-
2011	B-	B-	A-	B	A	B-	C+	B	B	A-
2012	A-	B+	B-	B	A	B	C+	B	A-	B
2013	B-	B+	B-	A-	A	C+	C+	B	A	B+
2014	B-	B	B	B	A	B+	C+	B+	A-	B+
2015	B-	C+	A	B+	A	B+	C+	C+	A	A-
2016	A	C	B-	A-	A	A-	C	C+	B+	A-
2017	B-	B+	B-	B+	A-	B+	C	B-	B	B+
2018	A-	B	B-	B+	A	B+	C	B+	A	A-
2019	B-	B	A-	B	B-	B+	C+	C+	B-	C+
2020	B	B	B-	B+	B	A-	C+	B-	A	B+
2021	B+	B-	B-	B-	B	A-	C+	A-	B	B+

A3.2. US banks ESG combined ratings – Refinitiv.

	BAC	C	JPM	WFC	USB	TFC	PNC	COF	BK	MTB
2010	C	C+	C	C	B-	C-	B-	C+	C	C-
2011	C	C	C	C	B-	C	B+	B-	C	C
2012	C	C	C	C	B-	C-	B	C-	B-	C
2013	C	C	C	C	C+	C-	C+	C-	C	C-
2014	C-	C	C	C	C-	C	B+	B-	B	C
2015	C	C+	C	C+	C+	C+	B+	B+	C+	C+
2016	C	C+	C+	C	B-	B-	A-	B+	B	C+
2017	C+	C+	C+	C+	B-	B-	A-	B+	B+	C+
2018	C+	C+	C	C+	B-	B	A-	A-	B	C+
2019	C+	C+	C	C+	B-	B	B+	B-	B	C+
2020	C+	B-	C+	C	C-	B-	A-	A-	B-	B
2021	C+	B-	C+	B	C	B	B	B-	C+	B-