An Assessment of Banks' Capital Adequacy Add-On Charge Arising from Climate Transition Risk

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Abstract

As climate risk is progressively turning out to be a financial risk, this paper aims to explore how to incorporate it into credit risk portfolio models. The paper focuses on computing the add-on charge that banks should consider to adequate their capital to the threat deriving from the potential financial loss caused by the climate transition risk, and on comparing it with the add-on charge that takes merely credit risk into consideration. Particularly, the analysis focuses on computing the credit risk add-on charge and the climate transition add-on charge for a portfolio split into two differently rated bonds buckets (an AAA-A rated bonds bucket and a BBB-B rated bonds bucket) under GCAM and WITCH integrated assessment models and the StrPol-450 climate policy addressing the GDP MER forward-looking annual average growth in North America and Europe. Climate transition risk is computed as the % change in the forward-looking GDP MER annual average growth on a decade-to-decade base setting 2020 as the base year. The outcomes show that, as expected, the add-on charge considering the climate transition risk is higher than the one originating from the credit risk under both integrated assessment models and in both regions.

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1 Executive Summary

Climate change constitutes a considerable financial risk affecting the financial sector through several channels. Therefore, financial institutions that own portfolios of instruments strongly exposed to climate risk should seriously start incorporating it in their credit risk models. However, very few studies develop theoretical models addressing this necessity.

This paper is aimed at filling the gap existing in the literature by exploring how to incorporate climate risk into portfolio models of credit risk. Specifically, the paper focuses on climate transition risk and the add-on charge arising from it. The paper hypothesizes that the granularity add-on charge deriving from climate transition risk is higher than the one that considers only credit risk.

To test the above-mentioned hypothesis, the paper retrieves the theoretical framework from a model developed by Gordy (2003) for the computation of the granularity add-on charge under the VaR framework and an actuarial definition of loss setting , which is the loss that occurs only in the case of default, and from a model developed by Battiston and Monasterolo (2020) that focuses on the computation of climate transition risk and on the way to incorporate it at portfolio level.

Consequently, the paper applies the above-mentioned methodology to a portfolio of corporate bonds divided into two differently-rated buckets (an AAA-A-rated corporate bonds bucket and a BBB-B-rated corporate bonds bucket). Specifically, the paper firstly deals with the baseline scenario, under which the add-on originating from credit risk is computed both for the AAA-A rated bonds bucket and the BBB-B rated bonds bucket. Secondly, it focuses on the StrPol-450 climate policy scenario (within the WITCH and GCAM integrated assessment models) addressing North America and Europe, under which, the climate transition risk is computed as the % change in the forward-looking GDP MER annual average growth setting 2020 as a base year. The climate transition % change is eventually used to compute the climate-related granularity add-on for both corporate bond buckets.

The results confirm the hypothesis. Banks and financial institutions should consider a higher add-on charge to mitigate the impact of climate transition risk on their portfolios.

Ultimately, the paper underlines its pitfalls. The major issue is the estimation of the climate transition risk. The paper computes it as the % change in the GDP MER annual average growth under a specific climate policy and two specific integrated assessment models. However, climate transition risk should be estimated more precisely, taking into consideration portfolio instruments' exposure to climate transition risk. Moreover, instead of considering only the actuarial definition of loss, the paper could have focused also on the loss that arises from an obligor's instrument downgrading. Additionally, since the literature on which the paper relies mainly uses a Value-at-Risk paradigm to address the climate transition risk threat, the paper encourages developing a climate transition risk model through other metrics such as the expected shortfall, which overcomes VaR limitations. Ultimately, as the analysis' findings show, while climate transition risk is perfectly reflected in climate add-on charges, VaR does not capture such threat. Therefore, further research should be conducted in order to overcome this flaw.

2 Introduction

Climate change is increasingly becoming an irreversible threat to humankind. It is expected to cause the extinction of species, harm infrastructures, and produce shortages of primary resources such as food, water, and raw materials.

Therefore, climate change, which is expected to generate several business slowdowns and collapses, constitutes a considerable financial risk affecting the financial sector through several channels. Climate change can be either a physical risk or a transition risk. The former is related to all the weather extreme events to which firms' assets are exposed; the latter is related to the inability of firms to foresee and quickly adapt to the introduction of new climate change policies aimed at setting regulatory standards to drive the carbon economy toward a more sustainable one. Both climate - physical risk and climate- transition risk, thus, constitute a threat to financial institutions that hold portfolios of instruments strongly exposed to climate change. Financial institutions should, thereof, be willing to incorporate climate risk in their credit risk models. However, it appears that the climate change threat is still underestimated by the financial sector, and financial regulations do not address it appropriately.

This paper is, therefore, aimed at exploring how to incorporate climate risk into portfolio models of credit risk. Specifically, the paper focuses on climate transition risk, and the add-on charge deriving from less than perfectly diversified idiosyncratic risk originating from it.

The paper is structured as follows: first, it explores the climate-risk-related literature explaining the difference between climate physical risk and climate transition risk, the impact of the two risks on the economy, and, specifically, on the financial sector. Moreover, the paper investigates the studies conducted on the subject, with a specific focus on models that try to handle climate transition risk as a financial risk and try to include it in portfolio management dynamics.

Secondly, the paper describes the theoretical models supporting its analysis. The paper specifically relies on a model, developed by Gordy (2003) for the computation of the granularity add-on charge capturing, not only the credit risk component of returns, but also the undiversified idiosyncratic component under the Value-at-Risk framework and the actuarial loss setting (entailing a loss only in the case of default), and on a model, developed by Battiston and Monasterolo (2020), that focuses on the estimation of climate transition risk and on the way to incorporate it at portfolio level. The paper hypothesizes that the granularity add-on considering the climate transition risk is higher than the granularity add-on taking only credit risk into account.

The analysis takes a portfolio of corporate bonds split into two buckets with different ratings (an AAA-A-rated corporate bonds bucket and a BBB-B-rated corporate bonds bucket) to test its hypothesis. Specifically, the paper firstly deals with a baseline scenario under which it computes the add-on originating from credit risk for both buckets within the actuarial loss setting. Secondly, it focuses on the StrPol-450 climate policy scenario (within the WITCH and GCAM integrated assessment models), under which climate transition risk is computed as the % change in the forward-looking GDP MER annual average growth on a decade-to-decade basis setting 2020 as the base year. The transition risk is ultimately used to compute the climate transition risk granularity add-on for both corporate bonds buckets. The results show that the add-on charge necessary to adequate banks' capital to the threat stemming from the potential financial loss caused by climate transition risk is higher than the one deriving merely from credit risk. Particularly, findings show that the add-on deriving from climate transition risk is particularly higher for the BBB-B rated bonds buckets and that, while in Europe the StrPol-450 policy under both the integrated assessment models seems to have an immediate impact on GDP MER, in North America, the climate policy seems to impact the GDP MER annual average growth later under the WITCH scenario.

Ultimately, the paper underlines its pitfalls. The major issue is the estimation of the climate transition risk. The paper computes it as the % change in the GDP MER annual average growth under a specific climate policy and two specific integrated assessment models. However, climate transition risk should be estimated more precisely, taking into consideration portfolio instruments' specific vulnerability to climate transition risk. Moreover, instead of considering only the actuarial definition of loss, the paper encourages evaluating the add-on under a market-to-market loss setting, which counts changes in instruments' market value due to rating downgrades or upgrades as a loss. Additionally, since the literature on which the paper relies mainly uses a Value-at-Risk paradigm to address the climate transition risk threat, the paper suggests that a model that incorporates climate transition risk under an Expected Shortfall (ES) framework needs to be developed because ES overcomes Value-at-Risk's limitations. As the analysis' findings show, while climate transition risk is perfectly reflected in climate add-on charges, VaR does not capture such threat. Therefore, further research should be conducted in order to overcome this flaw.

3 Literature

Banks need to have a minimum amount of capital to absorb losses. During the great financial crisis, the losses experienced by banks exceeded the minimum capital requirements (Varotto, 2011)[see 17, p.136]. As a result, the Basel Committee immediately began a thorough overhaul of bank regulation, proposing to add two new capital requirements to boost the loss-absorbing capacity of banks: the stressed Value-at-Risk measures and Incremental Risk Capital Charge (IRC), capturing both the risk of losses from default and credit migration events (Varotto, 2011) [see 17, p.136]. However, financial regulators have not sent the same prompt response to the climate change threat. Only recently have some central banks become aware of the threat that climate change poses to the integrity of the financial system, and several regulatory actions have recently begun to be implemented (Feridun and Güngör, 2020) [see 8, p.5]. But, climate change seems to be still underestimated as a financial risk.

Climate change challenges to the financial sector seem to come from several channels. Regulations aimed at reducing GHG emissions, climate-related physical impacts, repercussions for companies due to their corporate positions on climate change, and competitive pressures in the marketplace are just a few of the challenges that the sector will face (Labatt and White, 2011)[see 15, p.21].

Companies in the financial services sector have a great responsibility as they have to provide their clients with products and services to make them face the climate threat (Labatt and White, 2011)[see 15, p.21]. This responsibility involves several financial players. Amongst them, trustees of institutional investors have to investigate the connection between climate change and their fiduciary duty, institutional investors have to take part in the climate policy process, investment consultants have to integrate climate change into the advice they provide institutional investors, and, fund managers have to evaluate how climate change affects investment decision making (Labatt and White, 2011)[see 15, p.23].

Understanding climate risk's impact on the financial sector is a quite complex task especially if considering the complexity of the phenomenon. Climate risk is characterized, in fact, by a forward-looking dimension due to the long-term nature of its effects. This is problematic because financial market investors, instead, make decisions within short-term horizons relying on historical performance benchmarks (Battiston and Monasterolo, 2020)[see 3, p.6]. Climate change is also characterized by non-linearity, because the probability of forward-looking climate shocks cannot be implied from historical data being not linear and not normally distributed, and by deep uncertainties, because the exact localization and severity of climate-related shocks are uncertain and depend on countries' ability to implement climate policies (Battiston and Monasterolo, 2020)[see 3, p.6]. Additionally, since agents often behave irrationally, understanding how they will modify their consumption and production behaviors given climate change shocks, is quite complicated (Battiston and Monasterolo, 2020)[see 3, p.6]. Ultimately, climate risk is characterized by endogeneity and circularity, because the chance of reaching global climate goals is reliant on how climate policies are implemented, as well as investors' expectations about the financial risk resulting from the very same policies. As a result, investment decisions would produce a multiple equilibria scenario in which a rational agent is unable to determine a desirable investment strategy. (Battiston and Monasterolo, 2020) [see 3, p.6].

The context is even more complicated if considering that there is not just one type of climate risk. The literature has identified two major types of financial risk arising from climate change: climate-physical risk and climate-transition risk.

Climate physical risk arises from the threat of climate-related extreme events and global warming to the human and natural system, and, consequently, to the economy (Batten, Sowerbutts, and Tanaka, 2016) [see 2, p.5]. Global warming, for instance, could reduce the growth rate of the economy due to several factors such as a decrease in labor productivity caused by the diminished physical and cognitive performance of human capital, a reduction in the rate of capital accumulation due to long-term damage to capital, and a reduction in the growth rate of total factor productivity (TFP) because of resource redirecting from research and development toward adaptation to climate change events (Batten, Sowerbutts, and Tanaka, 2016) [see 2, p.23].

However, while extreme weather events and natural disasters are likely to have significant short-term impacts on the economy, the literature on the long-term effects of natural disasters is limited and with mixed results. Cavallo and Noy (2009), for instance, suggest that, while natural disasters tend to have contractionary effects on economic growth due to losses caused by damages, they also can have expansionary effects due to creative destruction processes, especially in developed countries [see 6, p.18].

Concerning the financial sector, climate physical risk could affect financial markets through several channels. The most likely scenario is that climate-related natural disasters can potentially affect the integrity of financial institutions because of their exposure to firms facing extreme weather events(Batten, Sowerbutts, and Tanaka, 2016)[see 2, p.7].

However, although extreme weather events are a potential threat to banks, Blicke, Hamerling, and Morgan (2021) suggest that even small banks facing extreme disasters are not significantly endangered [see 4, p.15]. Their resilience seems to lie in the fact that disasters stimulate the demand for loans and earnings on new loans balance losses on existing loans, and, in fact, banks' income increases after disasters (Blicke, Hamerling, and Morgan, 2021) [see 4, p.15].

Despite physical climate risk being worth monitoring, as it constitutes a risk that will be more prominent in the medium-to-long term, climate transition risk could occur in the very short-term and be more financially significant (Battiston and Monasterolo, 2020)[see 3, p.4]. Climate transition risk is the risk of economic and financial fallouts due to the transition to a carbon-constrained economy (Batten, Sowerbutts, and Tanaka, 2016)[see 2, p.12]. Climate regulations aimed at reaching a low-carbon economy urge firms highly relying on the use of fossil fuels to turn their carbon-intensive production into sustainable production. If these climate policies to de-carbonize the economy are gradually introduced, firms would be able to adapt their business to them in an orderly way. If instead, climate policies are suddenly introduced, negative economic and financial shocks would arise from firms' inability to anticipate them, consequently boosting a disorderly transition to a low-carbon economy(Batten, Sowerbutts, and Tanaka, 2016)[see 2, p.12].

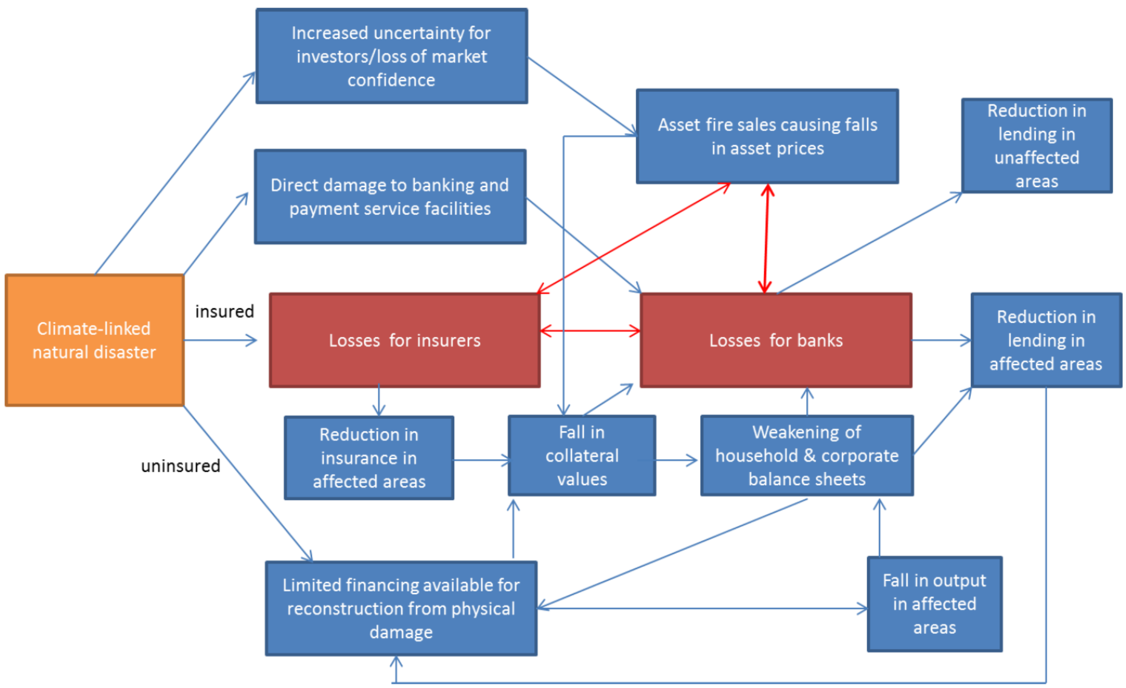

Figure 1: Channels through which climate-related natural disasters affect the financial sector and the macroeconomy. Source:(Batten, Sowerbutts, and Tanaka, 2016)[see 2, p.7]

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Climate transition risk, therefore, can affect the financial sector due to financial investors' incapacity to price climate policies into their investment strategies or to change their portfolios' allocations (Battiston and Monasterolo, 2020) [see 3, p.7], and due to financial institutions' exposure to firms with businesses not conforming to the standards of a low-carbon economy. For example, banks that lend to carbon-intensive firms could struggle because of the increase in their loan portfolios' default risk due to climate transition (Jung, Engel, and Berner, 2021) [see 14, p.1]. More generally, carbon-intensive firms facing climate transition shocks are more likely to give rise to carbon-stranded assets and transmit the shock to the value of financial contracts, and, consequently, to the value of the portfolios of investors. This would certainly imply asset price volatility and financial instability (Battiston and Monasterolo, 2020) [see 3, p.2]. As a result, unlike physical risk, which is likely to harm the financial system only if the scale and the frequency of climate disasters are severe, transition risk is most likely to affect the financial system in a more pervasive way (Batten, Sowerbutts, and Tanaka, 2016) [see 2, p.18].

Fried, Novan, and Peterman (2022), who try to assess the specific impact of climate transition risk on the macro-economy, suggest that, first, climate policy transition risk reduces fossil capital's expected return with respect to clean capital, and, second, climate policy transition risk reduces output by 0.34 percent because it shifts the composition of capital away from the traditional allocation chosen within a non-transition risk setting [see 9, p.2].

Amongst those who try to quantify climate transition risk, Reboredo and Ugolini (2022) recommend using the CRS (Carbon Risk Score) to estimate firms' exposure to transition risk [see 16, p.1]. CRS is a score evaluated at the sub-industry level and taking into consideration also firm-specific adjustments accounting for firms' deviations from the sub-industry values [see 16, p.4]. The CRS reflects the unmanageable carbon risk left after management's measures to align firms' business to a sustainable economy have already been implemented [see 16, p.4]. Reboredo and Ugolini (2022) use the CRS metric to investigate transition risk impacts on future profitability for a sample of European and US firms over the period 2013–2018 (Reboredo and Ugolini, 2022)[see 16, p.2]. Their empirical findings show that firms with little exposure to climate transition risk outperform in terms of returns on assets (ROA), returns on equity (ROE), and EBITDA, and that, while all European firms are highly sensitive to transition risk, only the most exposed US firms experience a significant reduction in profitability as the economy adapts to climate regulatory standards (Reboredo and Ugolini, 2022)[see 16, p.2].

Panel A. European firms					
	Negligible Risk	Low Risk	Medium Risk	High Risk	Severe Risk
ROA	8.298	6.783	5.431	2.896	1.420
	(10.38)	(7.47)	(7.08)	(7.88)	(6.48)
	17.339	16.153	12.646	5.276	−3.671
ROE	(23.04)	(17.73)	(18.60)	(21.85)	(21.29)
	14.335	11.352	9.536	9.019	6.567
EBITDA/TA	(12.28)	(9.31)	(8.00)	(9.28)	(9.58)
	2.832	1.923	1.595	1.252	1.138
Tobin's q	(2.03)	(1.39)	(1.15)	(0.55)	(0.21)
	15.179	16.405	15.996	17.023	17.242
Size	(1.65)	(2.17)	(1.88)	(2.41)	(1.05)
	23.449	23.139	25.212	25.791	27.002
D/TA	(21.62)	(17.51)	(16.27)	(14.90)	(15.67)
	0.806	0.705	0.635	0.736	0.786
S/TA	(0.65)	(0.61)	(0.52)	(0.42)	(0.72)
	0.808	0.944	0.864	0.812	0.750
Dividends	(0.39)	(0.23)	(0.34)	(0.39)	(0.44)
	11.405	5.677	6.306	2.178	1.685
M/B	(46.97)	(28.48)	(36.62)	(2.83)	(1.26)
Annual returns	10.510	6.934	4.475	2.433	−3.896
	(33.44)	(27.67)	(32.52)	(31.49)	(33.70)

Figure 2: European firms' performance according to their exposure to climate transition tisk. Source:(Reboredo and Ugolini, 2022)[see 16, p.6]

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Panel B. US firms					
	Negligible Risk	Low Risk	Medium Risk	High Risk	Severe Risk
ROA	6.684	7.578	6.039	4.524	1.096
	(9.10)	(6.69)	(5.73)	(5.29)	(8.60)
	19.233	26.165	17.393	8.433	0.556
ROE	(34.29)	(40.13)	(26.91)	(18.96)	(19.31)
	12.983	13.154	11.072	10.126	9.250
EBITDA/TA	(10.63)	(9.08)	(7.63)	(5.88)	(9.97)
	3.081	2.476	1.899	1.554	1.418
Tobin's q	(2.00)	(1.77)	(1.13)	(0.56)	(0.54)
	15.813	16.585	16.231	16.445	16.417
Size	(1.42)	(1.60)	(1.36)	(1.26)	(1.04)
	27.550	32.377	29.632	34.454	28.512
D/TA	(20.69)	(23.23)	(18.79)	(18.45)	(11.86)
	0.748	0.736	0.654	0.674	0.555
S/TA	(0.59)	(0.70)	(0.66)	(0.51)	(0.76)
	0.507	0.817	0.814	0.884	0.660
Dividends	(0.50)	(0.39)	(0.39)	(0.32)	(0.48)
	14.596	7.942	6.489	10.390	2.219
M/B	(50.26)	(25.64)	(29.48)	(51.46)	(1.39)
Annual	11.892	8.092	7.721	5.603	−7.899
returns	(29.45)	(27.08)	(27.04)	(34.01)	(39.38)

Figure 3: United States firms' performance according to their exposure to climate transition risk. Source:(Reboredo and Ugolini, 2022)[see 16, p.6]

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Not only firms but also financial institutions are highly exposed to climate transition risk. To estimate financial portfolios' exposure to climate transition risk, Alessi and Battiston (2022) use the Transition-Exposure Coefficients (TECs) [see 1, p.6]. Through the TECs, losses are not quantified on individual sectors to avoid over-reliance on specific climate policies' targets and emissions models (Alessi and Battiston, 2022) [see 1, p.6]. TECs are aimed at approximating the portion of portfolios' investments made in activities belonging to industries that are considerably vulnerable to transition risk losses (Alessi and Battiston, 2022) [see 1, p.7]. By the means of these coefficients, Alessi and Battiston (2022) estimate that the exposure to transition risk is 12% for investment funds, 5% for banks, and 15.1% for insurers [see 1, p.2]. As it can be seen from the total transition exposure and the total % transition exposure in Figure 4 and Figure 5, Alessi and Battiston (2022) show that equity portfolios are slightly more exposed to transition risk than bond portfolios, indicating that particularly climate transition risky activities are financed by stocks purchase, and this is concerning, because in the event of a massive sale of carbon-assets, stocks would be particularly vulnerable [see 1, p.11].

Holder sector	Total investment (EUR bn)	Taxonomy eligible (EUR bn)	Taxonomy aligned (EUR bn)	Transition exposure (EUR bn)	Taxonomy eligible (%)	Taxonomy aligned (%)	Transition exposure (%)
Investment funds (Non-MMF)	1496.3	410.5	24.5	118.4	27.4%	1.6%	7.9%
Non-financial corp.	1329.5	286.2	39.8	155.8	21.5%	3.0%	11.7%
Households	735	224.8	20	101.6	30.6%	2.7%	13.8%
Other financial corp.	710.1	150.1	10.7	123	21.1%	1.5%	17.3%
Other households and non-profit	291.4	83.2	2.8	10.4	28.6%	1.0%	3.6%
Insurance corp.	242.4	63.2	5.5	22	26.1%	2.3%	9.1%
Banks	219.1	66.4	3.3	43.2	30.3%	1.5%	19.7%
Central gov.	120.2	56.8	4.1	53.7	47.3%	3.4%	44.7%
Other General Gov.	97.8	41.4	9.1	20.1	42.3%	9.3%	20.6%
Non-financial investors	72.5	38	7.9	24.9	52.5%	10.9%	34.3%
Pension funds	69.3	20.3	1.9	9.2	29.3%	2.7%	13.2%
Non-EA other investors	63.4	17.4	1	3.4	27.4%	1.6%	5.4%
Non-profit institutions	37.3	9.5	1	7.9	25.6%	2.6%	21.3%
Social security funds	33.6	13.3	1.3	4.9	39.5%	3.8%	14.5%
State gov.	21.9	2.5	0.1	2.1	11.2%	0.5%	9.8%
Local gov.	17.7	4.1	1.4	1.9	23.1%	7.9%	10.7%
Financial vehicle corp.	4.1	0.8	0	0.5	20.1%	0.9%	12.3%
Money market funds (MMF)	1.5	0.2	0	0.1	12.4%	0.3%	6.9%
Unallocated	0.1	0	0	0	36.9%	5.4%	18.9%
Non-EA central banks & gov.	0	0	0	0	100.0%	0.0%	0.0%
Total	5563.2	1488.7	134.4	703.1	26.8%	2.4%	12.6%

Figure 4: Taxonomy alignment and transition exposure of investors' equity portfolios. The figures refer to the equity portfolio and to securities issued by Euro Area resident firms. Source:(Alessi and Battiston, 2022)[see 1, p.14]

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Despite the valuable contribution provided by the above-mentioned research, one of the main climate-related challenges is to understand how to incorporate climate transition risk into financial models of portfolio management. Battiston and Monasterolo (2020) have been the only ones trying to address this issue. They developed a model that performs valuation adjustments of sovereign bonds based on climate transition risk (Battiston and Monasterolo, 2020) [see 3, p.1].

Specifically, within their model, they consider a risk-averse investor, in a situation of incomplete information and deep uncertainty, willing to capture the exposure of the portfolio to climate transition risk (Battiston and Monasterolo, 2020)[see 3, p.9]. Consequently, they de-

Holder sector	Total investment (EUR bn)	Taxonomy eligible (EUR bn)	Taxonomy aligned (EUR bn)	Transition exposure (EUR bn)	Taxonomy eligible (%)	Taxonomy aligned (%)	Transition exposure (%)
Banks	1801	90.5	13.5	57	5.0%	0.8%	3.2%
Investment funds (Non-MMF)	1360	404.6	66.9	225.5	29.8%	4.9%	16.6%
Insurance corp.	1019	283.3	54.7	168.6	27.8%	5.4%	16.6%
Households	201.9	25.9	4	13.4	12.8%	2.0%	6.7%
Pension funds	160.3	42.3	8.5	23.6	26.4%	5.3%	14.8%
Other financial corp.	115.4	8.1	1	5.4	7.0%	0.9%	4.7%
Non-financial corp.	94.8	14.2	1.9	8.5	15.0%	2.1%	9.0%
Money market funds (MMF)	59.3	14.6	1.3	9.4	24.6%	2.2%	15.9%
Financial vehicle corp.	56.3	11.6	1.2	3.9	20.7%	2.1%	6.9%
Non-EA other investors	37.3	11.6	1.9	6.1	31.2%	5.2%	16.2%
Central gov.	37	3.6	0.6	2.2	9.8%	1.7%	6.0%
Other households and non-profit	26	1	0.1	0.7	3.7%	0.5%	2.6%
Social security funds	25.1	4.9	0.9	2.5	19.7%	3.6%	9.8%
Other General Gov.	24.2	13.4	3.8	6.5	55.2%	15.7%	27.0%
Non-profit institutions	24.1	4.9	0.7	3	20.3%	2.9%	12.3%
State gov.	12.5	0.4	0	0.3	3.0%	0.4%	2.1%
Local gov.	11.9	0.8	0 .1	0.2	6.5%	0.8%	1.5%
Non-EA central banks & gov.	4.1	0.3	0	0.3	8.1%	0.4%	7.3%
Non-financial investors	2.5	1.1	0.1	1	44.9%	3.5%	39.3%
Unallocated	0	0	0	0	40.3%	6.8%	21.0%
Total	5072.5	937.1	161.4	538.1	18.5%	3.2%	10.6%

Figure 5: Taxonomy alignment and transition exposure of investors' bond portfolios. The figures refer to the bond portfolio and to securities issued by Euro Area resident firms. Source: (Alessi and Battiston, 2022)[see 1, p.15]

fine a carbon-intensive scenario, a climate policy scenario corresponding to Green House Gasses emissions targets in different countries, a set of economic output trajectories for each country and different sectors under each climate policy scenario, and, ultimately, a set of forward-looking climate-policy shock scenarios entailing a disorderly transition from the carbon-intensive scenario to the climate policy one (Battiston and Monasterolo, 2020)[see 3, p.10]. Within this setting, Battiston and Monasterolo (2020) compute the ten-year sovereign bonds portfolio's climate spread, remarking that a positive shock on the bonds' yield correspond to negative shocks on the value of the sovereign bonds [see 3, p.26]. The climate transition risk is computed within WITCH and GCAM, two LIMITS' Integrated Assessment Models (IAMs), and under the stringent climate policy StrPol-450, which is aimed at keeping global mean temperature below the two degrees centigrade (Jewell, et al., 2013) [see 13, p.8]

Figure 7 shows that Australia, Norway and Poland show the largest negative shocks on their sovereign bonds' value, and, consequently, the highest yields (Battiston and Monasterolo, 2020) [see 3, p.27]. In contrast, Figure 7 shows positive shocks on sovereign bonds'value for Austria and Portugal (Battiston and Monasterolo, 2020) [see 3, p.27]. The positive shocks in sovereign bonds' values in these countries arise from the renewable energy sources growing shares of their gross value added (GVA) (Battiston and Monasterolo, 2020) [see 3, p.27].

Although the above-mentioned research show that financial institutions are strongly exposed to climate transition risk, a number of barriers prevent them from evaluating and integrating it into their investment models. Barriers are encountered at the political level, as regulators' uncertainties hinder the development of long-term emissions reductions targets (Labatt and White, 2011)[see 15, p.127-128]. Additional difficulties are seen at the analytical level, where low awareness of climate change result in poor data availability (Labatt and White, 2011)

Country code	Country	Region in models	WITCH: bond shocks (%)	WITCH: yield shock (%)	GCAM: bond shock (%)	GCAM : yield shock (%)
AT	Austria	EUROPE	1.30	-0.16	0.13	-0.02
AU	Australia	REST_WORLD	-17.36	2.45	n.a.	n.a.
BE	Belgium	EUROPE	0.84	-0.10	0.03	0.00
CA	Canada	PAC_OECD	-5.21	0.67	-18.29	2.61
CH	Switzerland	REST_WORLD	3.65	-0.44	n.a.	n.a.
CL	Chile	LATIN_AM	-6.10	0.79	-4.22	0.54
CR	Costa Rica	LATIN_AM	-0.50	0.06	-0.34	0.04
CZ	Czech Republi	EUROPE	1.24	-0.15	-0.11	0.01
DE	Germany	EUROPE	-1.27	0.16	1.18	-0.15
DK	Denmark	EUROPE	-0.36	0.04	-0.42	0.05
EE	Estonia	EUROPE	3.75	-0.45	0.51	-0.06
ES	Spain	EUROPE	1.58	-0.19	1.05	-0.13
FI	Finland	EUROPE	2.64	-0.32	0.47	-0.06
FR	France	EUROPE	1.34	-0.16	0.21	-0.03
GB	United Kingdo	EUROPE	-0.46	0.06	0.66	-0.08
GR	Greece	EUROPE	0.50	-0.06	-0.07	0.01
HU	Hungary	EUROPE	0.78	-0.10	-0.08	0.01
IE	Ireland	EUROPE	1.94	-0.24	0.42	-0.05
IT	Italy	EUROPE	-1.42	0.18	0.33	-0.04
JP	Japan	PAC_OECD	-5.05	0.65	-5.48	0.71
KR	Korea	REST_ASIA	-0.48	0.06	-0.50	0.06
LT	Lithuania	EUROPE	2.60	-0.32	0.58	-0.07
LU	Luxembourg	EUROPE	1.85	-0.23	0.44	-0.05
LV	Latvia	EUROPE	2.45	-0.30	0.47	-0.06
MX	Mexico	LATIN_AM	-6.30	0.82	-2.71	0.34
NL	Netherlands	EUROPE	-5.05	0.65	-0.91	0.11
NO	Norway	REST_WORLD	-14.82	2.05	n.a.	n.a.
PL	Poland	EUROPE	-12.85	1.75	-2.49	0.32
PT	Portugal	EUROPE	1.86	-0.23	0.27	-0.03
SE	Sweden	REST_WORLD	-1.54	0.19	n.a.	n.a.
SI	Slovenia	EUROPE	2.30	-0.28	0.32	-0.04
SK	Slovak Republ	EUROPE	-0.36	0.05	-0.77	0.10
TR	Turkey	REF_ECON	-2.63	0.33	-0.01	0.00
US	United States	NORTH_AM	-4.04	0.52	-1.06	0.13

Figure 6: Impact of climate policy shock on the value of sovereign bonds and sovereign bonds' yields computed with GCAM and WITCH under the climate policy scenario StrPol-450. Source:(Battiston and Monasterolo, 2020)[see 3, p.27]

[see 15, p. 128]. Moreover, at the market level, complexities within emissions trading markets discourage financial institutions from getting more involved (Labatt and White, 2011)[see 15, p. 128]. Ultimately, green investments consititute a small portion in investment fund, thus requiring relatively high transaction costs (Labatt and White, 2011) [see 15, p. 128].

4 Methodology

4.1 Computation of the Granularity Add-On Charge

In order to compute the capital charge add-on deriving from undiversified idiosyncratic risk, the paper relies on Michael Gordy's paper "A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules" (2003). Specifically, Gordy (2003) focuses on a ratings-based risk-bucketing scheme, under which banks' assets are grouped into buckets, to which a fixed capital charge per dollar of exposure is associated [see 11, p.200]. Gordy (2003) takes portfolio-invariance to be the essential property of ratings-based capital rules, meaning that the capital charge on a given instrument depends only on its own characteristics and not on the characteristics of the portfolio in which it is held [see 11, p.201].

Gordy (2003) shows that two necessary and sufficient conditions have to be fulfilled to compute capital charges under portfolio-invariance within a VaR framework: i) the portfolio must be asymptotically fine-grained, meaning that no single exposure in the portfolio can account for more than an arbitrarily small share of total portfolio exposure, and ii) there must be at most a single systematic risk factor [see 11, p.201]. However, the real world does not provide perfectly fine-grained portfolios, because banks' portfolios have finite numbers of obligors and capital charges are calibrated in a way that assumes a complete diversification of idiosyncratic risk. To overcome this bias, Gordy (2003) computes the add-on charge to compensate for less-than-perfect diversification of idiosyncratic risk [see 11, p.201].

The paper specifically focuses on what Gordy (2003) defines as the book value accounting (actuarial) framework, under which credit loss arises only in the event of obligors' default, neglecting changes in market value due to rating downgrades or upgrades [see 11, p.202]. Under this setting, the definition of the conditional probability of default is specified. Unlike the unconditional probability, which is the probability of default before some horizon given all information currently observable, the conditional default probability is the default probability assigned to obligors if the realized value of the systematic risk factors at the horizon is known (Gordy, 2003) [see 11, p.203]. The systematic risk factors can be specific observable quantities, such as industrial sector performance indicators, or can also be unspecified (Gordy, 2003) [see 11, p.203]. Thus, the conditional probability of default is computed as follows:

$$p_i(x) = p_i(1 + \sum_{k=1}^{K} w_{ik}(x_k - 1))$$

where p_i is the unconditional default probability, X denotes the systematic risk factors $(X_1, ..., X_k)$, which are assumed to be gamma-distributed random variables, $p_{i(}x)$ denotes the probability of default for $obligor_i$ conditional on realization x of X, and w_{ix} constitutes a vector of factor loadings with sum in [0,1] (Gordy, 2003) [see 11, p.203].

Associated with each $obligor_i$, there is a latent variable R_i representing the return on the firm's assets:

$$R_i = \psi_i \epsilon_i - X w_i$$

where ϵ_i is an iid N(0, 1) white noise representing the idiosyncratic factor (obligor-specific risk), w_i and ψ_i are scaling parameters (Gordy, 2003)[see 11, p.203]. Specifically, the weight on the idiosyncratic factor is:

$$\psi_i = (1 - w_i \Omega w_i)^{\{1/2\}}$$

Under the actuarial definition of loss, a borrower defaults if and only if its asset return falls below a threshold value γ_i (Gordy, 2003) [see 11, p.204]. In other words, to obtain the conditional default probability function $p_{i(}x)$, it has to be noticed that default occurs if and only if $\epsilon_i \leq (\gamma_i + Xw_i)/\psi_i$, meaning that the default of an $obligor_i$ conditional on $X = x$ is an independent Bernoulli event with probability:

$$p_{i(}x) = Pr(\epsilon_i \leq (\gamma_i + xw_i)/\psi_i) = \Phi((\gamma_i + xw_i)/\psi_i)$$

where Φ is the standard normal cumulative distribution function (cdf) (Gordy, 2003) [see 11, p.204]. Since, the unconditional probability of default is $\Phi(\gamma_i)$, the threshold value is $\gamma_i = \Phi^{\{-1\}(p_i)}$ (Gordy, 2003) [see 11, p.204].

In order to obtain the qth quantile of the distribution of loss of the portfolio of obligors under the actuarial paradigm, the portfolio loss ratio has to be computed. Starting from the the loss given default (LGD), which is a lender's projected loss in case of borrowers' defaults and is computed as 1-recovery rate, the portfolio loss ratio L_n for a portfolio of n obligors is obtained as the ratio of total losses to total portfolio exposure:

$$L_n \equiv (\sum_{i=1}^{n} U_i A_i)/(\sum_{i=1}^{n} A_i)$$

where A_i is the exposure to $obligor_i$, which is the expected dollar exposure in the event of obligor default, and the random variable U_i denotes the loss per dollar exposure (Gordy, 2003) [see 11, p.204]. In other words, in the event of survival, $U_i = 0$, otherwise, U_i is the percentage LGD on isntrument i (Gordy, 2003) [see 11, p.204].

Ultimately, under the actuarial definition of loss, value-at-risk is defined as the qth quantile of the distribution of loss (Gordy, 2003) [see 11, p.205] , and is defined as:

$$VaR_q[L_n] = a_q(L_n)$$

Since, as mentioned before, no portfolio is infinitely fine-grained, Gordy (2003) develops a methodology to assess the capital add-on charge to offset a portfolio's undiversified residual idiosyncratic risk [see 11, p.212]. The asymptotic slope β used to compute the granularity add-on charge is computed as:

$$\beta = \frac{1}{2\lambda}(\lambda^2 + \eta^2)(\frac{1}{\sigma^2}(1 + \frac{\sigma^2 - 1}{a_q(X)})(a_q(X) + \frac{1-w}{w}) - 1) \tag{4.1}$$

where λ is the mean and η^2 is the variance of the gamma-distributed LGD for each obligor (Gordy 2003) [see 11, p.213].

Since real-world portfolios are heterogeneous and are made of differently rated bonds, Gordy (2003) suggests to compute the β asymptotic slope for each bonds' bucket because within each bucket B, every facility has the same PD p_b, the same factor loading w_b, the same expected LGD λ_b and LGD volatility η_b [see 11, p.215]. The exposure sizes A_i are the only thing that vary within a bucket (Gordy, 2003) [see 11, p.215]. Moreover, to measure the extent to which bucket b exposure is concentrated in a small number of facilities, Gordy (2003) implements the computation of the within-bucket Herfindahl index:

$$H_b \equiv \sum_{i=b}^{B} A_i^2 / (\sum_{i=b}^{B} A_i)^2 \tag{4.2}$$

because the higher is H_b, the more concentrated is the exposure within the bucket, so the more slowly the idiosyncratic risk is diversified away [see 11, p.215].

According to Gordy(2003) [11], the computation of the asymptotic slopes for differently rated buckets requires the following restrictions to be fulfilled:

1. s_b denotes the share of total portfolio exposure held in bucket b:

$$s_b \equiv \sum_{i=b}^{B} A_i / \sum_{i} A_i \tag{4.3}$$

2. the exposure weighted expected default rate $p^* = \sum_{b=1}^{B} p_b s_b$ and the expected portfolio loss rate $\lambda^* p^* = \sum_{b=1}^{B} \lambda_b p_b s_b$ are equated, thus λ^* is the expected loss rate divided by the expected default rate :

$$\lambda^* = \sum_{b=1}^{B} \lambda_b p_b s_b / \sum_{b=1}^{B} p_b s_b \tag{4.4}$$

3. The contribution of systematic risk takes this form:

$$V[E[L_n|X]] = \sigma^2 (\sum_{b=1}^{B} \lambda_b p_b w_b s_b)^2 \tag{4.5}$$

$$V[E[L^*|X]] = \sigma^2 (\lambda^* p^* w^*)^2 \tag{4.6}$$

which implies:

$$w^* = \sum_{b=1}^{B} \lambda_b p_b w_b s_b / \sum_{b=1}^{B} \lambda_b p_b s_b \tag{4.7}$$

where w^* is an expected loss-weighted average of the w_b.

4. The contribution of idiosyncratic risk to loss variance, $\mathrm{E}[\mathrm{V}[\mathrm{L}_n|X]]$, is:

$$V[E[L_n|X]] = \sum_{b=1}^{B}(\lambda_b^2(p_b(1-p_b)-(p_b w_b \sigma)^2)+p_b\eta_b^2)H_b s_b^2 \tag{4.8}$$

$$V[E[L^*|X]] = \frac{1}{n^*}(\lambda^{*2}(p^*(1-p^*)-(p^*w^*\sigma)^*)^2+p^*\eta^{*2}) \tag{4.9}$$

5. $\lambda^2(p(1-p)-(pw\sigma)^2)$ represents the contribution of idiosyncratic default risk, and pη^2 represents the contribution of idiosyncratic recovery risk. These two contributions are matched so that the number of exposures in the portfolio is:

$$n^* = \sum_{b=1}^{B}(\Lambda_b H_b s_b^2)^-1 \tag{4.10}$$

where

$$\Lambda_b \equiv \lambda_b^2(p_b(1-p_b)-(p_b w_b\sigma)^2)/\lambda^{*2}(p^*(1-p^*)-(p^*w^*\sigma)^2) \tag{4.11}$$

6. The variance of LGD is given by

$$\eta^{*2} = \frac{n^*}{p^*}\sum_{b=1}^{B}\eta_b^2 p_b H_b s_b^2 \tag{4.12}$$

where $\eta_b = 0.5\sqrt{\lambda_b(1-\lambda_b)}$ (Gordy, 2003) [see 11, p.216].

Finally, once the asymptotic slope β is calculated for the target quantile q, the granularity add-on is given by β_q^*/n^* (Gordy, 2003)[see 11, p.217].

4.2 Climate Spread for Bond Portfolios

To compute the climate transition risk and understand how to incorporate it at portfolio level, the paper relies on Battiston and Monasterolo's paper "The Climate Spread of Corporate and Sovereign Bond" (2020). As already mentioned in the literature, Battiston and Monasterolo (2020) define a carbon-intensive scenario, a climate policy scenario, and forward-looking climate-policy shock scenarios entailing a disorderly transition from the former scenario to the latter (Battiston and Monasterolo, 2020)[see 3, p.10]. Within this setting, Battiston and Monasterolo (2020) compute the ten-year sovereign bonds portfolio's climate spread.

Battiston and Monasterolo (2020) starts by defining the value of a risky bond of corporate issuer j, issued at with maturity T, with bond recovery rate R and loss-given-default LGD as follows:

$$\nu_j(T)\begin{cases} R_j = (1-LGD_j) \\ \hfill 1 \end{cases} \tag{4.13}$$

where the former occurs if j defaults (with probability q_j) and the latter occurs in case of non-default (with probability 1-q_j) (Battiston and Monasterolo, 2020)[see 3, p.16].

The expected value of bond's payoff can then be written as:

$$E[\nu_j] = (1 - q_j) + q_j R_j = 1 - q_j(1 - R_j) = 1 - q_j LGD_j \tag{4.14}$$

and the bond price ν_j^* is equal to the bond discounted expected value, with y_f risk-free rate (Battiston and Monasterolo, 2020)[see 3, p.16]. Consequently, according to Battiston and Monasterolo (2020) [3], the price defines implicitly the yield y_j of bond j in the following way:

$$\nu_j^* = e^{-y_f T} E[\nu_j] = e^{-y_f T}(1 - q_j LGD_j) = e^{-y_j T} \tag{4.15}$$

Ultimately, the bond spread is defined as:

$$s_j = y_j - y_f \tag{4.16}$$

with $e^{-s_j T} = (1 - q_j LGD_j)$ (Battiston and Monasterolo, 2020)[see 3, p.16].

Battiston and Monasterolo (2020) define the default conditions of a corporate bond portfolio relying on the Merton model:

$$A_j(T) = A_j(t_0)(1 + \eta_j(T)) < L_j(T) \tag{4.17}$$

where $A_j(t_0)$ and $A_j(T)$ are the value of the assets in the corporate bond issuer j's balance sheet, with t_0 being the time of issuance and T the maturity, $L_j(T)$ being the liabilities, and $\eta_j(T)$ denoting the idiosyncratic shock (Battiston and Monasterolo, 2020) [3, p.16].

Consequently, Battiston and Monasterolo (2020) add the climate policy shock denoted by $\xi_j(T)$ on j's assets, causing a shift in the distribution of the idiosyncratic shock η_j [see 3, p.17]. Thus, the new default conditions of the corporate bond portfolio is denoted as follows:

$$A_j(T) = A_j(t_0)(1 + \eta_j(T) + \xi_j(P)) < L_j(T) \tag{4.18}$$

$$\iff \eta_j(T) \leq \theta_j(P) = L_j(T)/A_j(t_0) - 1 - \xi_j(T, P) \tag{4.19}$$

with $\theta_j(P)$ denoting the default threshold under the climate policy scenario (P) (Battiston and Monasterolo, 2020) [see 3, p.17].

The default probability $q_j(P)$ of issuer j, under the climate policy scenario (P), is denoted as follows:

$$q_j(P) = P(\eta_j < \theta_j(P)) = \int_{\eta_i nf}^{\theta_j(P)} \phi_P(\eta_j)\, d\eta_j \tag{4.20}$$

with $\phi_P(\eta_j)$ being the probability distribution of the idiosyncratic shock η_j, and $\eta_i nf$ the lower bound of distribution of support (Battiston and Monasterolo, 2020)[3, p.17].

Battiston and Monasterolo (2020) [3] define the climate spread Δs_j as the change in the spread s_j conditional on the climate policy shock scenario:

$$\Delta s_j = s_j(q_j(P) - s_j(q_j(B))) \tag{4.21}$$

According to Battiston and Monasterolo (2020), conditional to the climate policy shock scenario, the climate spread $s_j(P)$ increases with the magnitude of the policy shock if $\xi_j(P) < 0$, and decreases with the magnitude of the policy shock if $\xi_j(P) > 0$ [see 3, p.19].

Ultimately, Battiston and Monasterolo (2020) define the Value-at-Risk (the worst case loss for a given level of confidence) of a bonds portfolio conditional to climate transition risk.

By denoting an investor i's portfolio value z_i and the portfolio rate of return π_i at T with W_{ij} amount of j's bond purchased by i, Battiston and Monasterolo (2020) [3], define the portfolio's value and its rate of return in the following way:

$$z_i(T) = \sum_j W_{ij}\nu_j(T) \tag{4.22}$$

$$\pi_i = \frac{z_i(T) - z_i(t_0)}{z_i(t_0)} \tag{4.23}$$

The climate VaR is defined by Battiston and Monasterolo (2020) [3] as the Value-at-Risk of the portfolio of the investor, conditional to climate policy shock scenario with π portfolio return, $\psi_P(\pi)$ distribution of returns conditional to the climate policy shock, and $cVaR$ as confidence level:

$$ClimateVaR(P) = \int_{-1)}^{ClimateVaR} \psi_P(\pi)\, d\pi = cVaR \tag{4.24}$$

Given the definition of climate VaR, Battiston and Monasterolo (2020) proceed by stating that, conditional to the policy shock scenario $B \rightarrow P$ [1], climate VaR(P) increases with magnitude of policy shock if $\xi_j(P) < 0$, and decreases viceversa, and that climate VaR increases with the default probability adjustment $\Delta_{qj}(P)$ of bond j [see 3, p.19].

[1] $B \rightarrow P$ refers to the transition from a business-as-usual scenario (i.e. carbon intensive economy) to a climate policy scenario

5 Dataset and Results

5.1 The Granularity Add-On Given the Credit Risk Factor

This paper is aimed at applying the over-mentioned theoretical framework to a corporate bond portfolio made of two buckets : an AAA-A rated bonds bucket and a BBB-B rated bonds bucket. First, relying on Gordy (2003)'s model [11], the paper computes the granularity add-on charge considering only the credit risk factor for each bucket. Secondly, after computing climate transition risk following Battiston and Monasterolo (2020) [3], the paper computes the granularity add-on charge arising from it, and tries to incorporate it at portfolio level.

The selected portfolio is the Morgan Stanley Institutional Fund Trust (MSIFT) corporate bond portfolio. The portfolio is made of bonds belonging to different sectors and industries and with different rating quality. The portfolio is primarily made of investment grade corporate bonds, belonging to different industrial sectors (i.e. communications, energy, technology, transportation, etc.) and to different financial sectors (i.e. banking, finance companies, insurance, and other financial institutions) and agencies (see Figure 37 in the Appendix). MSIFT's assets mainly belong to North America, Western Europe, and the Asia Pacific (see Figure 40 in the Appendix). Concerning the instruments' quality, the portfolio is mainly made of BBB-rated, B-rated, and A-rated assets (see Figure 36 in the Appendix).

The paper groups the MSIFT portfolio into an AAA-A rated bonds bucket (made of Aaa, Aa, and A rated bonds according to Moody's rating standard) and a BBB-B-rated bonds buckets (made of Baa1, Baa2, Baa3, Ba1, Ba2, Ba3, and B rated bonds according to the Moody's rating standard). Thus, the paper focuses on a portfolio made of 280 instruments: 92 AAA-A rated bonds and 188 BBB-B rated bonds. MSIFT dataset is retrieved forom Bloomberg as of date 10th February 2022 and, for each instrument, the dataset entails weight, market value in US $ currency, position, closing price and the % accrued interest rate.

The paper starts from defining the vector of risk factor X, which is a gamma-distributed random variable. Since risk factor (X) may be identified as any industrial sector performance indicator, a gamma distribution has been fit on SP500 stock market index retrieved from Bloomberg. Specifically, from the SP500 stock market index closing price, the vector of squared returns has been computed and a gamma distribution has been fit on it so to retrieve the α shape parameter and the β scale parameter set to create a risk factor vector of gamma random variables both for the AAA-A rated bonds bucket and the BBB-B rated bonds bucket.

As the factor loadings measure the sensitivity of obligor i to the risk factors, the paper retrieves the adjusted betas (measuring the volatility of a security in comparison to the market as a whole) from Bloomberg for each instrument and fits a gamma distribution on them to create the vector of factor loadings that is eventually normalized so that their sum is in between 0 and 1. Consequently, gamma-distributed factor loadings have been used to compute the portfolio factor loadings for the AAA-A rated bonds bucket and the BBB-B rated bonds bucket replicating equation (6.13).

In order to compute the loss given default (LGD), the recovery rate has been set equal to 0.4.

The number of exposure n^* of the AAA-A rated bonds bucket and the BBB-B rated bonds bucket has been computed by replicating equation (6.18) and setting σ equal to 1.0, 1.5 and 4.0. Gordy (2000), in fact, suggests that σ is roughly one, an estimaton that is based on a single-sector calibration of the model, which is equivalent to setting all the factor loadings equal to one [see 10, p.135]. However, since when $\sigma = 1$ in Gordy(2000)'s calibration some of the factor loadings exceed one, Gordy (2000) suggests to set $\sigma = 1.5$ and $\sigma = 4.0$ so that factor laodings are all bounded in (0,1) [see 10, p.135]. Thus, n^*, and consequently the granularity add-on charge, are computed for each bucket for the three different values of σ.

The computation of each obligor$_i$ return has been done by by setting the vector of the obligor-specific risk ϵ_i as a normal random variable with mean 0 and variance 1, and by computing ψ_i. To compute the scaling factor on idiosyncratic risk, Ω has been set as the variance-covariance matrix of the returns of each asset, where the returns are computed from the closing prices of the MSFIT's instruments retrieved from Bloomberg.

In order to compute each obligor$_i$ conditional probability of default, the 1-year horizon probability of default for each instrument is retrieved from Bloomberg and it is set as the unconditional probability of default.

After computing the portfolio loss ratio L_n, the paper sets the distribution of portfolio losses as a gamma-distributed random variable centered around L_n for each bucket. Ultimately, after computing the q_{th} quantile of the distribution of losses for the 90% and 95% level of confidence for each bucket, the paper computes the asymptotic beta for each bucket and the granularity add-on charge.

Table 4 and Table 5 show that that the granularity add-on charge arising only from credit risk does not vary if considering $\sigma = 1$, $\sigma = 1.5$, $\sigma = 4$, but, it does vary according to the different rating quality, with the BBB-B rated instruments bucket requiring an higher idiosyncratic-recovery add-on charge (27.2020 and 106.3680 respectively for the 90% and 95% confidence interval) with respect to the AAA-A rate bonds bucket's the add-on charge required by the AAA-A rate bonds bucket (0.0032 and 0.0101 respectively for the 90% and 95% confidence interval).

Table 1: VaR of the AAA-A rated bonds bucket and VaR of the BBB-B rated bonds bucket

AAA-A Bucket VaR and BBB-B Bucket VaR		
% Quantile	A-Bucket VaR	B-Bucket VaR
90%	0.0045	0.00002087
95%	0.0011	0.000021

Table 2: Asymptotic Beta of the AAA-A rated bonds bucket

Asymptotic Beta of the AAA-A bucket			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0126	0.0126	0.0126
95%	0.0401	0.0401	0.0401

Table 3: Asymptotic Beta of the BBB-B rated bonds bucket

Asymptotic Beta of the BBB-B bucket			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0183	0.0183	0.0183
95%	0.0715	0.0715	0.0715

Table 4: Granularity add-on of the AAA-A rated bonds bucket

AAA-A Bucket Granularity Add-On			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0032	0.0032	0.0032
95%	0.0101	0.0101	0.0101

Table 5: Granularity add-on of the BBB-B rated bonds bucket

BBB-B Bucket Granularity Add-On			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	27.2020	27.2020	27.2020
95%	106.3680	106.3680	106.3680

5.2 The Granularity Add-On Given Climate Transition Risk

The climate transition risk has been included in the model following Battiston and Monasterolo (2020)'s theoretical framework. In other words, data used to compute the climate transition risk have been downloaded from the LIMITS scenario database. Specifically, as Battiston and Monasterolo (2020), the paper takes into considerations the GCAM and WITCH scenarios.

The Global Change Assessment Model (GCAM) represents five interconnected systems: energy, water, land, socio-economics, and climate)(Calvin et al.,2019) [5, p.678].

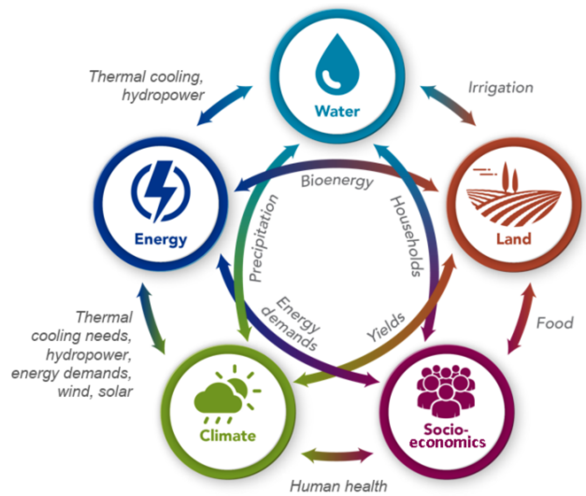

Figure 7: Linkages between GCAM's five systems. Source:(Calvin et al.,2019)[5, p.678]

Within the GCAM framework, markets, which exist for several goods and services such as physical flows of electricity or tradable emissions permits, are the major means by which representative agents interact (Calvin et al.,2019) [5, p.679]. GCAM's representative agents use information on prices, costs, and other factors to make decisions about resources allocation (Calvin et al.,2019) [5, p.678].

GCAM is aimed at solving for a set of market prices such that supplies and demands are equal for all markets in the model, and the process involves iterating on market prices until this equilibrium is reached [2](Calvin et al.,2019) [5, p.679]. GCAM is also a dynamic recursive model because decision makers, within the GCAM framework, base their decisions only on currently available information, and the model uses the resulting state of the world, accounting for all the consequences arising from the decisions made in that time

[2]As an example of GCAM's operating process, in any single model period, GCAM derives a demand for natural gas accounting for any use of gas such as power generation, cooking, and industrial energy uses; it computes the gas-related supplies, and, ultimately, it sums all the supplies and demands for commodities, and it consequently adjusts prices so that in every market within that single period supplies and demands match (Calvin et al.,2019) [5, p.679].

step, as a starting point of its operating process in the next time step (Calvin et al.,2019) [see 5, p.679].

The World Induced Technical Change Hybrid model (WITCH) is a regional integrated assessment model whose objective is to assess world economies' response to climate shocks and the socio-economic impacts of climate policies (De Cian, Bosetti, and Tavoni, 2012) [7, p.123].

The model is based on the distinction between the power generation sector and the final use of primary sources, and on the distinction between fuels (coal, oil, natural gas, traditional biomass et al.) and power generation technologies (nuclear power, wind turbines and photovoltaic panels, hydroelectric power, et al.) (De Cian, Bosetti, and Tavoni, 2012) [7, p.123]. WITCH groups countries in 12 regions interacting on emissions, innovations, and the use of fossil fuels (De Cian, Bosetti, and Tavoni, 2012) [7, p.123].

Within these two integrated assessment settings, the paper specifically focuses on the stringent StrPol-450 policy. The StrPol is an ambitious interpretation of Copenhagen emission reduction commitments, whereas the 450 scenario introduces a global carbon tax to reach a 450 ppm CO2-eq greenhouse gas concentration in 2100; together, the StrPol and the 450 scenarios are referred to as the climate policy scenario (Jewell et al., 2013) [13, p.8].

To estimate the climate transition shock, the paper addresses forward-looking GDP MER [3]trajectories under the impact of the StrPol-450 policy within both the GCAM and the WITCH scenarios in North America and in Europe. Particularly, the paper takes GDP MER forward-looking annual average growth and, setting 2020 as the base year, the paper computes the percentage change between the 2020 GDP MER annual average growth and the 2030 GDP MER annual average growth, between the 2020 GDP MER annual average growth and the 2040 GDP MER annual average growth, between the 2020 GDP MER annual average growth and the 2050 GDP MER annual average growth, until 2090. As a result, the climate transition risk is estimated as the percentage change in GDP MER annual average growth under the StrPol-450 setting. As suggested by Battiston and Monasterolo (2020)'s, the climate transition shock has then been added to the idiosyncratic factor ϵ and to the risk-factor X so that the percentage change in the GDP MER is directly reflected in the returns of the firms' assets, in the conditional probabilities of default, in the asymptotic betas, and, ultimately, in the add-on charges.

5.2.1 Granularity Add-On Under the StrPol-450 Policy within the GCAM Framework in North America

In this section the paper computes the granularity add-on accounting for forward-looking data under the StrPol-450 climate policy and the GCAM setting in North America.

[3]The choice of considering GDP MER (Market Exchange Rates) instead of GDP PPP (Purchasing Power Parity rates) relies on data availability issues. The LIMITS database has more data available in terms of GDP MER with respect to GDP PPP. The issue is further explained in the "Further Research and Pitfalls" chapter.

To give an idea of the effects of the StrPol-450 policy under the GCAM setting in North America, the forward-looking trajectories regarding oil, fossil, and CO2 emissions in this region are shown. Figure 8 and Figure 9 show that the StrPol-450 policy under the GCAM setting will cause a decline in oil and fossil in North America from 2005 to 2100. Figure 10 and Figure 11 show that, under the StrPol-450 policy and the GCAM setting, a reduction in CO2 emissions will occur in North America from 2005 to 2100. Contrarily to the oil and fossil trajectories, CO2 emissions will not only be affected by a considerable reduction, but they will also reach negative values starting from 2060.

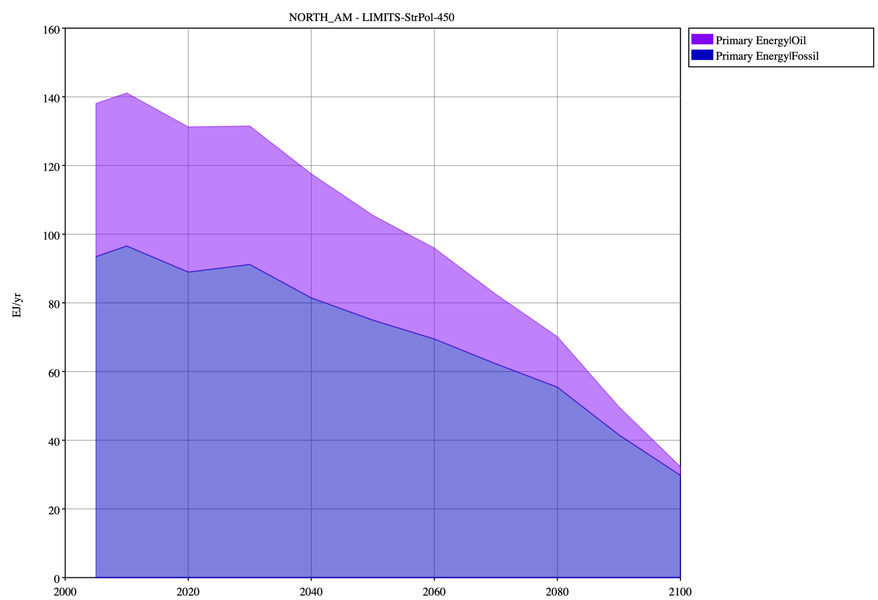

Figure 8: Graph representing forward-looking data about oil and fossil used in North America from 2005 to 2100 within the primary energy sector under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Primary Energy|Fossil	EJ/yr	93	97	89	91	81	75	69	62	55	42	30
Primary Energy|Oil	EJ/yr	45	45	42	40	36	31	26	20	15	8	3

Figure 9: Forward-looking data about oil and fossil used in North America from 2005 to 2100 within the primary energy sector under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

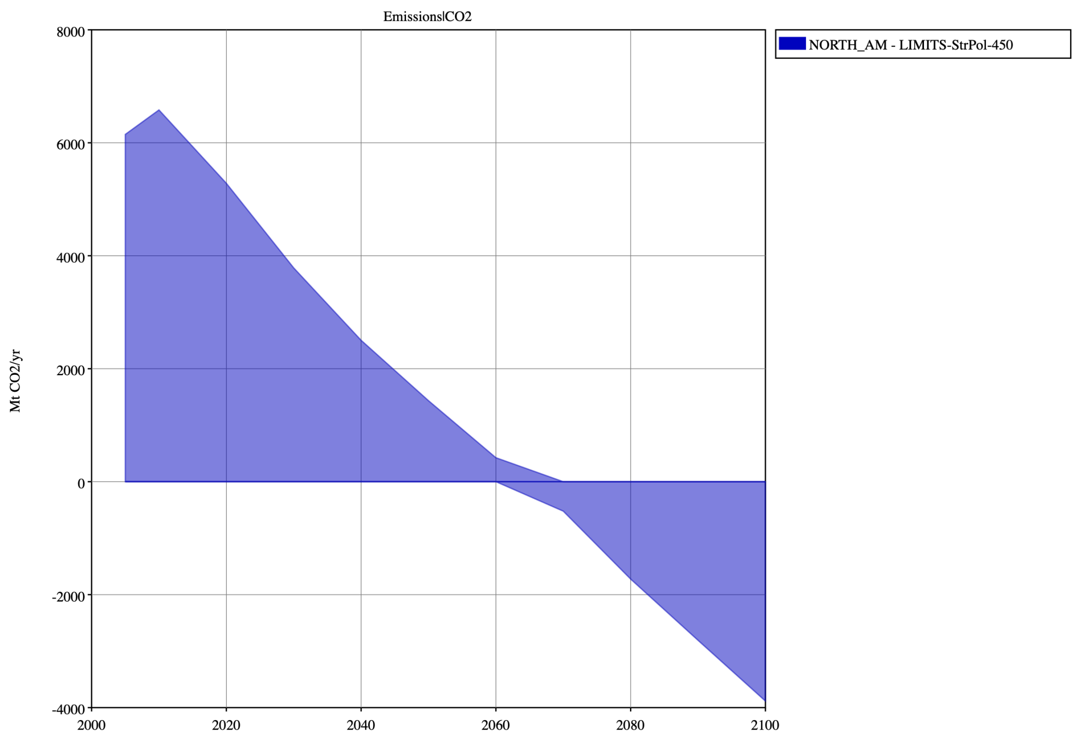

Figure 10: Graph representing forward-looking data about CO2 emissions in North America from 2005 to 2100 under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Emissions|CO2	Mt CO2/yr	6148	6582	5283	3785	2504	1434	425	-522	-1725	-2809	-3884

Figure 11: Forward-looking data about CO2 emissions in North America from 2005 to 2100 under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

The paper reports below the estimation of GDP MER annual average growth from 2005 and 2100 in North America within the GCAM framework and under the StrPol-450 policy, and the percentage change in the GDP MER annual average growth computed within the same framework and in the same region, setting 2020 as the base year.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090
GDP|MER	Annual Average Growth [%]	1,0	2,3	2,0	1,8	1,8	1,8	1,8	1,8	1,8	1,8

Figure 12: Annual Average Growth in GDP (MER) in North America under the StrPol-450 policy within the GCAM framework. Source: LIMITS Scenario Database.

Variable	Unit	2020	2030	2040	2050	2060	2070	2080	2090
GDP|MER	% Δ in Annual Average Growth		-10%	-8%	-9%	-9%	-10%	-12%	-10%

Figure 13: % Change in the GDP MER Annual Average Growth in North America under the StrPol-450 policy within the GCAM framework, setting 2020 as the base year.

Figure 12 shows that the GDP MER annual average growth under the StrPol450 policy and the GCAM scenario is still a positive growth (1.8%) in 2030 and remains as such in the following decades. However, despite being positive, the growth is lower than the one that occurred in 2020 (2%). In order to capture this GDP MER growth decline, the paper computes the % change between the GDP growth in 2020 and the GDP growth in the future decades. Figure 13 shows that the % change between the GDP growth in 2020 and the GDP growth in 2030 is considerable. Specifically, in 2030, the GDP grows 10% less than it did in 2020 and it keeps growing at a similar pace until 2090.

Table 6 shows that none of the buckets' VaR is able to capture the climate transition risk in the way in which it is computed. Both the AAA-A rated bonds bucket VaR and the BBB-B rated bonds bucket VaR, in fact, are equal to the ones computed within the baseline scenario. However, the granularity add-on charge is able to capture the climate shock. Table 7 and Table 8 show the results concerning the climate granularity add-on given that the climate transition risk is computed as the % change between the North American GDP (MER)annual average growth in 2030 and the North American GDP (MER)annual average growth in 2020 under the StrPol450 policy and the GCAM scenario. It can be observed that, as for the baseline scenario, the add-on charges do not vary with the standard deviations used for the computation of the asymptotic betas, but, under the StrPol450 policy and the GCAM framework, both the buckets' add-on charges are higher than the add-on charges computed within the baseline scenario. Specifically, the BBB-B rated bond bucket seems to be more sensitive to the impact of the StrPol450 measure than the AAA-A rated bonds bucket as the BBB-B rated bonds bucket add-on charge significantly increases.

Table 6: VaR of the AAA-A rated bonds bucket and VaR of the BBB-B rated bonds bucket under the StrPol-450 policy and the GCAM setting in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket VaR and BBB-B Bucket VaR		
% Quantile	A-Bucket VaR	B-Bucket VaR
90%	0.0045	0.00002087
95%	0.0011	0.000021

Table 7: Granularity add-on of the AAA-A rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol450 policy and the GCAM scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket Add-On - GDP MER - North America -StrPol450 GCAM			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0033	0.0033	0.0033
95%	0.0113	0.0113	0.0113

Table 8: Granularity add-on of the BBB-B rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol450 policy and the GCAM scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

BBB-B Bucket Add-On - GDP MER - North America -StrPol450 GCAM			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	28.6169	28.6169	28.6169
95%	131.8646	131.8646	131.8646

5.2.2 Granularity Add-On Under the StrPol-450 Policy within the WITCH Framework in North America

In this section the paper computes the granularity add-on accounting for forward-looking data under the StrPol-450 climate policy and the WITCH setting in North America.

To give an idea of the effects of the StrPol-450 policy under the WITCH setting in North America, the forward-looking trajectories regarding oil, fossil, and CO2 emissions in this region are shown. Figure 14 and Figure 15 show that the StrPol-450 policy under the WITCH setting will cause a decline in oil and fossil in North America from 2005 to 2100. Figure 16 and Figure 17 show that, under the StrPol-450 policy and the WITCH setting, a reduction in CO2 emissions will occur in North America from 2005 to 2100. Contrarily to the oil and fossil trajectories which approach 0 from 2080, CO2 emissions will not only be affected by a considerable reduction, but they will also reach negative values starting from 2060.

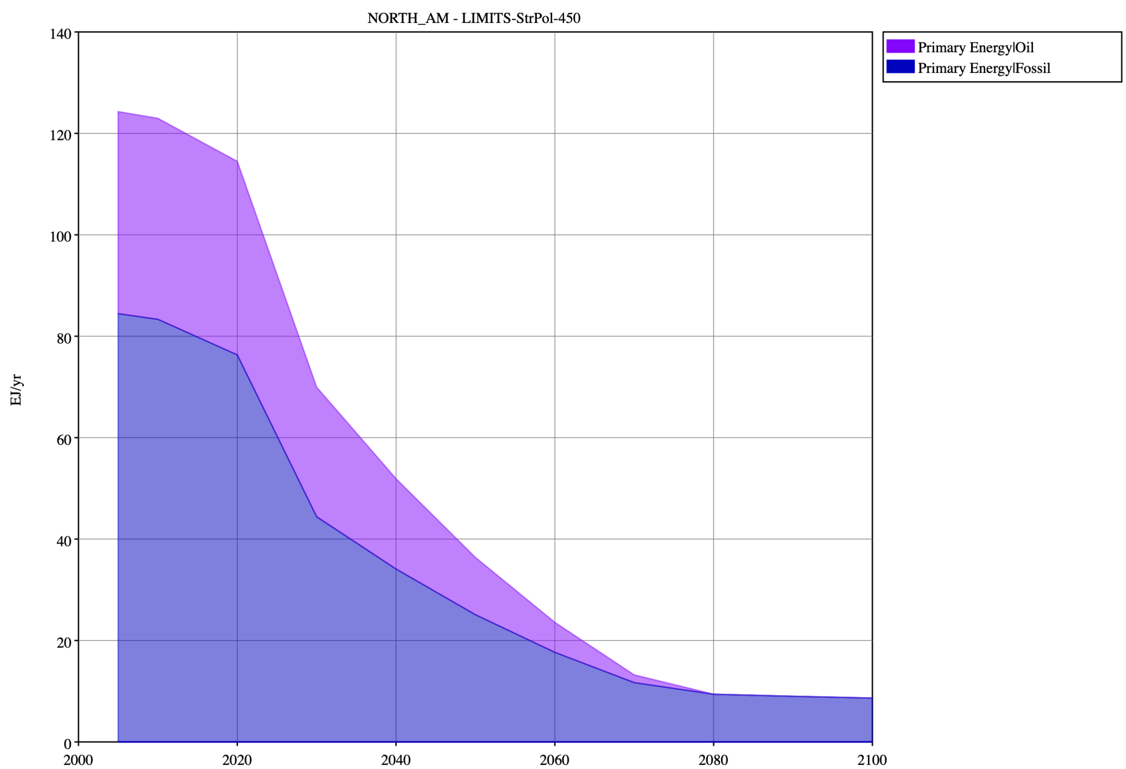

Figure 14: Graph representing forward-looking data oil and fossil used in North America from 2005 to 2100 under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Primary Energy|Fossil	EJ/yr	84	83	76	44	34	25	18	12	9	9	9
Primary Energy|Oil	EJ/yr	40	40	38	26	18	11	6	2	0	0	0

Figure 15: Forward-looking data about oil and fossil used in North America from 2005 to 2100 under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

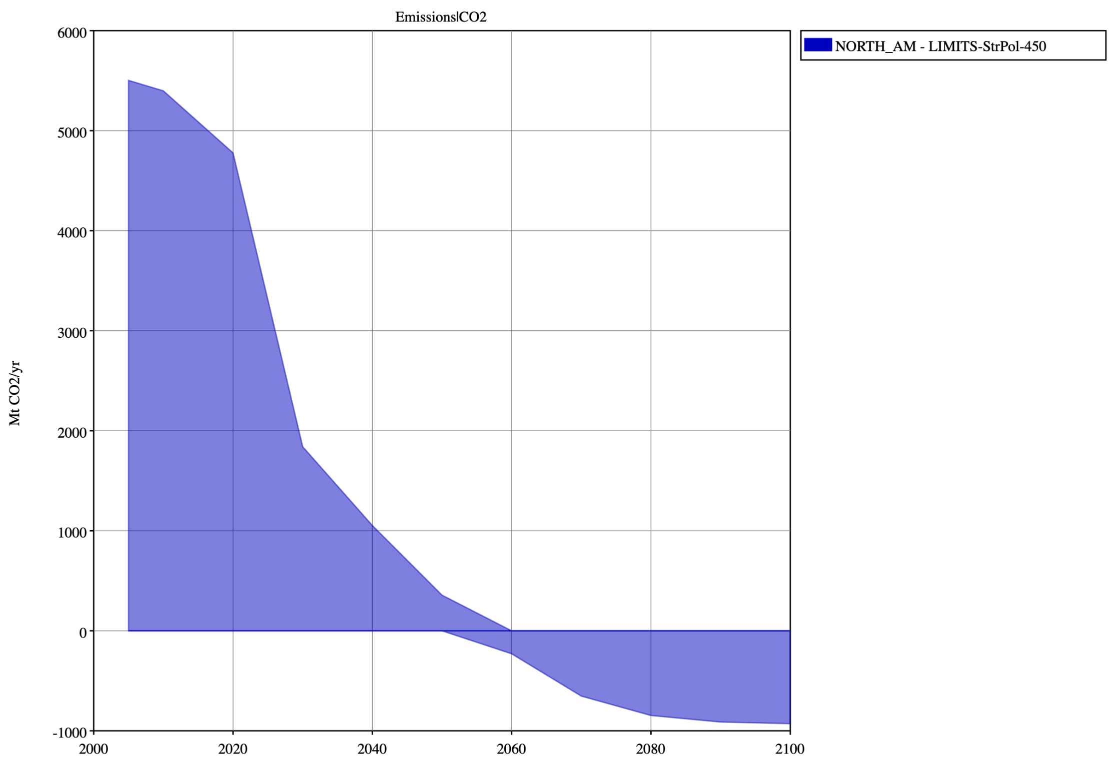

Figure 16: Graph representing forward-looking data about CO2 emissions in North America from 2005 to 2100 under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Emissions|CO2	Mt CO2/yr	5503	5398	4778	1841	1053	357	-230	-653	-847	-912	-928

Figure 17: Forward-looking data about CO2 emissions in North America from 2005 to 2100 under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

The paper reports below the estimation of GDP MER annual average growth from 2005 to 2100 in North America within the WITCH framework and under the StrPol-450 policy, and the percentage change in the GDP MER annual average growth computed within the same framework and in the same region, setting 2020 as the base year.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090
GDP|MER	Annual Average Growth [%]	0,6	2,5	1,6	1,7	1,7	1,4	1,4	1,4	1,4	1,3

Figure 18: Annual Average Growth in GDP (MER) in North America under the StrPol-450 policy within the WITCH framework. Source: LIMITS Scenario Database.

Variable	Unit	2020	2030	2040	2050	2060	2070	2080	2090
GDP|MER	% Δ in Annual Average Growth		9%	4%	-10%	-13%	-13%	-11%	-16%

Figure 19: % Change in the GDP MER Annual Average Growth in North America under the StrPol-450 policy within the WITCH framework, setting 2020 as the base year.

Figure 18 shows that the GDP MER annual average growth under the StrPol450 policy and the WITCH scenario in 2030 is not only positive, but also higher than the one occurred in 2020. The same result can be observed in Figure 19, where the % change between the GDP MER annual average growth in 2020 and the GDP MER annual average growth in the future decades is reported. Particularly, it can be seen that the % change between the GDP MER annual average growth in 2020 and the GDP MER annual average growth in 2030 is 9%, and that the % change between the GDP MER annual average growth in 2020 and the GDP MER annual average growth in 2040 is 4%.

Table 9 and Table 12 show that, even under the WITCH setting, both buckets' VaR does not capture the threat arising from climate transition risk. As expected from the above-mentioned considerations, Table 10, Table 11, Table 13, and Table 14 show that the add-on computed on both buckets under the WITCH scenario given the climate transition shock from 2020 to 2030 and from 2020 to 2040 is, in both cases, lower than the one computed for both buckets within the baseline setting.

Table 9: VaR of the AAA-A rated bonds bucket and VaR of the BBB-B rated bonds bucket under the StrPol-450 policy and the WITCH setting in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket VaR and BBB-B Bucket VaR		
% Quantile	A-Bucket VaR	B-Bucket VaR
90%	0.0045	0.00004285
95%	0.0011	0.000037

Table 10: Granularity add-on of the AAA-A rated bonds bucket given the % change in the GDP MER annual average growth the StrPol-450 policy under the WITCH scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket Add-On - GDP MER- North America -StrPol450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0031	0.0031	0.0031
95%	0.0093	0.0093	0.0093

Table 11: Granularity add-on of the BBB-B rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol-450 policy and the WITCH scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

BBB-B Bucket Add-On - GDP MER - North America -StrPol-450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	26.0662	26.0662	26.0662
95%	90.8821	90.8821	90.8821

Table 12: VaR of the AAA-A rated bonds bucket and VaR of the BBB-B rated bonds bucket under the StrPol-450 policy and the WITCH setting in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2040 and the GDP MER annual average growth in 2020).

AAA-A Bucket VaR and BBB-B Bucket VaR		
% Quantile	A-Bucket VaR	B-Bucket VaR
90%	0.0045	0.00002607
95%	0.0011	0.000007

Table 13: Granularity add-on of the AAA-A rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol450 policy and the WITCH scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2040 and the GDP MER annual average growth in 2020).

AAA-A Bucket Add-On - GDP MER - North America -StrPol-450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.031	0.031	0.031
95%	0.0097	0.0097	0.0097

Table 14: Granularity add-on of the BBB-B rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol-450 policy and the WITCH scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2040 and the GDP MER annual average growth in 2020).

BBB-B Bucket Add-On - GDP MER - in North America-StrPol-450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	26.6970	26.6970	26.6970
95%	99.0415	99.0415	99.0415

Table 15: VaR of the AAA-A rated bonds bucket and VaR of the BBB-B rated bonds bucket under the StrPol-450 policy and the WITCH setting in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2050 and the GDP MER annual average growth in 2020).

AAA-A Bucket VaR and BBB-B Bucket VaR		
% Quantile	A-Bucket VaR	B-Bucket VaR
90%	0.0045	0.00002607
95%	0.0011	0.000007

Therefore, the paper computes the granularity add-on under the StrPol-450 policy within the WITCH framework in North America considering the % change between the GDP MER annual average growth in 2020 and the GDP MER annual average growth in 2050, a year, in which, as it is evident from Figure 18, the % change is -10%. Table 15 shows that, even in this context, VaR does not capture the climate transition risk. However, Table 16 and Table 17 show that the add-on belonging to this scenario is higher, for both buckets than the one computed within the baseline framework.

Table 16: Granularity add-on of the AAA-A rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol-450 policy and the WITCH scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2050 and the GDP MER annual average growth in 2020).

AAA-A Bucket- Add-On - GDP MER- North America -StrPol-450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0033	0.0033	0.0033
95%	0.0113	0.0113	0.0113

Table 17: Granularity add-on of the BBB-B rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol-450 policy and the WITCH scenario in North America (the transition risk is computed as the % change between the GDP MER annual average growth in 2050 and the GDP MER annual average growth in 2020).

BBB-B Bucket- Add-On - GDP MER - North America -StrPol-450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	28.6357	28.6357	28.6357
95%	132.2656	132.2656	132.2656

5.2.3 Granularity Add-On Under the StrPol-450 Policy within the GCAM Framework in Europe

In this section the paper computes the granularity add-on accounting for forward-looking data under the StrPol-450 climate policy and the GCAM setting in Europe.

To give an idea of the effects of the StrPol-450 policy under the GCAM setting in Europe, the forward-looking trajectories regarding oil, fossil, and CO2 emissions in this region are shown. Figure 20 and Figure 21 show that the StrPol-450 policy under the GCAM setting will cause a decline in oil and fossil in Europe from 2005 to 2100. Figure 22 and Figure 23 show that, under the StrPol-450 policy and the GCAM setting, a reduction in CO2 emissions will occur in Europe from 2005 to 2100. Contrarily to the oil and fossil trajectories, even in this case, CO2 emissions will not only be affected by a considerable reduction, but they will also reach negative values starting from 2060.

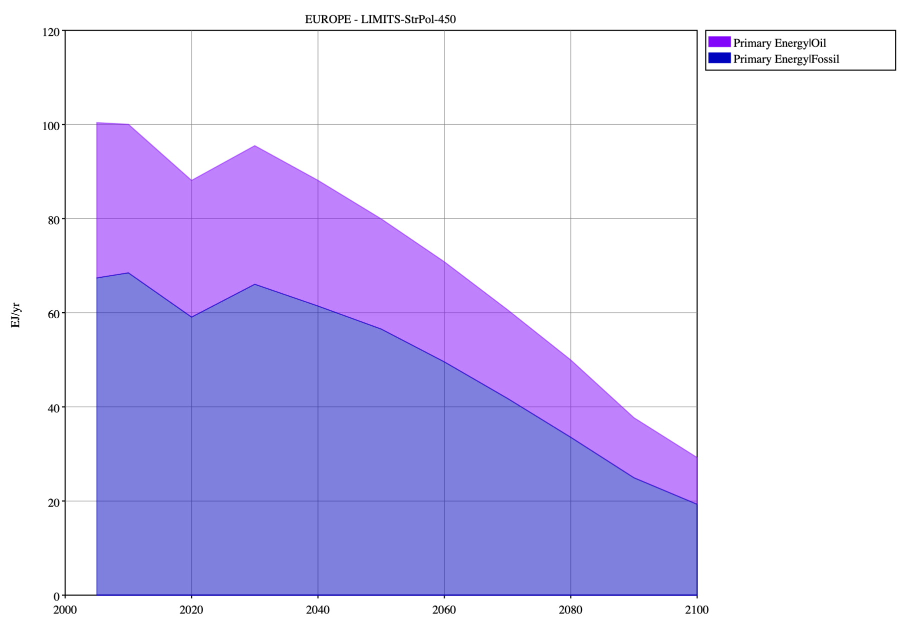

Figure 20: Graph representing forward-looking data about oil and fossil used in Europe from 2005 to 2100 within the primary energy sector under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Primary Energy|Fossil	EJ/yr	67	68	59	66	61	57	50	42	34	25	19
Primary Energy|Oil	EJ/yr	33	32	29	29	27	23	21	19	16	13	10

Figure 21: Forward-looking data about oil and fossil used in Europe from 2005 to 2100 under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

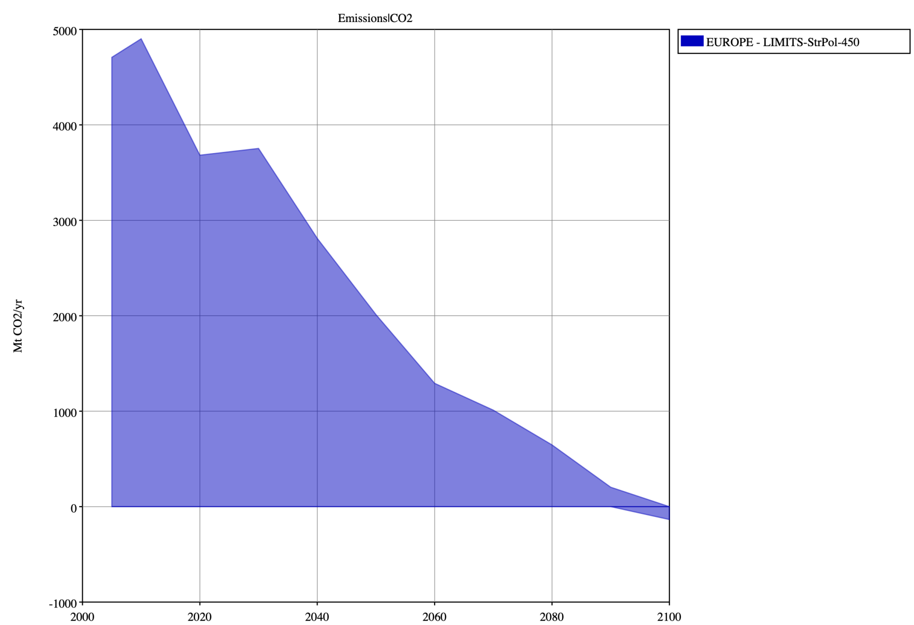

Figure 22: Graph representing forward-looking data about CO2 emissions in Europe from 2005 to 2100 within the primary energy sector under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Emissions|CO2	Mt CO2/yr	4708	4902	3683	3753	2812	2013	1292	1011	647	204	-135

Figure 23: Forward-looking data about CO2 emissions in Europe from 2005 to 2100 under the StrPol-450 policy and the GCAM scenario. Source: LIMITS Scenario Database.

The paper reports below the estimation of GDP MER annual average growth from 2005 to 2100 in Europe within the GCAM framework and under the StrPol-450 policy, and the percentage change in the GDP MER annual average growth computed within the same framework and in the same region, setting 2020 as the base year.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090
GDP|MER	Annual Average Growth [%]	0,5	1,6	1,5	1,2	1,1	1,1	1,1	1,0	1,1	1,4

Figure 24: Annual Average Growth in GDP (MER) in Europe under the StrPol-450 policy within the GCAM framework. Source: LIMITS Scenario Database.

Variable	Unit	2020	2030	2040	2050	2060	2070	2080	2090
GDP|MER	% Δ in Annual Average Growth		-20%	-26%	-26%	-26%	-30%	-27%	-5%

Figure 25: % Change in the GDP MER Annual Average Growth in Europe under the StrPol-450 policy within the GCAM framework.

As for North America, Figure 24 shows that European GDP MER annual average growth under the StrPol-450 policy and the GCAM scenario is still characterized by a positive growth (1,2%) in 2030 and remains as such for the following decade until 2090. However, despite being positive, the GDP MER growth occurred in 2030 is lower than the one that occurred in 2020 (1,5%). In order to capture this growth decline, the paper computes the % change between the GDP growth in 2020 and the GDP growth in the future decades. Figure 25 shows that, under the StrPol-450 policy and the GCAM scenario, the % change between the GDP growth in 2020 and the GDP growth in 2030 is considerable. Specifically, in 2030, the GDP will grow 20% less than it did in 2020 and it will keep growing at a similar pace until 2080.

Table 18 show that, even under the GCAM setting in Europe, both buckets' VaR does not capture the threat arising from climate transition risk. Instead, climate transition risk is reflected in both buckets' granularity add-on charges within this framework. Table 19 and Table 20 show that, as for the baseline scenario, the add-on charges do not vary with the standard deviation used for the computation of the asymptotic betas. However, both the AAA-A rated bonds bucket's add-on and the BBB-B rated bonds bucket's add-on are higher than the add-on charges computed within the baseline scenario. Specifically, the BBB-B rated bonds bucket seems to be more sensitive to the impact of the StrPol-450 measure.

Table 18: VaR of the AAA-A rated bonds bucket and VaR of the BBB-B rated bonds bucket under the StrPol-450 policy and the GCAM setting in Europe (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket VaR and BBB-B Bucket VaR		
% Quantile	A-Bucket VaR	B-Bucket VaR
90%	0.0045	0.00002087
95%	0.0011	0.000021

Table 19: Granularity add-on of the AAA-A rated bonds bucket given the % change of GDP (MER) annual average growth under the StrPol-450 policy and the GCAM scenario in Europe (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket Add-On - GDP MER- Europe -StrPol450 GCAM			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0034	0.0034	0.0034
95%	0.0128	0.0128	0.0128

Table 20: Granularity add-on of the BBB-B rated bonds bucket given the % change the GDP (MER) annual average growth under the StrPol-450 policy and the GCAM scenario in Europe (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

BBB-B Bucket Add-On - GDP MER- Europe -StrPol-450 GCAM			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	30.1949	30.1949	30.1949
95%	173.6992	173.6992	173.6992

5.2.4 Granularity Add-On Under the StrPol-450 Policy within the WITCH Framework in Europe

In this section the paper computes the granularity add-on accounting for forward-looking data under the StrPol-450 climate policy and the WITCH setting in Europe.

To give an idea of the effects of the StrPol-450 policy under the WITCH setting in Europe, the forward-looking trajectories regarding oil, fossil, and CO2 emissions in this region are shown. Figure 26 and Figure 27 show that the StrPol-450 policy under the WITCH setting will cause a decline in oil and fossil in Europe from 2005 to 2100. Figure 28 and Figure 29 show that, under the StrPol-450 policy and the WITCH setting, a reduction in CO2 emissions will occur in Europe from 2005 to 2100. Contrarily to the oil and fossil trajectories, CO2 emissions will not only be affected by a considerable reduction, but they will also reach negative values starting from 2060.

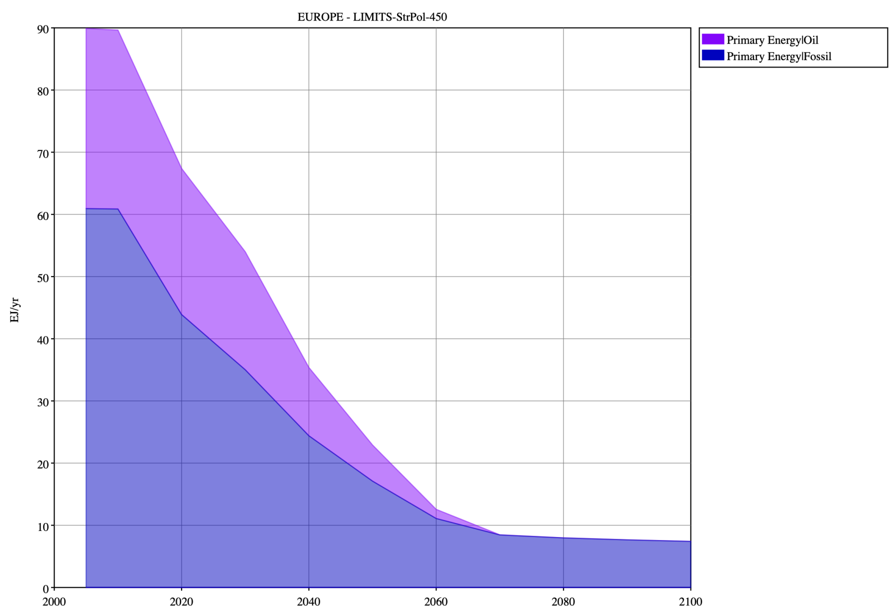

Figure 26: Graph representing forward-looking data about oil and fossil used in Europe from 2005 to 2100 within the primary energy sector under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Primary Energy|Fossil	EJ/yr	61	61	44	35	24	17	11	8	8	8	7
Primary Energy|Oil	EJ/yr	29	29	24	19	11	6	1	0	0	0	0

Figure 27: Forward-looking data about oil and fossil used in Europe from 2005 to 2100 under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

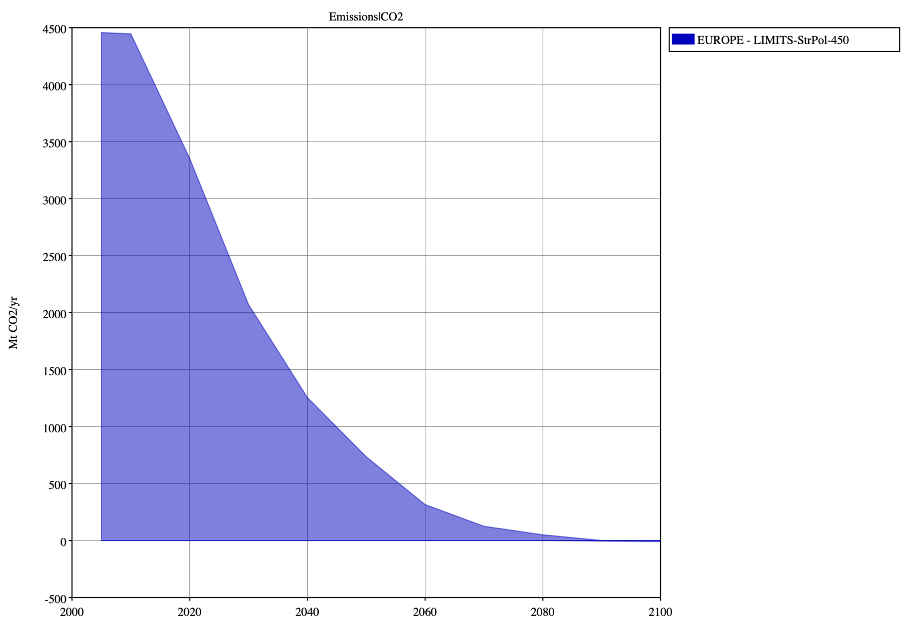

Figure 28: Graph representing forward-looking data about CO2 emissions in Europe from 2005 to 2100 within the primary energy sector under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Emissions|CO2	Mt CO2/yr	4457	4446	3352	2070	1255	734	315	125	50	-6	-11

Figure 29: Forward-looking data about CO2 emissions in Europe from 2005 to 2100 under the StrPol-450 policy and the WITCH scenario. Source: LIMITS Scenario Database.

The paper reports below the estimation of GDP MER annual average growth from 2005 to 2100 in Europe within the WITCH framework and under the StrPol-450 policy, and the percentage change in the GDP MER annual average growth computed within the same framework and in the same region, setting 2020 as the base year.

Model	Scenario	Region	Variable	Unit	2005	2010	2020	2030	2040	2050	2060	2070	2080	2090
WITCH	LIMITS-StrPol-450	EUROPE	GDP|MER	Annual Average Growth [%]	0,8	2,1	1,7	1,4	1,4	1,3	1,4	1,4	1,3	1,4

Figure 30: Annual Average Growth in GDP (MER) in Europe under the StrPol-450 policy within the WITCH framework. Source: LIMITS Scenario Database.

Model	Scenario	Region	Variable	Unit	2020	2030	2040	2050	2060	2070	2080	2090
WITCH	LIMITS-StrPol-450	EUROPE	GDP|MER	% Shock Annual Average Growth		-13%	-16%	-24%	-16%	-18%	-19%	-17%

Figure 31: % Change in the GDP MER Annual Average Growth in Europe under the StrPol-450 policy within the WITCH framework.

Unlike the WITCH scenario addressing the GDP MER annual average growth in North America, Figure 30 shows that, in Europe, the GDP MER annual average growth in 2030 under the StrPol-450 policy and the WITCH scenario is still positive, but lower than the one occurred in 2020. Figure 31 shows that the GDP MER annual average growth in 2030 will grow 13% less than the GDP MER annual average growth occurred in 2020. In other words, contrarily to North America, the impact of the StrPol-450 measure under the WITCH scenario in Europe in 2030 is similar to the same policy's impact within the GCAM framework.

Table 21 shows that even in Europe, under the WITCH scenario, both buckets' add-on charges do not capture climate transition risk. Table 22 and Table 23, show that, although the add-on charges do not vary with the standard deviation used for the computation of the asymptotic betas, under the StrPol-450 policy within the WITCH framework, both the AAA-A rated bonds bucket's add-on and the BBB-B rated bonds bucket's add-on are higher than the add-on charges computed within the baseline scenario. Therefore, there is no need to compute the buckets' add-on deriving from the % change between the GDP MER annual average growth in 2040 and the GDP MER annual average growth in 2020.

Table 21: VaR of the AAA-A rated bonds bucket and VaR of the BBB-B rated bonds bucket under the StrPol-450 policy and the WITCH setting in Europe (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket VaR and BBB-B Bucket VaR		
% Quantile	A-Bucket VaR	B-Bucket VaR
90%	0.0045	0.00002087
95%	0.0011	0.000021

Table 22: Granularity add-on of the AAA-A rated bonds bucket given the % change in the GDP MER annual average growth under the StrPol-450 policy and the WITCH scenario in Europe (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

AAA-A Bucket Add-On - GDP MER- Europe -StrPol450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	0.0033	0.0033	0.0033
95%	0.0117	0.0117	0.0117

From the above-mentioned results we can observe that, while the climate add-on for the AAA-A rated bonds bucket does not vary much from the one generated by the credit risk factor, the add-on deriving from the climate transition risk is particularly higher for the BBB-B rated bond buckets than the one computed in the baseline scenario. Evidently, lower-quality instruments portfolio would be more affected by the sudden introduction of stringent climate measures aimed at setting targets to turn a carbon-intensive economy into an environmentally sustainable one. Moreover, while in Europe the StrPol-450 policy in both the scenarios seem to have a considerable and immediate impact on the economy, in North America, the climate policy seems to impact the GDP MER later under the WITCH scenario.

Table 23: Granularity add-on of the BBB-B rated bonds bucket given the % change in the GDP MER annual average growth unde the StrPol-450 policy and the WITCH scenario in Europe (the transition risk is computed as the % change between the GDP MER annual average growth in 2030 and the GDP MER annual average growth in 2020).

BBB-B Bucket Add-On - GDP MER- Europe -StrPol-450 WITCH			
% Quantile	$\sigma = 1.0$	$\sigma = 1.5$	$\sigma = 4.0$
90%	29.0329	29.0329	29.0329
95%	141.1888	141.1888	141.1888

6 Pitfalls and Further Research

In this section, the paper analyzes its limitations. The first limitation regards the VaR framework under which the granularity add-on has been computed. Value-at-Risk, in fact, is not without shortcomings. VaR provides no information on the magnitude of loss experienced when capital is depleted, since it is based on a single quantile of the loss distribution (Gordy, 2003)[11, p.202]. Therefore, the above-mentioned analysis should be performed on the expected shortfall (ES), which is the expected loss reliant on the shape of the tail of the portfolio returns' distributions (Gordy, 2003) [see 11, p.202] and is defined in the following way:

$$ES_q[Y] = (1-q)^-1(E[Y * 1_{\{Y_q(Y)\}})]_{a_q(Y)(q-Pr(Y<a_q(Y)))} \tag{6.1}$$

According to Gordy (2003), another alternative to VaR is the expected excess loss (EEL). For a random variable Y and target loss rate $\theta > 0$, EEL is defined as:

$$EEL_\theta\ [Y] \equiv inf\left\{y : E[(Y-y)^+] \leq \theta\right\}) \tag{6.2}$$

where Y^+ denotes max(Y, 0) [see 11, p.219]. Under the EEL paradigm, an institution holds capital and reserves so that the expected credit loss in excess of capital is less than or equal to the target loss rate (Gordy, 2003) [see 11, p.219].

Contrarily to the Value-at-Risk, the expected excess loss is sensitive to the tail of the loss distribution like the expected shortfall, but EEL is irreconcilable with portfolio-invariancy (Gordy, 2003) [see 11, p.219].

The second limitation consists in the fact that the model focuses on the actuarial definition of loss and neglects the market-to market loss framework. In this way, much of the credit risk is missed, in fact, no credit loss is recognized when an A-rated loan downgrades to grade B (Gordy, 2003) [11, p.210]. Instead, the mark-to-market (MTM) loss includes the risk of downward or upward rating migration (Gordy, 2003) [see 11, p.210].

According to Gordy (2003) [11], under the market-to-market loss setting, assuming a rating system with G non-default grades (grade G+1 denoting default), and for each obligor i a set of unconditional transition probabilities for grade g at the horizon, threshold values γ_{ig} for obligor i's asset return R_i , such that obligor i defaults if $R_i \leq \gamma_i, G$, and transits to live grade g if $\gamma_i, G < R_i \leq \gamma_i, g1$, the conditional transition probabilities are given by

$$p_i g(X) = \Phi((\gamma_i, g-1+xw_i)/\sqrt{1-w_i^2}) - \Phi((\gamma_i, g+xw_i)/\sqrt{1-w_i^2}) \tag{6.3}$$

and the unconditional transition probabilities determine the thresholds as

$$\gamma_i, g = Phi^-1(p_i, g+1+...+p_i, G+1). \tag{6.4}$$

The conditional expected market-to-market value at the horizon is:

$$MTM_i(X) = \sum_{g=1}^{G} \nu_i g(x) p_i g(x) + A_i(1 - E[LGD_i|x]) p_i, G + 1(x) \tag{6.5}$$

where A_i is the size of the bank's claim on the obligor in the event of a default (Gordy, 2003)[see 11, p.211].

The conditional expected loss function $\mu_i(x)$ is then given by:

$$\mu_i(x) = exp(-rT)/A_i(E[MTM_i(X)] - MTM_i(x))$$

where T is the time to horizon and r is the risk-free yield for term T (Gordy, 2003)[see 11, p.211] .

The third limitation of the model lies on the difficulty in estimating climate transition risk and the computation of the climate transition % shock. The paper computes it considering forward-looking regional trajectories of the overall economy GDP MER's annual average growth. However, the paper does not consider the specific obligor's instrument exposure to the climate transition risk. It assumes that the negative % shock affecting the overall economy will be equally reflected on each obligor's returns, completely neglecting that obligors could be impacted asymmetrically by climate transition risk. Therefore, future studies could try to incorporate obligors' instruments specific exposure.

Moreover, the analysis' findings show that, while climate transition risk, as it is computed, is perfectly reflected in climate add-on charges under the StrPol-450 policy and the integrated assessment models, VaR does not capture such threat. Therefore, further research should be conducted in order to overcome this flaw by finding new techniques to compute climate transition risk so that it is reflected in the VaR metrics.

As already mentioned before, another issue concerning the computation of the climate transition risk shock lies in the fact that the paper has taken GDP MER forward-looking trajectories because of data availability issue. However, several scholars suggest that the use of GDP PPP over GDP MER is highly recommended. According to Holtsmark and Alfsen (2005), using MER means overestimating the economic growth and the potential for energy efficiency improvements in the developing countries [12](p.13). Even if this does not constitute a real issue for the analysis, as it has been performed in developed regions such as North America and Europe, further research could be conducted on the best available GDP trajectories.

7 Conclusion

The adverse effects of climate change urge a transition to a low- carbon economy. This transition, however, implies risks for the profits and values of firms, and, consequently, for the entire financial sector.

Unlike climate physical risk, climate transition risk constitutes a pervasive type of threat that is difficult to define, and, consequently, to price. Although several studies have been conducted in order to measure the exposure of firms and financial institutions to climate transition risk and their consequent distress due to their inability to anticipate and adapt to policies aimed at turning the current economy into a low-carbon intensive one, very few studies have been conducted on the way to incorporate climate transition risk in bonds' portfolios.

Therefore, this paper constitutes an attempt to fill the gap left by the existing literature. It tries to compute climate transition risk and to include it within the computation of the granularity-add-on charge for less than perfectly diversified idiosyncratic risk for differently rated bonds buckets, hypothesizing that the add-on charge including climate transition shock is higher than the one that does not include it. The findings of the paper perfectly fulfill the hypothesis, confirming that financial institutions should consider a climate granularity add-on charge necessary to cover for climate transition risk.

However, as already mentioned, the analysis is characterized by several pitfalls. One is the limitation in the computation of the transition risk, as it is very difficult to estimate, especially if the aim of the analysis is to assess the exposure of each single obligors' instrument to this type of risk. Another limitation of the paper is that its theoretical framework relies on the actuarial definition of loss, which entails that loss occurs only in case of default, totally neglecting defaults that may arise from instruments' rating downgrades. Additionally, the paper computes the granularity add-on charge within the Value-at-Risk paradigm, without focusing on more precise metrics to estimate loss such as ES and EEL. Moreover, the empirical findings show that, while both buckets' add-on charges capture climate transition risk, both buckets' VaR does not capture such a threat. Therefore, further research should be conducted on the topic, with a special focus on climate transition risk estimation.

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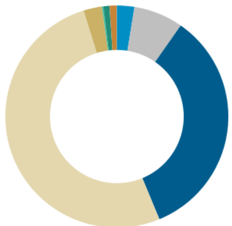
8 Appendix



AAA	2.54
AA	7.17
A	34.08
BBB	51.39
BB	2.71
B	0.19
Not Rated	0.89
Cash	1.04

Figure 32: MSIFT Assets Quality Distribution (% of Total Net Assets). *Source: Morgan Stanley.*

Investment Grade Corporates	**89.03**
Industrial	43.26
Basic Industry	2.20
Capital Goods	3.05
Communications	7.95
Consumer Cyclical	6.49
Consumer Non-Cyclical	6.73
Energy	7.51
Technology	6.90
Transportation	2.44
Utility	10.73
Financial Institutions	35.04
Banking	24.15
Brokerage/Asset Managers/Exchanges	0.27
Finance Companies	3.06
Insurance	4.67
REITs	2.43
Financial Other	0.47
Convertible Bonds	**1.46**
Emerging Market Corporates & Quasi Sovereign	**2.34**
High Yield Corporates	**4.80**
Cash & Equivalents	**2.37**

Figure 33: MSIFT Industry Assets Allocation (% of Total Net Assets) . *Source: Morgan Stanley.*

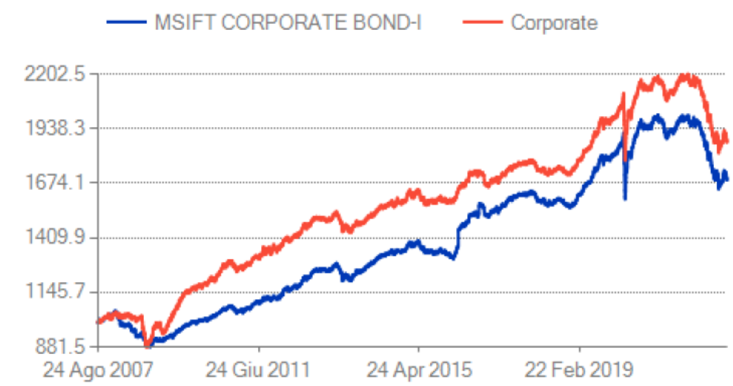


Figure 34: MSIFT Portfolio Performance vs Corporate Index. *Source: Bloomberg.*

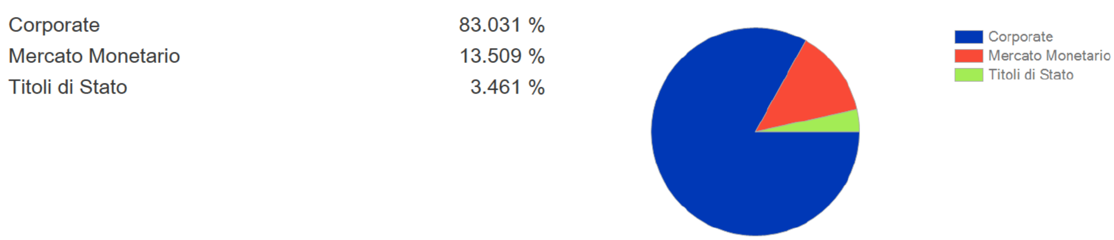


Figure 35: MSIFT Financial Market Segment Assets Allocation. *Source: Bloomberg*

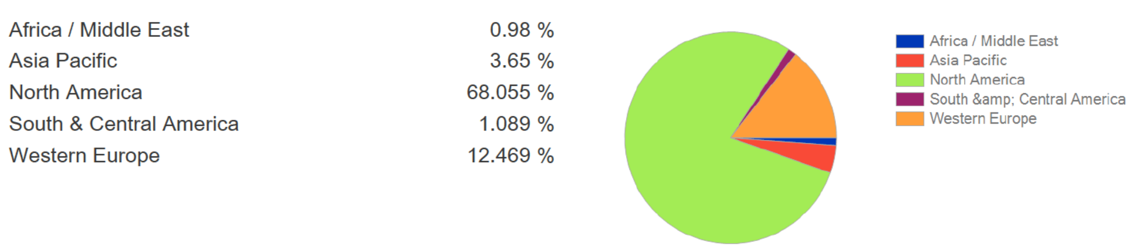


Figure 36: MSIFT Geographical Assets Allocation. *Source: Bloomberg*

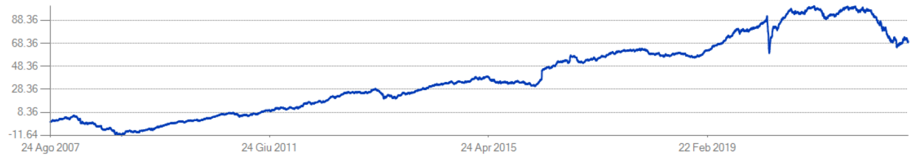


Figure 37: MSIFT Portfolio Total Return *Source: Bloomberg*

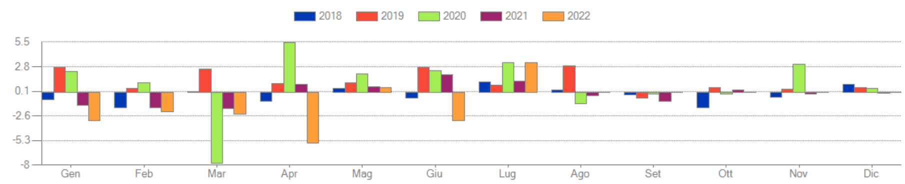


Figure 38: MSIFT Portfolio Seasonality *Source: Bloomberg*

9 Summary

Climate change is progressively turning into a threat to humankind and is also expected to constitute a considerable financial risk affecting the financial sector through several channels. Specifically, climate transition risk, which is the risk arising from firms' and investors' inability to anticipate climate policies' effects, constitutes a real threat, and financial institutions that own portfolios whose instruments belong to carbon-intensive firms should seriously start to incorporate this type of risk in their credit risk model.

Amongst the attempt to quantify climate transition risk, Reboredo and Ugolini (2022) recommend using the Carbon Risk Score (CRS), a measure of firms' exposure to climate transition risk computed at sub-industry level and accounting also for firms' specific adjustments. Alessi and Battiston (2022) propose, as a measure of climate transition risk, the Transition-Exposure Coefficients (TECs), which approximates the portion of portfolios' investments made in industries that are highly exposed to climate transition risk without relying on specific climate policies and models, which instead constitute the core of Battiston and Monasterolo (2020)'s analysis. Battisotn and Monasterolo (2020), in fact, computes climate policy shock as the transition from a macroeconomic trajectory output related to a specific energy sector within the traditional economic setting to a macroeconomic trajectory output under a specific climate policy setting (StrPol-450) within Integrated Assessment Models (IAMs) framework.

The above-mentioned studies' findings suggest that: European banks and financial institutions are more sensitive to climate transition risk than US firms; that, as expected, equity portfolios are slightly more exposed to climate transition risk than bond portfolios, and that countries not characterized by an increasing share of renewable energy sources on their Gross Value Added (GVA) experience a negative climate tranistion shocks on their sovereign bonds' value.

Despite the literature showing the harmful impact of the climate transition risk on the financial sector, financial regulators have still not provided a satisfying response to this threat and only few studies suggest how to incorporate it into financial institutions credit risk models. Thus, this paper constitutes an attempt to fill the gap existing in the literature. Specifically, the paper computes the add-on charge deriving from less than perfectly diversified idiosyncratic risk originated from commercial banks' incapacity to mitigate portfolios' climate-related financial distress. The hypothesis of the paper is that the granularity add-on charge considering climate transition risk is higher than the one that does not.

To test the above-mentioned hypothesis, the paper retrieves the theoretical framework from a model, developed by Gordy in 2003, for the computation of the granularity add-on charge, and from a model, developed by Battiston and Monasterolo in 2020 [3], that suggests how to compute climate transition risk and how to incorporate it at portfolio level. Specifically, from Gordy (2003), the paper retrieves the assumptions and the formulas to compute the granularity add-on charge under an actuarial (book-to-value) definition of loss, according to which loss occurs only in case of default, neglecting the loss arising from instruments' rating upgrade and downgrade. Battiston and Monasterolo (2020)'s paper [3], instead, has been used in order to understand under which Integrated Assessment Models (IAMs) and policy scenario the climate transition shock could have been computed, on which database climate change data could be retrieved and how to incorporate climate policy shock into the granularity add-on charge computation.

Consequently, the paper applies the methodology to a portfolio of corporate bonds divided into two differently-rated buckets (an AAA-A corporate bonds bucket and a BBB-B corporate bonds bucket). Specifically, the paper first deals with the credit-risk scenario (the baseline scenario), under which the add-on originated by traditional credit risk factors is computed both for the A-AAA bond bucket and the B-BBB bond bucket, and then, it focuses on the StrPol-450 climate policy scenario (within the WITCH and GCAM integrated assessment models), under which the climate transition shock is computed as the % change in GDP MER annual average growth and, it is, eventually, used to compute the climate transition risk add-on charge. This analysis has been performed both for the North American and the European GDP MER annual average growth.

The results confirm the hypothesis. Financial institutions should consider an higher add-on charge to mitigate the impact of climate transition risk on their portfolios, whose instruments belong to obligors unable to anticipate and quickly adapt to climate policies introduced to turn the carbon-based economy to a green-economy. Specifically, the results show that both in Europe and in North America the granularity add-on charge is higher under the StrPol-450 setting both for the AAA-A rated bonds bucket and the BBB-B rated bonds bucket.

Finally, the paper underlines the pitfalls of its analysis. For instance, instead of relying on the VaR paradigm, studies could develop a climate transition risk model under the expected shortfall theoretical framework. The VaR framework, in fact, has some shortcomings and limitations as it is based on a single quantile of the loss distribution, without providing information on the magnitude of loss incurred in the event of default. Assessing the climate transition risk impact on the granularity add-on charge under a more robust risk measure such as the expected shortfall (ES), which is the expected loss conditional the tail of the portfolio's returns distributions , could be a perfect way to implement further research. Another way to overcome the pitfall of the analysis is to compute the portfolio loss ratio under a market-to-market framework, which entails that loss occurs not only in case of default, but also in case of instruments' rating upgrade and downgrade. Moreover, further research should address the estimation of climate transition risk. The paper, in fact, computes it considering forward-looking regional trajectories of the overall economy GDP MER's annual average growth, assuming that the negative % shock affecting the overall economy will be equally reflected on each obligor's instrument returns, completely neglecting that obligors could be impacted differently by climate transition risk. Future studies could therefore focus on the computation of a transition risk that takes into consideration instruments specific exposure to it.