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Climate stress-test of the financial system related to syndicated loan market

A study about how the financial system is exposed to regulations with respect to climate change and the corresponding transition risk.

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Abstract

The purpose of this paper is to investigate the exposure to transition risk within the syndicated loan market under various scenarios. The target reductions, as presented in the Paris Agreement alongside notions of reducing negative impacts of climate change provide a rationale for investigating the topic. In the investigation, data consisting of 30858 (780) observations was utilized for the respective scenarios constructed. The results indicate that exposure to transition risk depends on the speed of transitioning. While a fast transition would induce severe losses to the most exposed banks, even a slow transition will result in non-negligible losses, which is exacerbated further by inherent industry exposures.

Keywords: Transition risk, disaster risk, Paris Agreement, stranded assets, Monte Carlo simulation.

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1. Introduction

With global warming posing significant risks to humanity as a whole, the need for regulation and limitation of fossil fuel emissions are apparent. During the world economic forum's annual meeting of 2024 the secretary-general of the United Nations, António Guterees, highlighted the consequences of fossil fuel emissions as droughts, storms, fires and floods are striking countries and communities (Forum Agenda, 2024). Guterres further emphasized the urgency regarding limitations of fossil fuel emissions by stating that “the phaseout of fossil fuels is essential and inevitable… Let's hope it doesn’t come too late” (Forum Agenda, 2024). Similar notions can be heard on the news and from organizations such as Greenpeace. The Paris Agreement, which is a legally binding international treaty on climate change, was adopted by 196 parties in Paris, France, on 12 December 2015 (United Nations, 2015). This agreement presents the goal of holding the global average temperature increase to 2°C above pre-industrial levels and furthermore underscores that crossing the threshold of 1.5°C risks unleashing substantial climate change impacts which includes more frequent and severe droughts, heatwaves and rainfall (United Nations, 2015). The Paris Agreement was enacted on 4th of November 2016 and stresses that in order to not pass the threshold of 1.5°C, greenhouse gas emissions must peak before 2025 and furthermore decline by 43% by 2030 (United Nations, 2015).

Since the implementation of the Paris Agreement in 2016, global carbon dioxide emissions (CO_2) have increased from 35.46 billion metric tons to 37.55 billion metric tons as of 2023, representing a 5.9% increase (Statista, 2023a). The consequences of increased greenhouse gas emissions are in academia commonly denoted as *disaster risk* - a concept that will be more thoroughly investigated in section 2.1. What can be noted, nonetheless, is that limiting the greenhouse gas emissions and hence the negative impacts stemming from it should be considered a good investment for current and future generations. However, within the realm of finance these limitations do not come without cost. Similar to classic portfolio theory, where risk and reward are thought of as moving in tandem, the reward of reducing disaster risk conversely results in increasing *transition risk.* Transition risk refers to the notion that regulations taken to mitigate climate change may cause adverse effects to institutions either directly or indirectly by limiting the prospects for future business opportunities by restricting the usage of fossil fuels. Naturally, disaster risk and transition risk are interconnected such that changing one will inevitably affect the other.

The purpose of this paper is to investigate the lending market’s exposure to transition risk under various climate sensitive scenarios, incorporating current emissions reduction targets and inherent uncertainty regarding the speed and stringency of their regulatory implementation. This paper contributes to the current literature by investigating the syndicated loan market, as previous literature mainly investigates the equities market. The motivation for examining the subject is twofold. Firstly, existing literature suggests that the exposure to transition risk may be more pronounced in the lending market as opposed to the equities market, but neglects to investigate the lending market itself, as in Battiston et al. (2017). Second, given the nature of climate change and measures taken to mitigate it, including the Paris Agreement, the question itself will become increasingly relevant in the near future. Particularly, companies within affected industries as well as risk management professionals face an increasing urgency to accurately evaluate the magnitude of this risk.

In an effort to examine the syndicated loan market and the exposure towards transition risk, several different scenarios have been constructed which incorporate increasingly more realistic assumptions regarding exposure. The dataset consists of up to 30858 (780) observations (for section 4.1 and 4.2 (4.3)). Our results suggest that a scenario in which the complete value of all companies operating in the climate sensitive industries is lost would induce losses for the top 20 most exposed banks in the span of 25% to 65% of their total syndicated lending. However, when instead incorporating the reductions necessary to meet the Paris Agreement by linking recovery rates to stranded asset values a less somber scenario is revealed, where lenders are able to recover at least some portion of their loans. Lastly, because it is unlikely that every brown energy firm will be forced into default due to transition risk, we employ a Monte Carlo simulation modeling default rates. In the simulation, loss multipliers constructed by proportion of stranded asset values are incorporated. The findings from the simulation suggest that while transition risk related to lending is unlikely to spell catastrophe for the financial system, resulting in at worst an Expected Shortfall of 10.5% of the total syndicated lending value at the 99% confidence level, it still represents significant risk to lending institutions. The fossil fuel industry (housing) is the most exposed (least exposed) in the brown energy sector with an *Expected Shortfall* of 19.2% (8.2%) at the 99% confidence level. Additionally, tail risk exposure differs between industries and the significance level considered - indicating that lending institutions need to account not only for transition risk but also inherent industry exposures.

The paper is divided into five parts. Part two introduces the reader to relevant background theory including disaster risk, transition risk, risk measures and Monte Carlo simulation. Part two also includes a literature review covering earlier findings within the subject. In the third part, the procedure for collecting data, mapping of industries to relate to earlier research as well as descriptive statistics is highlighted. In the methodology section, part four, the different scenarios in order to investigate the lending markets exposure is presented. The methodology section is constructed in chronological order in terms of more reasonable assumptions where subsequent sections incorporate the earlier but in a refined way. In the fifth section, results for the different subsections presented in the methodology section are presented and analyzed. A conclusion, shortcomings in the paper and suggestions for future research are presented in the last section.

2. Theoretical framework and previous research

2.1 Disaster risk and greenhouse gas emissions

Since 1940, global carbon dioxide emissions (CO_2) have increased by 672% and, as indicated by figure 2.1.1, the trend is undeniably increasing (Statista, 2023a). Furthermore, since 1990 the global CO_2 emissions have increased by more than 60 percent (Statista, 2023:a). The increase is largely driven by large economies, such as China, which in conjunction with rapid economic growth and subsequent industrialization saw its CO_2 emissions increase by a total of 400% since 1990 (Statista, 2023:a). Similar figures stem from other developing countries such as India, which experienced an increase in CO_2 emissions by 348% between 1990-2022 (Statista, 2023:b).

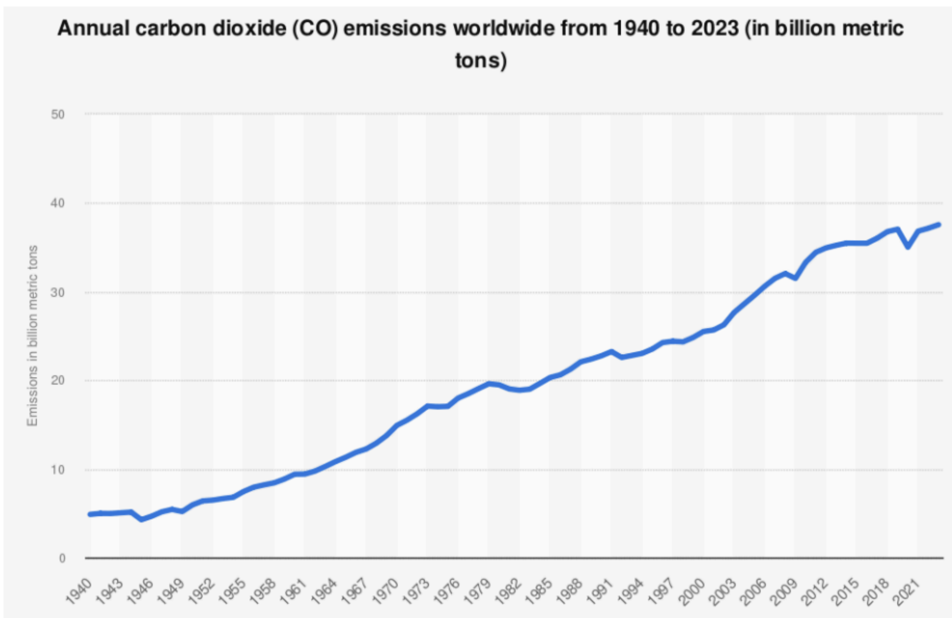

Figure 2.1.1: Global carbon dioxide emissions from 1940 to 2023, Statista (2023).

In conjunction with the increased emissions globally, the occurrence of natural disasters are projected to increase. The consequences, as presented by the European Commission (2024), include, among others, raised sea-levels, droughts, wildfires, floodings, and heatwaves. Moreover, global warming also affects the possibility of accurately predicting events and consequently the capacity of relevant organizations to act and respond accordingly (European Commission, 2024). Consequently, the aforementioned natural consequences pose threats to businesses, a concept in academic literature known as *disaster risk*. The United Nations Office for Disaster Risk Reduction describes disaster risk as "The potential loss of life, injury or destroyed or damaged assets which could occur to a system, society or a community in a specific period of time" (www.undrr.org, n.d.:a). These risks are becoming more pronounced as the average global temperature has already increased by 1.1°C which alters the risk profile of the planet, predominantly with respect to the magnitude, frequency and severity of disasters (www.undrr.org, 2021:b). More notably, extreme weather events have doubled over the last twenty-year period as compared to the preceding twenty years (www.undrr.org, 2021:b). Conjointly with extreme weather events, the costs associated with restoration of damages are also projected to increase. During the period from 2000-2019, damages related to extreme weather events are estimated to have cost approximately $2.8 trillion, or an average of $143 billion per year (Bennet, 2023). Furthermore, these numbers are likely to be an underestimation of the actual costs, as data for some extreme weather events are limited (Bennet, 2023). Additionally, the numbers are projected to increase rapidly to the span of $1.7-$3.1 trillion annually by 2050 (Bennet, 2023).

As outlined by the United Nations Office for Disaster Risk Reduction, these risks are furthermore compounding and as recognized by the Paris Agreement, a holistic approach must be taken when handling them - taking into account not only specific areas, but the earth as a whole (www.undrr.org, 2021:b). Handling these risks by limiting disaster risk and thereby its associated costs does not come without repercussions, as too quick of an adaptation may lead to unforeseen consequences for companies and the financial system as a whole stemming from what is labeled as transition risk.

2.2 Transition risk

During recent years, transition risk has become increasingly important following the release in 2017 of a report from Task Force on Climate-Related Financial Disclosures (TFCD) suggesting that climate-related risk analysis should be incorporated into investment decisions (NAIC, 2024). Transition risk is defined by The National Association of Insurance Commissioners as "the potential costs to society of evolving to a low carbon economy to mitigate climate change" (NAIC, 2024). Transition risks may be financially significant, particularly with respect to relevant sectors including energy production, utilities, transportation, agriculture and financial institutions (NAIC, 2024). The financial impact may stem from various effects including the erosion of market value due to changes in perceptions of companies' contributions to a sustainable economy, increased premium for insurance products as well as increased spending for new investments in technology (NAIC, 2024). These impacts on market values can be quantified using an assortment of measures, including Value at Risk and Expected Shortfall.

2.3 Measuring financial institutions exposure to transition risk

When considering risk, there exist several ways of quantifying it. One frequently used risk measure is Value at Risk, which we denote VaR_q where q denotes the level of significance. Considering the significance level allows us to answer questions about how certain we are that a loss, l, will not exceed an amount V in a specified time horizon T (Hull, 2023). In this sense, V represents the VaR_q - namely the loss that we are $q\%$ certain will not be exceeded (Hull, 2023). VaR_q is consequently a measure suitable for answering "what-if" questions and thereby aligns with the purpose of this thesis in measuring the exposures under transition risk. Furthermore, both VaR_q and ES_q are measures frequently used to assess risk in the banking sector. Depending on the properties of the loss distribution, VaR_q is defined differently. If we consider a discrete distribution then VaR_q is defined as in [1]:

$$VaR_q = min\{\, l\!: Pr(L > l) \ \leq \ 1 - q\,\} \tag{1}$$

Which in words implies choosing the largest loss l such that the probability of experiencing a higher loss is no more than $1 - q$. If the loss distribution is continuous, then an alternative expression is nested in [1], which is denoted as in [2]:

$$VaR_q = Pr\{\, L > VaR_q \} = 1 - q \tag{2}$$

Which implies that, given a continuous loss distribution, there exists a loss such that the probability of losing more than it exactly equals $1 - q$. In both cases [1] and [2], VaR_q is defined in monetary terms, for instance USD or SEK allowing for ease of interpretation. However, one drawback of VaR_q as a risk measure is that it is silent about the losses in case of rarer events where we consider the whole tail of the distribution (McNeil, Frey and Embrechts, 2015). As a consequence, Expected Shortfall, which we denote ES_q, may also be considered. In terms of VaR_q answering the question of how bad things can get, ES_q instead aims to answer the question of given that things get bad, what is the expected loss that may occur (Hull, 2023). Consequently, ES_q is the average VaR_q for all confidence levels $q \ \leq \ x \ \leq \ 1$, defined as:

$$ES_q = \frac{1}{1-q} \int_{x=q}^{x=1} VaR_x dx \tag{3}$$

The original expression of ES_q in [3] can be approximated as regular integrals by using the sum of rectangles. However, one can also exploit the expression in terms of quantiles to derive an alternative expression, as shown by McNeil, Frey and Embrechts (2015), suitable for discrete distributions:

$$ES_q = \frac{E[L^*I_{L>VaR_q}] + VaR_q[1-q - Pr(L>VaR_q)]}{1-q} \tag{4}$$

In expression [4], I_L, is an indicator function taking the value 1 if the loss exceeds VaR_q and 0 otherwise. The specification in [4] is suitable for a discrete distribution as it results in an exact answer as opposed to an approximation (McNeil, Frey and Embrechts, 2015). If, however, the distribution is continuous then by using the definition of VaR_q from [2] implies that the second term cancels out[1] resulting in the following equation:

$$ES_q = E[L\,(I_{L>VaR_q} = 1\,] = E[\,L|L > VaR_q\,] \qquad [5]$$

Which implies that ES_q can be interpreted as the expected loss conditional on the loss exceeding VaR_q. Accordingly, an alternative expression for ES_q is indeed conditional value at risk (Hull, 2023).

Lastly, it might be noted that there exist various other expressions for the two risk measures covered in this section, depending on for instance if the underlying distribution is normally distributed or student-t distributed. In this paper, we will not cover these alternative expressions as an assumption regarding the loss distribution will not be made other than for the random variables drawn in relation to the Monte-Carlo simulation. Indeed, in section 5.3, a Monte Carlo simulation will be implemented and VaR_q and ES_q calculated. Monte Carlo simulation itself will be covered in the ensuing subsection.

2.4 Monte Carlo Simulation and Credit Migration Tables

A Monte Carlo simulation is a statistical tool with a wide range of applications. Applications include, among others, drawing random variables to simulate scenarios for an options price or, as will be covered in this paper, the loss scenarios for a dataset of loans. Indeed, the underlying basis for Monte Carlo simulation is the capability of generating a sequence of random numbers, all with the same given distribution, including finite mean and variance (Bonate, 2001). Depending on the goal of the simulation, the need for simulating random numbers may differ, if the goal is to observe the variability of an outcome then many simulations need to be performed as a consequence of rare events occurring infrequently (Bonate, 2001). In the context of climate transition risk, one such rare event translates into a borrower defaulting as a consequence of stranded assets due to regulation. When considering defaults, credit ratings are useful, as the probability of defaulting as well as transitioning from one rating to another within a certain time period depends on the initial rating (Hull, 2023). One way of depicting the transitioning of ratings is through a credit migration table which shows the probability of a borrower changing credit rating (being upgraded or downgraded) within a certain year, or defaulting. One example of a credit migration table is depicted in Figure 2.4.1. Credit migration tables are used in this paper to calculate the probability of default in order to determine expected losses. This process is repeated through a series of simulations resulting in the actual Monte Carlo simulation.

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[1] From [2]: VaR_q = 1 - q, substituting into [4]: VaR_q [1 - q - (1 - q)] = 0.

Initial rating	Rating at Year-end AAA	AA	A	BBB	BB	B	CCC/C	D
AAA	89,86	9,35	0,55	0,05	0,11	0,03	0,05	0,00
AA	0,50	90,78	8,08	0,49	0,05	0,06	0,02	0,02
A	0,03	1,67	92,61	5,23	0,27	0,12	0,02	0,05
BBB	0,00	0,10	3,45	91,93	3,78	0,46	0,11	0,17
BB	0,01	0,03	0,12	5,03	85,99	7,51	0,61	0,70
B	0,00	0,02	0,08	0,17	5,18	85,08	5,66	3,81
CCC/C	0,00	0,00	0,12	0,20	0,65	14,72	50,89	33,42

Figure 2.4.1: Credit Migration Table for one year-ratings, Hull (2023).

In the figure above, in column A and in row BBB, 3.45 represents the percentage likelihood of a borrower with a credit rating of BBB being upgraded to A after one year (in this case, the probability is 3.45%). Furthermore, the probabilities in Figure 2.4.1 are such that if we take the inverse of the standard normal cumulative distribution function, $N^{-1}(x)$ where *x* denotes the probability from the credit migration table, the corresponding critical values can be retrieved, as outlined in Figure 2.4.2.[2]

Initial rating	Rating at Year-end AAA	AA	A	BBB	BB	B	CCC/C	D
AAA	5,61	-1,27	-2,41	-2,82	-2,89	-3,16	-3,29	-
AA	5,37	2,58	-1,36	-2,49	-2,97	-3,09	-3,35	-3,54
A	-	3,43	2,12	-1,58	-2,60	-2,89	-3,19	-3,29
BBB	-	-	3,09	1,81	-1,69	-2,44	-2,77	-2,93
BB	5,61	3,72	3,35	2,95	1,63	-1,35	-2,22	-2,46
B	5,61	5,61	3,54	3,09	2,78	1,60	-1,31	-1,77
CCC/C	5,61	5,61	5,61	3,04	2,73	2,34	1,01	-0,43

Figure 2.4.2: Credit Migration Table illustrating critical values for transitioning based on the inverse of the standard normal cumulative distribution function.

In the event of default, where the borrower ends up in column *D* above, a concept known as recovery rate becomes relevant. The recovery rate is simply the percent of the loan amount recovered in the event of default, as often a defaulting firm still has some cash and assets to at

[2] Example: The critical value for a currently AA rated loan transitioning to CCC/C is calculated as $N^{-1}(0{,}0002 + 0{,}0002) = -3{,}35$ and so forth.

least partially make up the debt to obligors. Recovery rates can be calculated as the amount recovered from a loan in default divided by the total loan amount.

2.5 Systemic risk

Although each respective bank/institution, due to current financial regulations such as the Basel capital requirements, may provide sufficient risk management in isolation, the aggregate risk in the system as a whole may not be appropriately handled (Acharya et al., 2016). This conclusion, drawn by Acharya et al. (2016) implies that when considering all banks the system may be fragile. This notion introduces the concept of systemic risk, which is the risk to the entire financial system, which is contributed to by large financial institutions, such as banks. Put differently, it is the risk of a crisis in the financial sector as a result of a financial institution collapsing and inducing negative externalities for the real economy (Vilhelmsson, 2024:c). As explained, for instance, by Vilhelmsson (2024:c) it can be thought of as the risk of a firm level shock causing a ripple effect resulting in instability or collapse in the entire financial system. Consequently, climate transition risk brings with it a degree of systemic risk.

In this paper, the application is the possibility that transition risk results in a substantial amount of defaults for a specific (large) lender, resulting in increased volatility to the entire markets. If instead no action is taken towards climate change, disaster risk is substituted for transition risk, and a similar notion applies. Naturally, firms operating within the brown energy sector are correlated with respect to the impact transition risk will have on them. Additionally, firms operating within the *same* brown energy industry will be even more correlated, as industry-affecting factors will apply to all firms within a given industry.

This possibility is higher if the likelihood of *multiple* large financial institutions, which each contribute their own degree of systemic risk to the system, are pushed into distress due to climate transition risk. When quantifying systemic risk, several risk measurements exist including *CoVaR* and *ΔCoVaR* as proposed by Adrian and Brunnermeier (2011). *CoVaR* can be defined as the value at risk for the financial system when a given firm is at a certain VaR level. *ΔCoVaR* is more illuminating, and measures how the *VaR* of the financial system increases when a given firm is distressed (at *q% VaR*) compared to the *VaR* of the system when the firm has a loss equal to the median loss, which in practice is close to or equal to zero.

2.6 Previous research

A growing body of literature examines the impact of climate change and transition risk on the financial markets. In this context, there exist several different perspectives from which it can be investigated. Some literature focuses on the pricing of carbon risk and investigates whether there exists a carbon premium as a result of stranded assets and the Paris Agreement, see for instance Ehlers, Packer and de Greiff (2021).

Other literature analyzes financial topics in relation to climate change and transition risk stemming from a scenario where the 2° target is met. However, most existing research tends to focus on the impact this will have on the equity market or insurance, rather than examining other financial instruments, such as bonds or loans. For example, Dietz et al. (2016) examines VaR for the equities market under a 2° scenario, aiming to answer what the impact of climate change is on global asset values. They do this by conducting a Monte Carlo simulation in order to estimate VaR at different probabilities, focusing on productivity growth rates, climate sensitivity, damage due to climate risk, and the costs of greenhouse gas emission mitigation. Dietz et al.'s (2016) study found that VaR for the entire financial system decreases under a scenario which mitigates global warming, compared to a scenario in which no mitigation methods are taken. Mitigation is especially relevant when considering the tail risk of VaR, reducing the 99th percentile by 7.7%. This is in part due to an increase in disaster risk under a scenario where global warming is not mitigated, and global temperatures increase 3-4° as outlined in Gros et al. (2016).

However, Gros et al. (2016) suggests that a positive impact on the economy due to steps taken to mitigate climate change is dependent on "the reliable supply of energy" due to the fact that "[c]arbon restrictions would severely affect not only energy production industries, but also emissions-intensive industries more generally, and other industries relying on energy or other carbon-intensive inputs," (Gros et al., 2016, p.10). Their paper investigates the effects of a "hard" (too late and too abrupt) vs "soft" (gradual change) landing with regards to climate policy. Gros et al. (2016) finds that both fossil-fuel and utilities firms are heavily debt financed, thus exacerbating the effects of sudden "hard-landing", especially on stranded assets. In fact, a 2014 paper analyzing the role of oil price shocks on U.S. recession by Killian and Vigfusson (2014) suggests that minimal shocks to energy prices, specifically oil, considerably affect U.S. GDP.

Further research conducted by Battiston et al. (2017) stress tests the financial system for transition risk with respect to the equities market. They start by creating a mapping system for so-called brown energy companies, finding the industries and companies most exposed to brown-energy consumption, and their relative exposures. These industries are listed in Table 4.1.1 in the following section, but overall the climate-sensitive industries are fossil fuel, utilities, energy-intensive, housing, and transport. In the first exercise conducted by Battiston et al. (2017) first and second round losses are calculated for the EU's largest banks. First round losses are calculated as "losses in banks' equity due to direct exposures to shocks" while second round losses are "indirect losses in banks' equity due to the devaluation of counterparties' debt obligations on the interbank credit market," (Battiston et al., 2017, p.286). Battiston et al. (2017) further explains that the magnitude of second-round losses can vary significantly depending on the methodology employed. More specifically, they argue that methods yielding small second round losses are only applicable under very specific market conditions including, in particular, a full recovery of the counterparties' assets during the liquidation. Consequently, when such market conditions are not fulfilled, they instead assert that the second round losses can be comparable in magnitude to the first-round effects. The aim of the first exercise is to determine an upper bound on the magnitude of losses by considering a scenario in which all equity value for a sector exposed to a shock is lost, which represents the maximum loss. Battiston et al. (2017) then extend their first exercise to a scenario in which 100% of equity value for listed firms in fossil fuel and utilities sectors is lost. Their results suggest that banks differ with respect to their exposure, some being more exposed to the first round loss whereas others having all their exposure concentrated within the second round. They conclude the exercise by stating that no systemic impact is apparent when only considering the equities channel.

Battiston et al. (2017) then proceed with their second exercise, which consists of constructing distributions of losses for fossil fuels and utilities sectors based on their respective economic impact. They then consider two portfolios which are to represent the average bank and differ with respect to the investment strategy employed. Losses are then found under both brown and green energy investment strategies for the top banks, and *VaR* is calculated. Under the brown scenario, with a portfolio exposed to utilities based on fossil fuels as well as investment in fossil fuels, their results indicate that the financial systems *VaR* at the 95% significance level is 1% of the bank's total capital. This limited magnitude is explained by the notion that the banks considered, Euro Area Banks, bear little equity holdings compared with the balance sheet. Nevertheless, Battiston et al. (2017) conclude their research advocating for a "soft-landing" scenario, similar to Gros et al. (2016), in order to reduce the magnitude of climate policy shocks and make systemic risk negligible. In contrast, they note that a "hard-landing" scenario will result in substantial systemic risk, not giving brown energy companies or banks enough time to adapt or adjust their holdings in accordance with new climate policies. However, a "soft-landing" scenario does not come without its own challenges.

As explained in a Bloomberg whitepaper by Bullard (2014), a soft-landing scenario begs the question of where institutions would reinvest over 4.6 trillion in capital invested in oil and gas as of 2014. Bullard (2014) stresses that "[s]ignificant divestment from coal would be much easier than significant divestment from oil and gas," because "[l]isted coal companies are small enough in aggregate that investors could divest and re-invest without unbalancing portfolios," (Bullard, 2014, p.1). Complicating divestment from oil and gas is the fact that the green energy asset class is too small in value to take in the trillions of dollars that would be generated from that divestment. Additionally, large institutional investors may be hesitant to relinquish their oil and gas holdings, sacrificing future growth and yield from a product which, at least for now, enjoys relatively inelastic demand. However, because coal equities make up less than 5% of the aggregate value of oil and gas, institutions face significantly less exposure to coal, which contributes heavily to greenhouse gas emissions. As a result, divestment from coal should be a significantly simpler task.

3. Data

3.1 Collection of data

In the collection of data we used the LPC/LSEG Dealscan dataset which consists of syndicated loans and covers primarily large corporate lending. The original dataset consists of both primary and secondary lending data, but the latter is disregarded as key inputs including industry groups are not presented. The corresponding data was then filtered by relevant industries, mirroring the procedure and mapping employed by Battiston et al. (2017). The five categories of industries exposed to transition risk, as presented by Battiston et al. (2017), were fossil-fuels, utilities, energy-intensive, housing and transportation. In our dataset, the original industry classifications do not fall into these categories and therefore a mapping mirroring Battiston et al. (2017) was conducted in order to produce comparable results. Oil and gas as well as chemicals, plastics, and rubber were sorted into the fossil fuels category. Utilities were sorted as simply utilities, and mining, construction, and general manufacturing were placed under the energy-intensive category. Both real estate and REITs (Real Estate Investment Trusts) were placed under the housing category and transportation, shipping, and automotive were deemed as transport. An overview of the mapping is compiled in Table 3.1.1

After filtering the data by sectors as outlined above, the data was narrowed to include only tranches with payments due in 2025 and beyond, keeping our data forward-facing in conjunction with how transition risk is defined. Consequently, all loans with tranches maturing in 2025 or later were selected, and the remaining were dropped. Tranches are effectively a decomposition of a loan implying that sorting by tranche maturity date allows us to ignore potential portions of the loan that have already been paid or expire prior to 2025 and instead focusing exclusively on future monetary obligations. The final dataset, of relevant transition risk exposed industries, consists of 30,858 observations.

Battiston et al (2017) mapping	**Mapping in this paper**
Fossil fuel	Oil and Gas | Chemicals, Plastics & Rubber
Utilities	Utilities
Energy intensive	Mining | Construction | General Manufacturing
Housing	Real Estate | REITS
Transport	Transportation | Shipping | Automotive

Table 3.1.1: Mapping of relevant industries from Battiston et al (2017) and this paper.

The overall amount of loans, consisting of both transition risk exposed industries and other, comprises a total of 62425 observations maturing in 2025 or later.

3.2 Descriptive statistics

Following the mapping conducted by Battiston et al. (2017), the corresponding lending exposures for the top 20 lenders, ranked by their exposure to brown energy industries, are depicted in Figure 3.2.1 and Figure 3.2.2 in absolute and relative terms, respectively. The total lending amount consisting of both transition risk exposed industries and "other" amounts to a total of $9.7 trillion. Of the total of $9.7 trillion, $3.9 trillion are loans towards the transition risk exposed industries (brown industries), representing a proportion of 40.2%. As indicated by Figure 3.2.1, the respective exposure differs between the banks. While Goldman Sachs & Co is the top lender, with nearly $780 billion in lending set to be received in 2025 or later, their exposure to brown industries is only 26.7% compared to Bank of China Ltd.'s approximately $306 billion in lending with a 66.1% exposure to brown industries.
Aggregating the exposure to each relevant industry for the top 20 lenders allows them to be ranked, with the vulnerability ranking as fossil fuels ($1.03 trillion), utilities ($0.9 trillion), energy intensive ($0.87 trillion), transportation ($0.82 trillion), and housing ($0.3 trillion). In relation to total lending, the exposure to fossil fuels subsequently represents 10.54% of total lending whereas the smallest, housing, represents 3.04%.

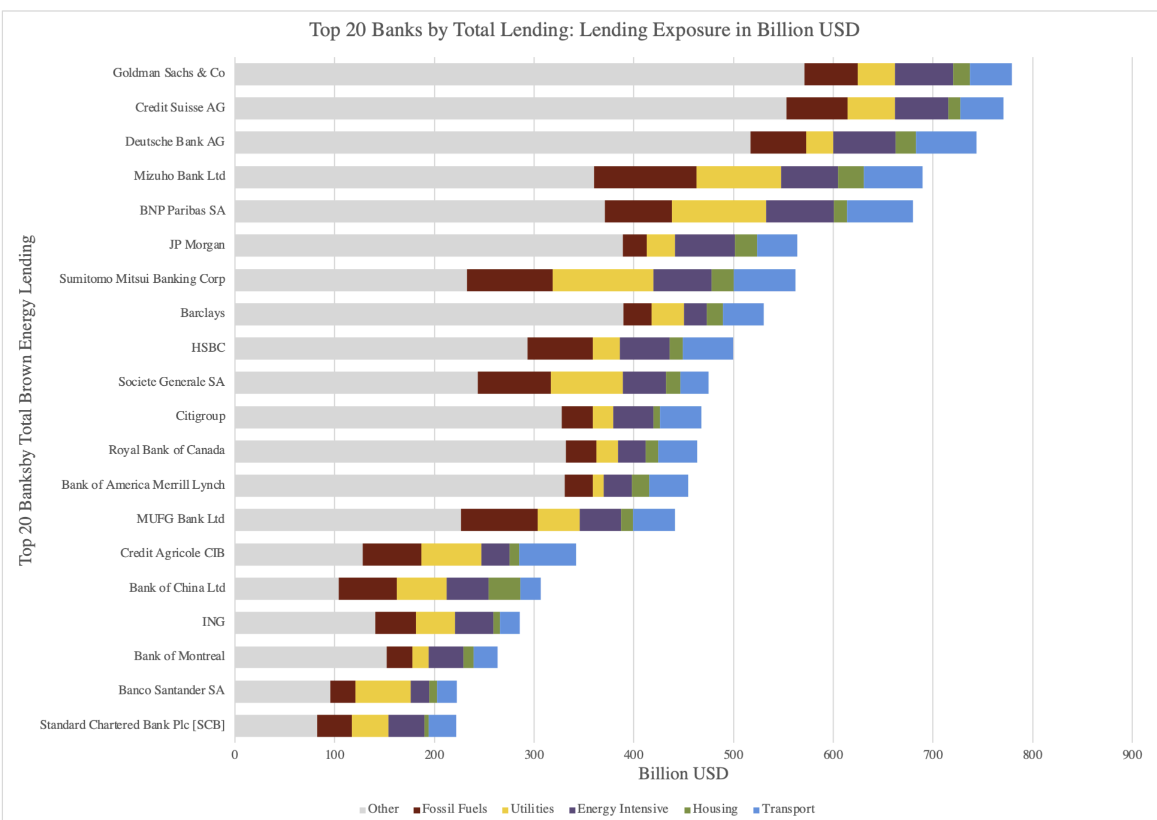


Figure 3.2.1: Top 20 banks by total lending exposure expressed in BUSD and divided into subsections depending on the industry.

Moreover, as depicted in Figure 3.2.2, out of the total 20 banks, six have an exposure towards brown industries representing 50% or more of the total exposure. The relative composition of exposures between the banks are however, exclusive of some outliers, relatively similar although differing in magnitude.

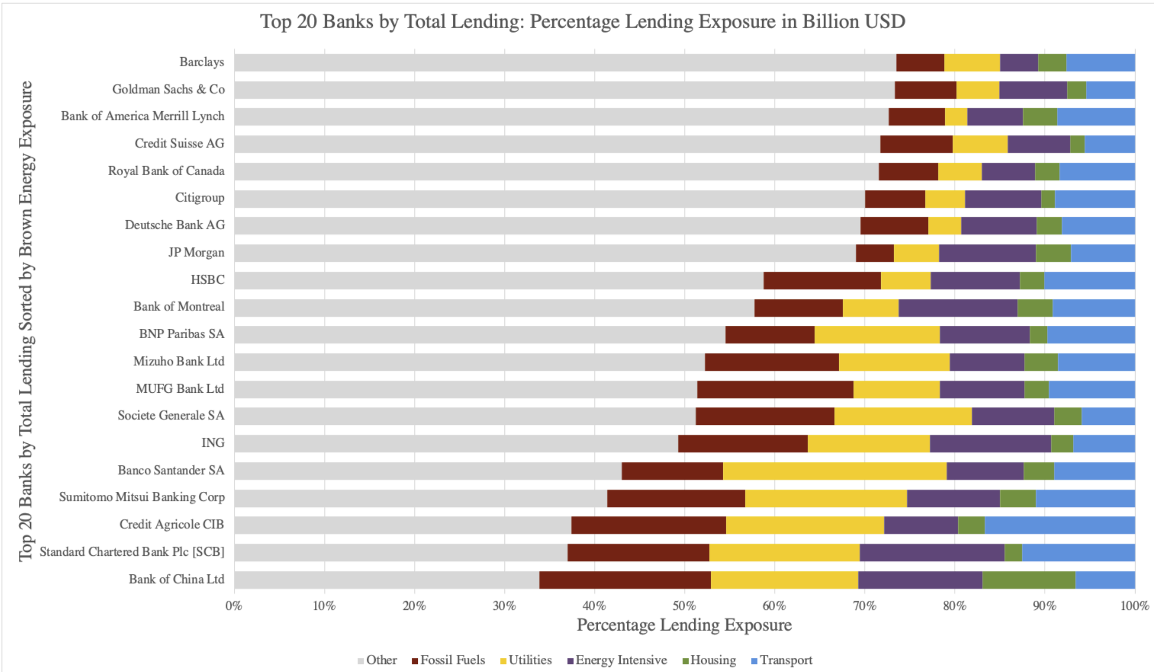


Figure 3.2.2: Top 20 banks by total lending exposure expressed in percentage terms and divided into subsections depending on the industry.

Descriptive Statistics						
Number of unique borrowers						3356
Number of unique lenders						2046
Tranche Amount Converted (MUSD)						
Sector	Fossil Fuel	Utilities	Energy Intensive	Housing	Transport	Total
Mean	713.93	319.17	365.96	248.97	458.64	396.25
Median	320.00	118.31	104.29	83.35	145.19	128.04
25th Percentile	112.14	35.52	30.00	32.12	51.49	39.75
75th Percentile	800.00	363.25	390.00	250.00	468.49	416.67
Minimum	0.33	0.10	0.42	0.42	0.01	0.01
Maximum	6284.17	8000.00	4135.00	3877.24	5000.00	8000.00
Standard Deviation	1080.33	618.79	621.10	450.92	760.88	715.94

Table 3.2.3: Decomposition of tranche amount, total unique borrowers, lenders and sectors.

Lastly, when considering the subsection of relevant industries, the decomposition of tranches, number of unique borrowers and lenders are depicted in Table 3.2.3, decomposed sector wise. As expected, since the data consists of syndicated loans, each individual tranche in relation to total lending of top 20 banks, is relatively small, suggesting that the top 20 banks account for a vast amount of the total lending.

4. Methodology

This subsection relates to the research question and aims to answer it by constructing several scenarios in which we calculate the losses stemming from transition risk as the world moves to more sustainable sources of energy and living. In this section we present three scenarios, firstly a full loss scenario where the transition happens instantaneously, and secondly a scenario in which weighing in relation to stranded assets forms the basis for evaluating losses across the relevant industries. Lastly, an alternative procedure involving a Monte Carlo simulation is employed where defaults and transition probabilities are evaluated conditional on transition risk. The ordering of the scenarios is important, as the ordering itself aims to introduce the reader to more realistic scenarios. Borrowers are all to some extent reliant on brown energy and consequently denoted as operating within exposed industries. Upcoming regulations will therefore affect their respective business opportunities through transition risk. Losses are incurred as a result of regulations affecting the respective borrowers to such an extent that they are unable to adapt, and therefore default due to their assets being stranded. What differentiates between the full loss, stranded asset weighted losses, and Monte Carlo Simulation sections is the extent to which both loan values are recovered and the proportion of distressed borrowers.

4.1 Full loss

The first scenario we examine is a situation in which the complete value in all companies operating in the brown energy sector is lost due to climate transition risk. This can be viewed as the complete elimination of all value in the categories not marked as “other” in Figures 3.2.1 and 3.2.2. This represents a 25% to 65% loss in syndicated corporate lending portfolios for the top 20 most exposed global banks in our dataset. While not completely catastrophic for banks like Goldman Sachs, we expect this scenario to have far reaching systemic consequences, due to systemically important institutions such as Bank of China Ltd. losing more than half of the value in their lending portfolio, likely resulting in the collapse of the bank especially if we consider losses in equity portfolios as well, as examined in Battiston et al. (2017). A full loss scenario stemming from an outright and sudden global ban on all fossil fuel extraction and consumption would be catastrophic for the global financial system and almost certainly result in a multi-year global recession.

An outright ban on fossil fuel usage is unlikely to be enacted, however. Regulators are more likely to target a “soft-landing”, as outlined in Gros et al. (2016), giving industries and markets time to adjust operations and their exposures to weather changing legislation. The gradual shift legislation will almost certainly not result in a complete restriction in fossil fuel use, but more plausibly target a reduction in consumption and greenhouse gas emissions to meet the 2°C warming by 2050 target set by the Paris Agreement. We examine this comprehensively in the following two subsections to account for increasingly more realistic scenarios.

4.2 Stranded asset weighted losses in relation to Paris Agreement

The full loss scenario covered in section 4.1, although indicating the exposure for the top 20 banks, neglects intermediate scenarios in which the transition risk does not result in a complete 100% loss with respect to exposure towards the relevant industries. To account for these intermediary losses, sector reductions in operations were estimated conditional on unburned estimates as presented by McGlade and Ekins (2015). The unburned estimates cover the percentage amounts of coal, oil, and natural gas reserves that must remain in the ground, i.e. becoming stranded assets, to meet the 2°C target by 2050 as agreed upon in the Paris Agreement. The corresponding unburned estimates as presented by McGlade and Ekins (2015) are 82% of coal reserves, 49% of natural gas reserves and 33% of oil reserves. These unburned estimates were subsequently multiplied with the respective fossil fuel usage in each of the five relevant sectors as presented in Table 3.1.1.

The actual procedure to find the amount of stranded oil and natural gas reserves for the fossil fuel industry was made possible by first summarizing the global amount of natural gas and oil reserves that are yet to be extracted, implying that they currently remain in the ground. These numbers amount to 430 billion barrels of oil and 95 trillion cubic meters of natural gas (McGlade and Ekins, 2015). The corresponding dollar value was then calculated as indicated by the spot price as of April 9th, 2024 (GmbH, finanzen net, 2024). The dollar amount of global oil reserves and global natural gas reserves as of April 9th, 2024 were respectively $37.2 trillion and $28.2 trillion. Under the assumption that these reserves are held equally across each company in the oil and gas industry, we find that 56.9% of the industry's monetary value stems from oil and 43.1% of the value is derived from natural gas. The industry decomposition (weights) were then reduced by the proportions to be stranded to meet the 2°C target, i.e the unburned estimate proportions, as outlined by McGlade and Ekins (2015) to retrieve the loss multiplier for the fossil fuels sector. Coal is omitted due to the nature of our dataset, which includes oil and gas industry for fossil fuel companies and not a precise decomposition for coal.

Furthermore, a similar process was used to find the reduction in the utilities sector attributable to stranded fossil fuels assets. We start by finding the types of energy responsible for global electricity production, which we use to estimate the reduction in productivity for the utilities industry. Coal is responsible for 38.1% of global electricity production as of 2018, oil for 3%, and natural gas for 23% (IEA, 2020). These weights are then reduced by the stranded assets multiplier from Mclade and Ekins, then summed, resulting in the stranded assets loss multiplier for the utilities industry. The corresponding loss stemming from brown energy is likely to be replaced, at least in part, by renewable alternatives. This means that our estimates might not fully reflect the actual future productivity of the utilities sector (or other brown energy sectors for that matter). Nonetheless, our estimates do reflect the decrease in production stemming from brown energy which impacts these borrowers.

Estimating the drop in production in the energy intensive sector necessitates a less precise process. Because the energy intensive sector stems from our own construction, it is difficult to find an accurate proxy for energy usage by type. We use Eurostat's breakdown of total industry

EU energy usage by energy type to find the amount of coal, oil, and natural gas used in industry overall, and then apply the 2°C target weights to these numbers (Eurostat, 2023).

Additionally, for the housing sector, we use global heating trends from the IEA (2023:a) to find the amounts of fossil fuel usage. We again apply the 2°C target weights to these numbers to find loss multipliers. Lastly, for the transportation sector, we find that 91% of energy usage relies on oil according to the IEA (2023:b). We apply the 2°C target weight for oil (33%) to retrieve the loss multiplier for transportation.

The results from our weighing procedure are summarized in Table 4.2.1 which shows the decomposition of the relevant industries with respect to coal, oil and natural gas, followed by reduction estimates to meet the 2°C goal, which are finally summed to retrieve the total sector reduction (loss multiplier).

Reduction in Fossil Fuel Usage by Sector to meet 2° by 2050 Global Warming Goal

Sector Brown Energy Reliance	Fossil Fuels (Oil and Gas)	Utilities	Energy Intensive	Housing	Transport
Coal	0.00%	38.10%	6.40%	6.29%	0.00%
Oil	56.88%	3.00%	9.80%	14.82%	91.00%
Natural Gas	43.12%	23.00%	32.70%	42.12%	0.00%
Reduction to meet 2° Goal					
Coal	0.00%	31.24%	5.25%	5.16%	0.00%
Oil	18.77%	0.99%	3.23%	4.89%	30.03%
Natural Gas	21.13%	11.27%	16.02%	20.64%	0.00%
Total Sector Reduction (loss multiplier)	39.90%	43.50%	24.51%	30.69%	30.03%

Table 4.2.1 Reduction in Fossil Fuel Usage by Sector required to meet the 2°C goal.

With the necessary weights constructed needed for calculating the corresponding dollar amount losses, we proceeded with calculating losses due to transition risk for each respective sector. In this procedure, the loss multipliers from Table 4.2.1 were mapped to the various sectors and then multiplied with the tranche amount resulting in the expected tranche loss as a result of transition risk. The top 20 biggest lenders, as ranked by their estimated tranche loss, are presented in Figure 4.2.2 which presents the aggregate loss alongside a decomposition with the various sectors. In conjunction with Figure 3.2.1 it can be seen that the ordering shifts when considering this weighting scheme and the most exposed lender, Sumitomo Mitsui Banking Corp, which represented the 7th largest lender in Figure 3.2.1 is now the most exposed bank in terms of the dollar value of their loans.

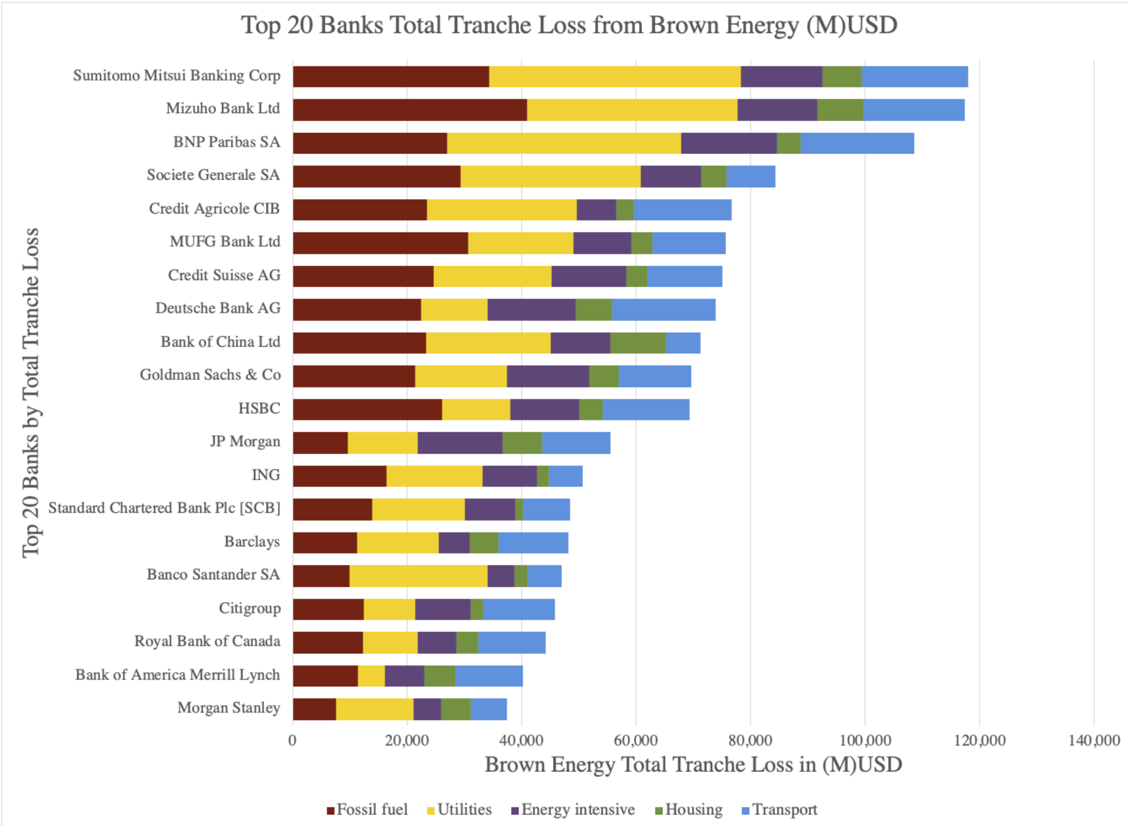


Figure 4.2.2. Top 20 banks sorted by the total dollar value of brown energy tranche losses.

The dollar amount in Figure 4.2.2 represents the tranche amount lent and consequently the amount to be repaid at the tranche maturity date. As the maturities differ, with some tranches maturing more than 40 years into the future, we extend our investigation to incorporate the transition risk induced losses in present value terms - thereby accounting for the time value of money. In this procedure, we began by calculating the interest rates by mapping the tranche currency to its corresponding country and then estimating the future interest rates for this particular tranche based on historic interest rates for the country in question. The interest rates were, with some exceptions, calculated based on 6 years spanning 2017-2022 with either monthly or annual frequency of observations and afterwards the average was calculated for each respective country to get average interest rates. The average interest rate, for each country, was then used as an estimate for the future interest rates. For a detailed summary of the interest rates, the reader is referred to section A1 in the appendix. In calculating the tranche losses, formula [6] was employed.

$$l_i = a_k N_i \, e^{-r_c (M_i - 2025)} \qquad [6]$$

In this formula, l_i, N_i and M_i represents the loss, amount and maturity date for tranche i, a_k is the loss multiplier for sector k and r_c denotes the interest rate for country c. The term in parenthesis represents the number of years discounted and, consequently, the present value is denoted in the value as of year 2025. The resulting top 20 biggest lenders when considering the present value are compiled in Figure 4.2.2. Although the same banks occur the ordering once again shifts, suggesting that the banks differ with respect to their exposure when accounting for time.

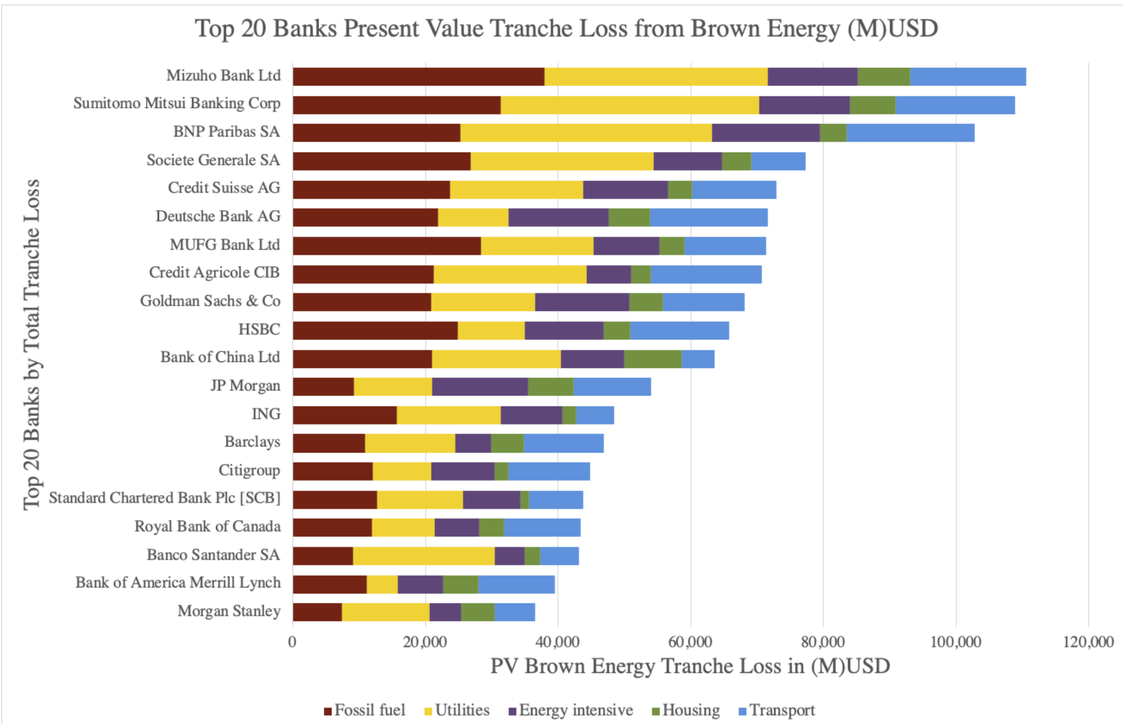


Figure 4.2.2. Top 20 banks sorted by the present value of total brown energy tranche losses.

4.3 Monte Carlo Simulation

Thus far, the methodology section has covered full losses, as outlined in section 4.1, and intermediate loss scenarios in which losses are calculated in relation to the fossil fuel usage for each relevant sector, as covered in section 4.2. However, in an effort to present a more reasonable scenario, this section covers a Monte Carlo simulation. The general idea in performing the simulation is to simulate individual defaulting tranches by utilizing a credit migration table from S&P. This allows us to link the credit ratings in the Dealscan dataset to the corresponding credit migration table. We then find losses by applying the loss multiplier constructed in the intermediate loss scenario to each tranche that defaults. The total simulation runs 100,000 scenarios for each tranche, from which VaR_q and ES_q are ultimately calculated at the 95% and 99% confidence level.

Performing the simulation began with extracting all tranches within the relevant industries, as defined in Table 3.1.1, for which one-year S&P credit ratings were available. This resulted in a total of 780 tranches which could be included in the subsequent simulation. A credit migration table from S&P, as presented in Hull (2023) and in Figure 2.4.2 containing the thresholds for credit transitions was then imported. The thresholds were obtained by taking the inverse of the standard normal cumulative distribution, $N^{-1}(x)$ where x denotes the probability from the credit migration table.

Next, a (*100,000x780*) matrix containing random numbers, $X \sim N(0, 1)$ was generated. In this matrix, each row refers to a simulation such that the random number with coordinates (22, 560) represents random number (simulation) 22 for tranche 560 and consequently each column represents a unique tranche from our dataset. Conceptually, we are simulating the credit rating transitions for each of the 780 tranches 100,000 times to find scenarios in which a tranche, or multiple, defaults, which then allows us to calculate the associated loss. The random numbers were generated using a multivariate random normal distribution. As outlined by Vilhelmsson (2024:a), it is likely the case that credit transitions do not occur independently. If we consider that a company within the fossil fuel sector is downgraded, it is reasonable that the probability of other companies within that same sector being downgraded then increases. Taking this into consideration, the random values *within* each simulation were correlated such that the correlation between two random numbers for tranches within the *same* industry was 0.5 and *between* industries was 0.3. The reasoning is that transition factors which cause one fossil fuel tranche to default, for example, are likely to impact other fossil fuel firms within the same simulation, and thus the default rates in each industry should be substantially correlated. Additionally, some degree of correlation should exist between every brown energy loan, due to the fact that they, to some extent, share the same exposure in terms of being climate sensitive and consequently affected by climate legislation.

With the matrix containing random numbers generated and correlated, the credit migration table containing thresholds, along with the original credit ratings was employed. In this procedure, new ratings for each tranche were received and the result was a new (*100,000x780*) matrix containing the new ratings. From this dataframe, tranche losses were calculated. In the tranche loss calculation, losses only occur if the tranche receives a default rating (*D*), in which case the loss multipliers from section 4.2 and Table 4.2.1 for the relevant sector were used. Again, a new dataframe with aforementioned dimensions was created containing the final tranche losses. Lastly, the tranche losses were summed simulation-wise to retrieve the corresponding total tranche loss for each simulation. From the final dataframe VaR_q and ES_q were calculated, which are presented in the upcoming section alongside a decomposition of the respective losses sorted by sector. A numerical example, considering an actual tranche which defaulted and the whole procedure from credit transitioning to tranche loss calculation is presented in appendix A2. Finally, the tranche loss distribution stemming from the 100,000 simulations is depicted in Figure 4.3.1.

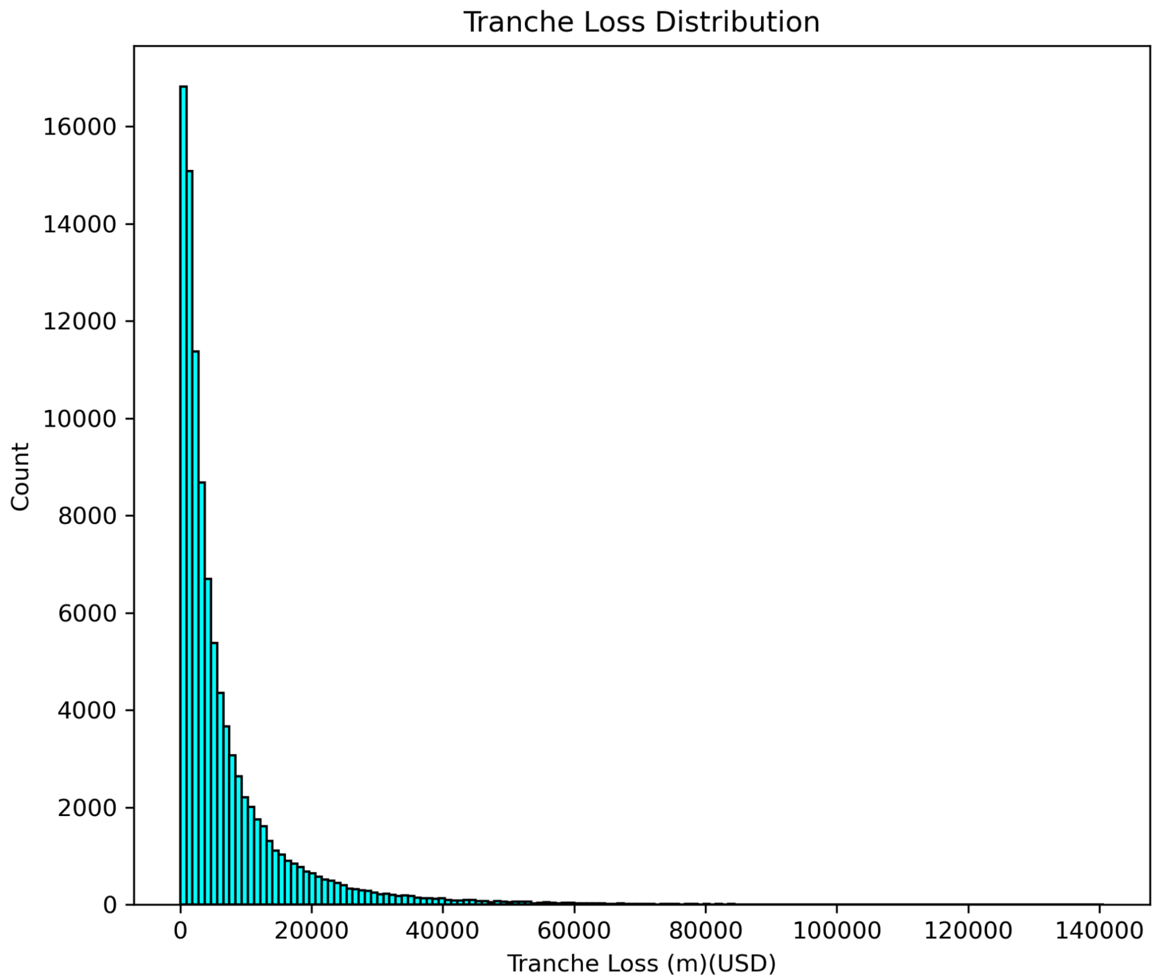


Figure 4.3.1: Tranche loss distribution showing the frequency of tranche losses and the tranche loss in MUSD from the Monte Carlo simulation.

Finally, with the Monte Carlo simulation concluded and the corresponding *VaR* and *ES* calculated we proceeded to extrapolate the findings to the dataset featured in section 5.2. Comparing the subsample of rated borrowers to the complete dataset, we find that the average tranche size in dollars for rated borrowers ($758 MUSD) is about twice that of unrated borrowers ($396 MUSD), suggesting that larger borrowers are more likely to receive ratings. We make the assumption that the subsample consisting of credit ratings, covering 780 tranches, is sufficiently representative of the full sample which consists of 30858 tranches. Following this assumption, the top 20 banks regarding total tranche amounts were extracted. Then, the *relative VaR* and *ES* at 95% and 99% confidence level stemming from the simulation were respectively multiplied with the tranche amount to retrieve the corresponding expected losses in MUSD.

5. Results

This subsection presents the main findings of the thesis and analyzes the findings. We conclude the section by discussing the reliability of the results obtained and methodology employed.

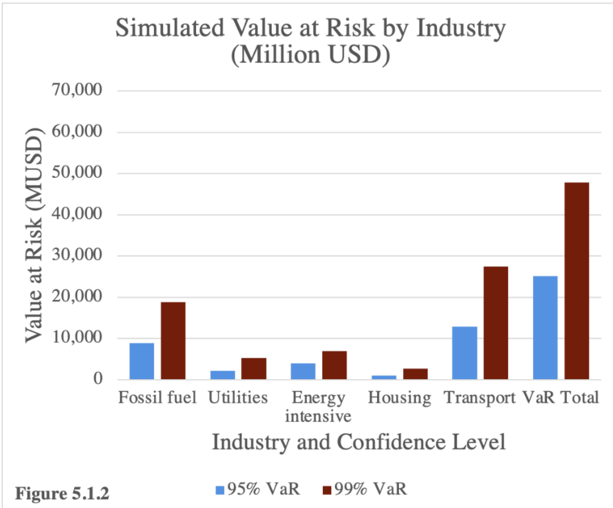
5.1 The different scenarios

Section	Measurement	*Fossil fuel*	*Utilities*	*Energy intensive*	*Housing*	*Transport*	*Total*	*Sample Size*
F.L	Losses	2 964 943	2 818 919	2 944 855	1 196 558	2 301 443	12 226 718	30 858
	Relative	*100,0%*	*100,0%*	*100,0%*	*100,0%*	*100,0%*	*100,0%*	
I.L	Losses	1 183 009	1 226 286	721 637	367 190	691 123	4 189 245	30 858
	Relative	*39,9%*	*43,5%*	*24,5%*	*30,7%*	*30,0%*	*34,3%*	
SIM	95% VaR	8 919	2 232	4 005	987	12 841	25 186	780
	Relative	*6,9%*	*2,2%*	*6,2%*	*2,0%*	*5,2%*	*4,3%*	
SIM	99% VaR	18 845	5 333	6 916	2 651	27 491	47 890	780
	Relative	*14,5%*	*5,3%*	*10,7%*	*5,4%*	*11,1%*	*8,1%*	
SIM	95% ES	14 993	4 302	5 782	2 058	21 724	39 185	780
	Relative	*11,6%*	*4,3%*	*9,0%*	*4,2%*	*8,8%*	*6,6%*	
SIM	99% ES	24 958	8 595	8 576	4 058	36 120	62 306	780
	Relative	*19,2%*	*8,6%*	*13,3%*	*8,2%*	*14,6%*	*10,5%*	

Table 5.1.1: Tranche losses from the scenarios conducted in section 4.1, 4.2, and 4.3. All numerical values, excluding sample size, are in millions of USD (MUSD). F.L = Full losses scenario (4.1), I.L = Intermediate losses scenario (4.2) and SIM = Monte Carlo simulation scenario (4.3).

The main findings from the full loss scenario (F.L), the intermediate loss scenario (I.L), and the Monte Carlo simulation (SIM) are summarized in Table 5.1.1. As can be immediately noted, the losses are in descending order as more realistic scenarios are considered. Furthemore, the sample size is substantially lower for the last section as compared to the previous ones. As indicated, the losses from section 4.1 are full losses corresponding to a relative loss of 100% in each case. Furthermore, the intermediate losses from section 4.2 which directly implement the loss multiplier on the corresponding tranche amounts result in a significantly higher loss for each industry respectively, as compared to the Monte Carlo simulation. Additionally, the relative measurement for the intermediate loss scenario is, by construction, the loss multipliers. What can be noted for the results from the Monte Carlo simulation is that the simulated losses in relation to total lending, i.e *relative* exposure, are highest for the fossil fuel industry irrespective of which confidence level or measurement (*VaR/ES)* that is used. After that, the ordering differs depending on the confidence level and measurement. If we begin by investigating *VaR* the energy intensive sector comes second followed by transport, in terms of relative exposure, when considering *VaR* at the 95% confidence level. The opposite is true when instead investigating the 99% confidence level. A similar result for *VaR* appears for the utilities sector which comes fourth place, followed by housing, at 95% confidence level, whereas the opposite order holds true for the 99%

confidence level. A graphical breakdown of the losses when considering *VaR* is depicted in Figure 5.1.2 and 5.1.3 for dollar amount and relative terms, respectively.



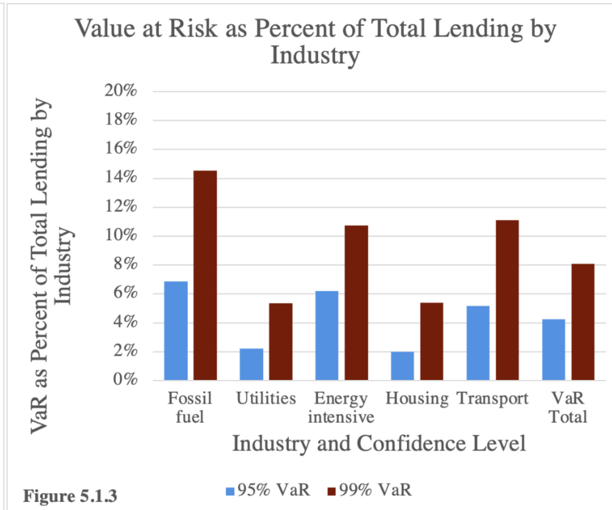
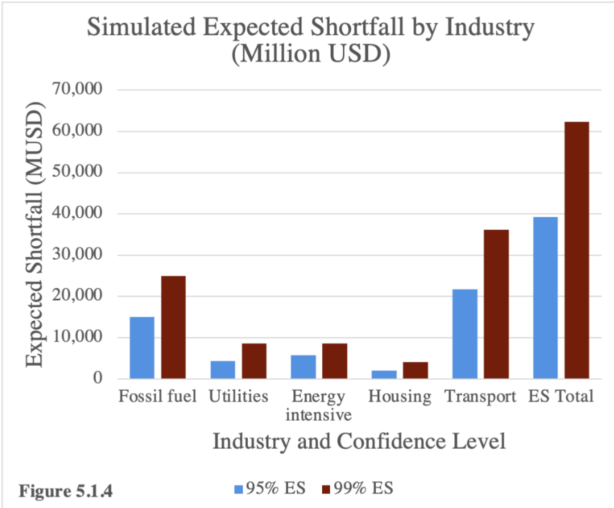


Figure 5.1.2 and Figure 5.1.3: Graphical representation of the *VaR* in dollar amount (MUSD) and relative terms (%) at the 95% and 99% confidence level. Both figures indicate both decomposed *VaR* for the investigated industries and the aggregate value when considering all the industries in total.

When instead investigating with respect to *ES*, the ordering is the exact same as for *VaR* when considering the 95% confidence level. The ordering is as follows, in relative terms: Fossil Fuel, Energy Intensive, Transport, Utilities and Housing. However, at the 99% confidence level, the ordering is the following for *VaR:* Fossil Fuel, Transport, Energy Intensive, Housing and Utilities. For *ES*, the ordering shifts such that utilities comes fourth place, followed by housing.

Lastly, it should be noted that the percentage breakdown for the Monte Carlo simulation is based on the aggregated tranche amount for the subsample consisting of 780 observations. For instance, when considering the relative exposure of fossil fuels the *VaR/ES* at confidence level q is divided by the total tranche amount associated with fossil fuel, and similarly for the other industries. This is also the reason why the dollar values between the full loss scenario, intermediate loss scenario, and Monte Carlo simulation are not directly comparable. Figure 5.1.4 and Figure 5.1.5 depict the relationship graphically for *ES*.



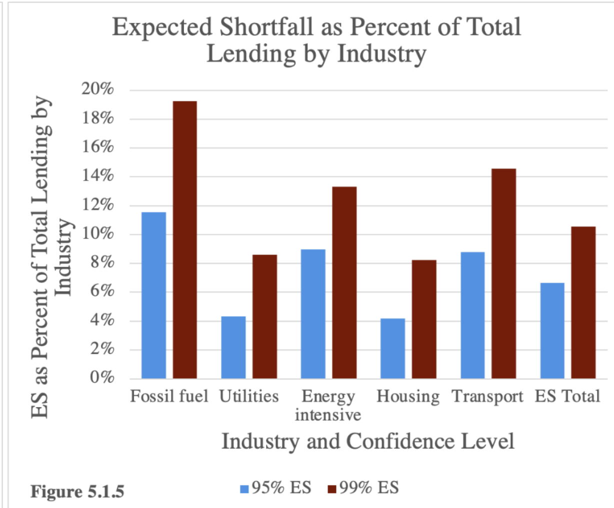
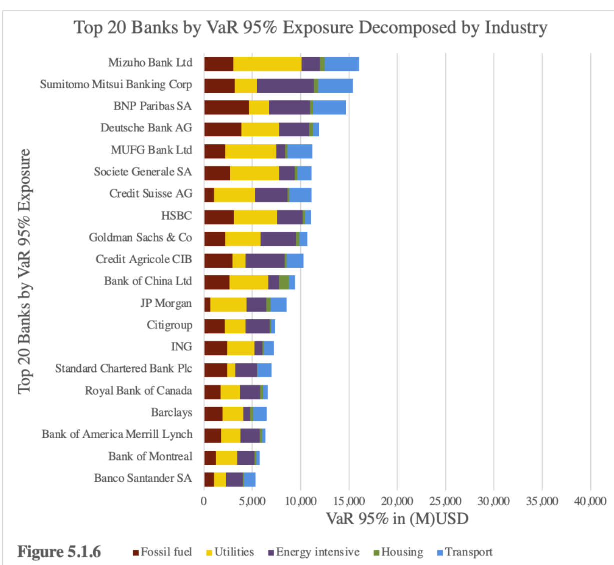


Figure 5.1.4 and Figure 5.1.5: Graphical representation of the *Expected Shortfall* in dollar amount (Million USD) and relative terms (%) at the 95% and 99% confidence level. By construction, these values are higher than for *VaR* since we are looking deeper into the tail of the tranche loss distribution.

In addition, the results from the exercise outlined in the last paragraph of section 5.3 concerning the extrapolation of the findings in the Monte Carlo simulation to the full sample consisting of 30858 observations is depicted, for *VaR*, in Figure 5.1.6 and 5.1.7 at 95% and 99% confidence level, respectively. By construction, both figures feature the same banking institutions although the ordering shifts depending on the confidence level considered.



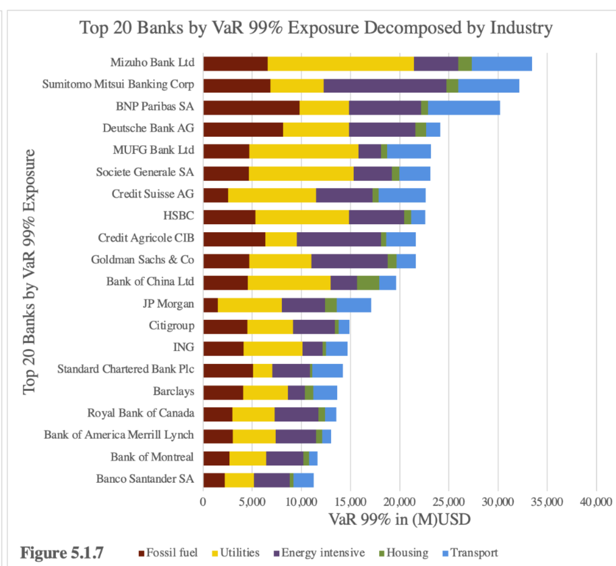
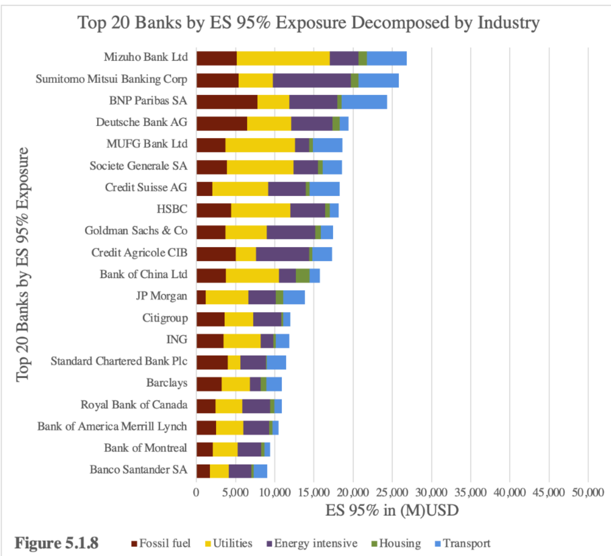


Figure 5.1.6 and Figure 5.1.7: Graphical representation of the *Value at Risk* in dollar amount (Million USD) for the top 20 most exposed banks by *Value at Risk* at both the 95% and 99% confidence level. *Value at Risk* is further decomposed by brown energy sectors for each bank.

Lastly, the corresponding *ES* results from the extrapolation exercise are depicted in Figures 5.1.8 and 5.1.9 below. What can be inferred from these figures is that, when considering the full tail of the loss distribution the ordering of exposure with respect to magnitude of losses differ, although slightly. However, the four most exposed banks in this representation, namely Mizuho Bank Ltd, Sumitomo Mitsui Banking Corp, BNP Paribas SA and Deutsche Bank AG, are all maintaining their order irrespective of the measurement (*VaR/ES)* or confidence level being used. In spite of this, it can be noted that some banks, for instance Bank of Montreal and Banco Santander SA, switch places when considering *ES* at different confidence levels, as indicated by the figures below.



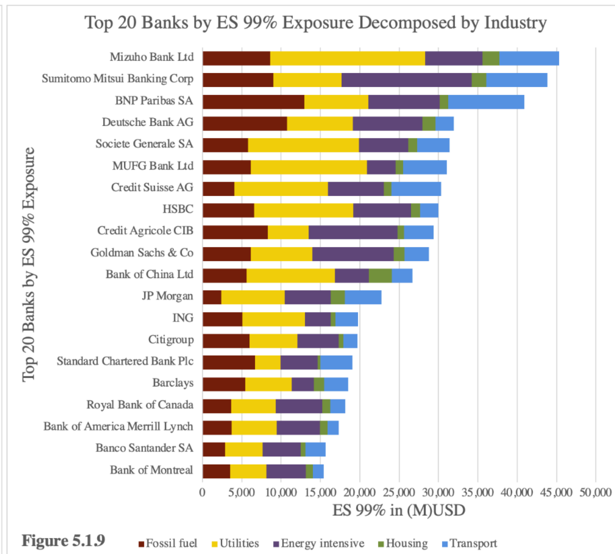


Figure 5.1.8 and Figure 5.1.9: Graphical representation of the *Expected Shortfall* in dollar amount (Million USD) for the top 20 most exposed banks by *Expected Shortfall* at both the 95% and 99% confidence level. *Expected Shortfall* is further decomposed by brown energy sectors for each bank.

5.2 Analysis

From our constructed scenarios in section 4.1-4.3 it becomes abundantly clear that the holdings in climate sensitive sectors represents a non-negligible exposure for banks. An immediate transition, implying an outright ban as in section 4.1, represents the most extreme case with respect to magnitude of losses. When comparing the magnitude of losses from section 4.1 to the first-round losses as featured in Battiston et al. (2017), the analysis is aggravated by the coverage of banks, as the presented paper covers just EU banks whereas this paper features global coverage. However, six banks[3] are overlapping from both papers. Most notably, Deutsche Bank AG has relatively similar exposure (loss) in both cases, with approximately 25% in Battiston et al. (2017) and 30.48% in this paper. For the other overlapping banks, the loss is much larger in this paper solidifying the notion by Battiston et al. (2017) that the loan market exposure is likely larger than that of the equity market.

If we instead consider the extrapolation exercise conducted at the end of section 4.3, a corresponding comparison to Battiston et al. (2017) for the six overlapping banks can be performed regarding the *VaR* results at the 95% confidence level. Also in this comparison, the magnitude of losses is significantly higher in our paper, which further solidifies the rationale of investigating the syndicated loan market and suggests that transition risk due to stranded assets is more pronounced when investigating the loan market as compared to the equities market.

Additionally, when accounting for the total sector reduction (loss multipliers) constructed in section 4.2 as a consequence of stranded assets the results suggest that all sectors are at risk of non-negligible losses stemming from the interval of 24.51% to 43.50%. More notably, utilities are the most exposed industry, perhaps in contrast to what would be suspected prior to conducting this research. Furthermore, as indicated in section 4.2, emphasis also needs to be placed on the maturity of each loan as highlighted by the shift in ordering when considering the present value of losses. We interpret these findings as banks with tranches maturing in the near future being more exposed. The reasoning is that regulations enacted in the near future will make the possibility lower for borrowers with maturity in the near future to transition – thereby exacerbating the risk of losses. Conversely, banks holding tranches maturing further in the future could be seen as more exposed, as transition risk-causing legislation becomes increasingly likely to be enacted approaching 2050. However, this conclusion is not readily available from our dataset.

Lastly, with respect to the Monte Carlo simulation, which represents the most probable scenario, the following findings emerge. Firstly utilities, albeit having the highest sector reduction, still represents the least to second-least exposed industry when considering *VaR/ES*.

---

[3] Deutsche Bank AG, Credit Agricole CIB, Standard Chartered Bank Plc [SCB], Societe Generale SA, Barclays, and BNP Paribas SA.

This result can be partly attributed to utilities being the sector with least CCC/C rated tranches[4] for which the default rating is highest. Overall, however, our simulation suggests that the relative exposure is the highest for the fossil fuel industry. Because the industry is directly dependent on oil and natural gas extraction, it follows that it will be most directly harmed by the Paris Agreement's implied restrictions on oil and natural gas production through the creation of large amounts of stranded assets within the industry. These stranded assets will have direct impacts on recovery rates for lenders in the case of defaults that are caused by transition risk. Despite being high in the chain of priority for repayment in the event of default, lenders may not be able to recover much value from defaulting fossil firms, due to a large amount of their assets being stranded. In essence, stranded assets for fossil fuel firms can both be a driver for defaults and reduced recovery rates, compounding the negative financial repercussions stemming from transition risk.

Other brown energy industries face smaller exposures than fossil fuels due to the fact that they are typically not fully reliant on fossil fuels, or can theoretically shift to alternative energy sources. Thus, while still impactful, the Paris Agreement will have smaller consequences for these firms, so long as technology for alternative energy production is sufficiently advanced by the time more stringent fossil fuel legislation is enacted. Transportation faces significant transition risk due to its heavy reliance on oil (91%, see Table 4.2.1).

The results from the Monte-Carlo simulation undoubtedly highlight the need for banks to consider the sector at which they lend. From the *VaR/ES* results it is shown that, depending on the significance level, the ordering of sectors with respect to exposure differs. These findings can be interpreted as tail risk being more pronounced within certain sectors – particularly transportation which becomes the second most exposed industry when investigating the 99% confidence level and relative exposure.

[4] Disregarding the housing sector for which no CCC/C rated tranches were present.

5.3 Sensitivity analysis

To further investigate the robustness of our results, we conducted a sensitivity analysis by changing the correlation coefficient used in the Monte Carlo simulation both within and between the respective industries. In this context, five scenarios were constructed, including the base scenario which our results and previous analysis relies on. The results for the various scenarios are presented in Table 5.3.1.

Scenario Analysis: Relative Risk by Industry							Correlations	
Scenario	Fossil Fuel	Utilities	Energy Intensive	Housing	Transport	Total	Between Industries	Within Industry
S1 95% VaR	6.9%	2.2%	6.2%	2.0%	5.2%	4.3%	0.1	0.3
S1 99% VaR	14.5%	5.3%	10.7%	5.4%	11.1%	8.1%	0.1	0.3
S1 95% ES	9.7%	3.5%	7.9%	3.2%	7.3%	5.4%	0.1	0.3
S1 99% ES	17.5%	7.2%	12.3%	6.9%	13.2%	9.2%	0.1	0.3
S2 95% VaR	6.2%	2.1%	5.7%	1.9%	4.7%	3.8%	0.2	0.4
S2 99% VaR	12.2%	4.6%	9.3%	4.5%	9.2%	6.6%	0.2	0.4
S2 95% ES	9.8%	3.8%	7.9%	3.6%	7.5%	5.5%	0.2	0.4
S2 99% ES	15.9%	6.9%	11.3%	6.6%	12.1%	8.3%	0.2	0.4
Base 95% VaR	6.9%	2.2%	6.2%	2.0%	5.2%	4.3%	0.3	0.5
Base 99% VaR	14.5%	5.3%	10.7%	5.4%	11.1%	8.1%	0.3	0.5
Base 95% ES	11.6%	4.3%	9.0%	4.2%	8.8%	6.6%	0.3	0.5
Base 99% ES	19.2%	8.6%	13.3%	8.2%	14.6%	10.5%	0.3	0.5
S3 95% VaR	7.5%	2.2%	6.7%	2.0%	5.7%	4.8%	0.4	0.6
S3 99% VaR	17.3%	6.1%	12.4%	6.4%	13.2%	9.8%	0.4	0.6
S3 95% ES	13.4%	4.8%	10.1%	4.8%	10.1%	7.8%	0.4	0.6
S3 99% ES	22.6%	10.4%	15.2%	10.1%	17.2%	12.9%	0.4	0.6
S4 95% VaR	8.1%	2.1%	7.1%	2.0%	6.0%	5.2%	0.5	0.7
S4 99% VaR	20.5%	6.8%	14.0%	7.6%	15.6%	11.5%	0.5	0.7
S4 95% ES	15.3%	5.3%	11.1%	5.5%	11.5%	9.1%	0.5	0.7
S4 99% ES	26.2%	12.6%	17.2%	12.2%	20.0%	15.4%	0.5	0.7

Table 5.3.1. Scenario Analysis: Relative Risk by Industry. S1 through S4 denotes the respective scenarios and Base, which was presented as SIM in Table 5.1.1, denotes the baseline scenario used in the paper, from which our conclusions and analysis are predominantly based on. Correlations between industries and within industries were adjusted in increments of 0.1 for each scenario.

The rationale for performing a sensitivity analysis relies on the fact that the original correlations between (0.3) and within (0.5) industries were picked arbitrarily because deriving the actual correlations necessitates a methodology that is unfeasible in practice. What is immediately apparent from Table 5.3.1 is that as the correlations between and within industries increase, the respective losses and consequently the *Value at Risk* and *Expected Shortfall*, tend to increase, with one exception. The risk measures calculated in Scenario Two are mostly lower than those in Scenario One, despite having higher correlations.

Risk measures tend to increase with correlation because higher correlations make it more likely for other tranches (both within and between industries) to default, given an individual tranche defaults. Intuitively, factors that affect one borrower operating within the brown energy sector are increasingly likely to affect other borrowers as the correlations are increased across the scenarios. In this sense, the correlations reflect the overarching effects of clean energy regulations across brown energy industries, and thus they also capture a degree of the systemic implications stemming from transition risk.

6. Conclusions and recommendations for future research

Our research outlined in section 4.1 suggests that a complete and sudden ban on fossil fuels spells disaster for multiple systemically important institutions in the lending market. Banks with high exposure to transition risk would be heavily impacted in this scenario, and likely pushed towards default, while banks with smaller exposures would likely survive, while facing significant financial turmoil. However, weighting losses in relation to stranded assets in section 4.2, as opposed to the complete loss scenario, shows a 60%-70% reduction in losses, depending on industry. While much less catastrophic for major financial actors, this scenario still places the lending market under extreme pressure. Finally, under the most realistic scenario, the Monte Carlo simulation outlined in section 4.3, the *VaR* and *ES* for the total lending market at the 99% level are only 8.1% and 10.5%, respectively. This suggests that transition risk's impact on lending is unlikely to be ruinous for the entire financial system. In itself, transition risk's negative impact on the lending market is unlikely to result in major financial institutions defaulting, although it still represents a serious concern that risk management departments should carefully consider. Additionally, the correlations between industries highlight the need for risk management departments to overview their relative composition of lending, as a too concentrated lending portfolio will exacerbate losses substantially if the true correlations are more pronounced than suggested by our baseline scenario.

However, it should be emphasized that this paper only examines the syndicated loan market. If one takes into account the findings from Battiston et al. (2017) to aggregate the results for both equities and loan markets, gross losses will be exacerbated. One shortcoming of this paper is that we do not utilize a network based approach, as Battiston et al. (2017) does, and thus it is not appropriate to aggregate these results. We therefore propose that subsequent research in the area of transition risk stemming from stranded assets focuses on the aggregate outlook, preferably combining the three main instrument classes of equities, lending, and bonds to generate a more refined picture of total transition risk exposure for both the financial system and systemically important institutions.

Additionally, it is likely that default rates for fossil fuel firms will not remain constant in the face of transition risk, as assumed in our methods for our Monte Carlo Simulation. The nature of this research area necessitates that uncertainty and assumptions form a foundation for subsequent calculations. The constructed loss multipliers stemming from stranded assets are one example of this and represent carefully considered estimations of losses for firms forced into distress by transition risk. However, for further practitioners, we recommend that research examining lending market losses in relation to *both* stranded assets and newly-constructed "climate adjusted default rates" be conducted. Incorporating climate adjusted default rates represents a significant challenge, but will result in an even more comprehensive forecast, strengthening the validity of new simulations.

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Appendix

A1: Interest rate summary

Unique Tranche Currencies	*Country*	*Year count*	*Years used*	*Frequency*	*Rate*	*Source*	*Note*
U.S. Dollar	USA	6	2017-2022	Monthly	2,11%	OECD	
Japanese Yen	Japan	6	2017-2022	Monthly	0,05%	OECD	
Euro	Europe	6	2017-2022	Monthly	0,91%	OECD	
Norwegian Krone	Norway	6	2017-2022	Monthly	1,69%	OECD	
Indian Rupee	India	6	2017-2022	Monthly	6,87%	OECD	
Malaysian Ringgit	Malaysia	6	2017-2022	Yearly	4,28%	The World Bank	
Chinese Yuan	China	6	2017-2022	Monthly	3,17%	OECD	
Australian Dollar	Australia	6	2017-2022	Monthly	2,07%	OECD	
Taiwan Dollar	Taiwan	6	2017-2022	Monthly	3,17%	OECD	*1
Saudi Arabian Riyal	Saudi Arabia	6	2017-2022	Monthly	1,97%	Trading Economics	*2
South Korean Won	South Korea	6	2017-2022	Monthly	2,24%	OECD	
Great Britain Pound	UK	6	2017-2022	Monthly	1,21%	OECD	
Canadian Dollar	Canada	6	2017-2022	Monthly	1,76%	OECD	
Brazilian Real	Brazil	6	2017-2022	Monthly	6,08%	OECD	
Singapore Dollar	Singapore	5	2017-2021	Yearly	5,27%	The World Bank	
Philippine Peso	Philippines	3	2017-2019	Yearly	6,28%	The World Bank	
Colombian Peso	Colombia	6	2017-2022	Monthly	7,65%	OECD	
Russian Ruble	Russia	6	2017-2022	Yearly	8,93%	The World Bank	
UAE Dirham	UAE	6	2017-2022	Monthly	1,51%	Trading Economics	
Pakistani Rupee	Pakistan	5	2017-2021	Yearly	9,68%	The World Bank	
Czech Koruna	Czech Republic	6	2017-2022	Monthly	1,98%	OECD	
Indonesian Rupiah	Indonesia	6	2017-2022	Monthly	7,01%	OECD	
Turkish Lira	Turkiye	5	2018-2022	Yearly	16,11%	Stats.OECD	
Bulgarian Lev	Bulgaria	6	2017-2022	Monthly	0,82%	OECD	
Mexican Peso	Mexico	6	2017-2022	Yearly	7,26%	The World Bank	
Israeli New Sheqel	Israel	6	2017-2022	Monthly	1,65%	OECD	
Swiss Franc	Switzerland	6	2017-2022	Monthly	-0,08%	OECD	
Hong Kong Dollar	Hong Kong	6	2017-2022	Yearly	5,04%	The World Bank	
Polish Zloty	Poland	6	2017-2022	Monthly	3,08%	OECD	
South African Rand	South Africa	6	2017-2022	Monthly	9,64%	OECD	
Swedish Krona	Sweden	6	2017-2022	Monthly	0,53%	OECD	
New Zealand Dollar	New Zealand	6	2017-2022	Monthly	2,29%	OECD	
Thai Baht	Thailand	6	2017-2022	Yearly	3,69%	The World Bank	
Vietnamese Dong	Vietnam	6	2017-2022	Yearly	7,60%	The World Bank	
Hungarian Forint	Hungary	6	2017-2022	Monthly	3,56%	OECD	
Bangladeshi Taka	Bangladesh	6	2017-2022	Yearly	8,58%	The World Bank	
Trinidad & Tobago Dollar	Trinidad & Tobago	6	2017-2022	Yearly	8,14%	The World Bank	
Kazakhstani Tenge	Kazakhstan	6	2017-2022	Monthly	10,35%	Trading Economics	
Egyptian Pound	Egypt	6	2017-2022	Yearly	14,00%	The World Bank	
Peruvian Sol	Peru	6	2017-2022	Yearly	13,70%	The World Bank	
Nigerian Naira	Nigeria	6	2017-2022	Yearly	14,55%	The World Bank	

Table A1: Summary of interest rates,inputs and sources for the calculation of average interest rates under "*Rate*".

*1: China interest rate used as a proxy.

*2: Repo rate used as proxy as long term interest rate not available

A2: Monte Carlo Simulation example

We start by considering the 46th tranche, for which the borrower was initially rated as CCC/C with a tranche amount of $448.48M. Since the borrower was initially rated as CCC/C this row is also the relevant one in the credit migration table in figure 2.4.2 from section 2.4 as listed below.

	Rating at Year-end							
Initial rating	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC/C**	**D**
AAA	5,61	-1,27	-2,41	-2,82	-2,89	-3,16	-3,29	-
AA	5,37	2,58	-1,36	-2,49	-2,97	-3,09	-3,35	-3,54
A	-	3,43	2,12	-1,58	-2,60	-2,89	-3,19	-3,29
BBB	-	-	3,09	1,81	-1,69	-2,44	-2,77	-2,93
BB	5,61	3,72	3,35	2,95	1,63	-1,35	-2,22	-2,46
B	5,61	5,61	3,54	3,09	2,78	1,60	-1,31	-1,77
CCC/C	5,61	5,61	5,61	3,04	2,73	2,34	1,01	-0,43

Figure 2.4.2: Credit Migration Table showcasing the critical values for transitioning based on the inverse of the standard normal cumulative distribution function.

During simulation 105, the random number generated for this tranche was -0.87 which is below the default threshold of -0.43, thereby resulting in a rating of D and consequently default.

Graphically, this can be depicted as in figure A2:1.

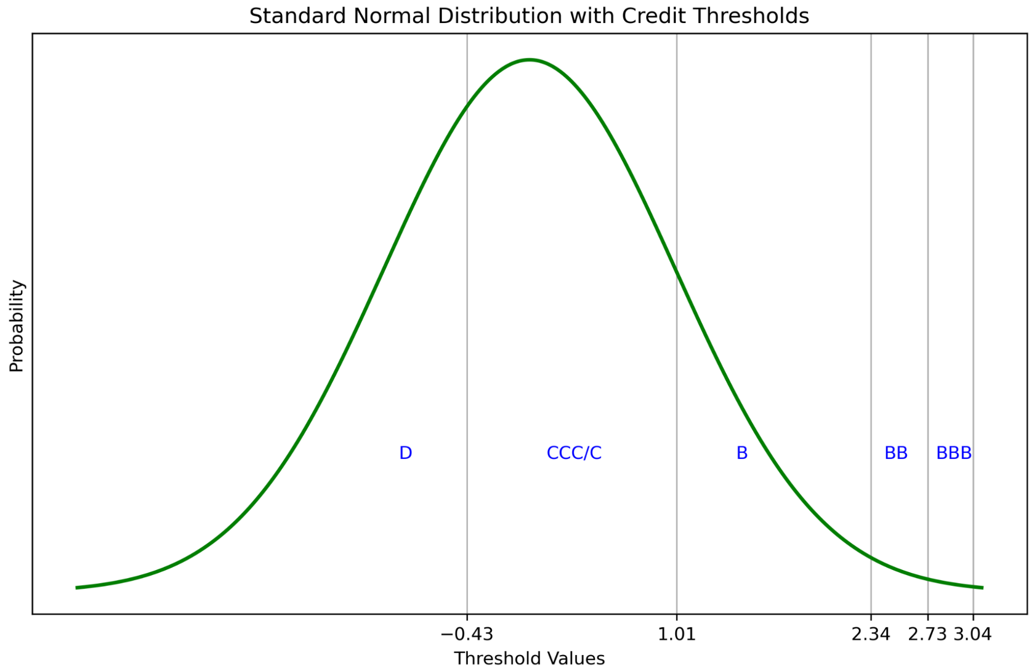

Figure A2:1: Graphical representation of thresholds for a borrower originally rated CCC/C.

From figure A2:1 the ratings above BBB have been disregarded for graphical purposes. Nevertheless, it can be noted that the random number generated falls into the default area, being lower than the threshold of –0.43. As the next step, therefore, the tranche amount for this borrower was multiplied by the loss multiplier of 0.3003 to retrieve the tranche loss amount of 134.679MUSD (0.3003*448.48). Repeating the same process for all the other tranches in simulation 105 results in the total tranche loss for this particular simulation. Lastly, repeating the same process for all simulations yield the tranche loss distribution as indicated in figure 5.3.1.