The Effects of Climate Change and Climate Policy on Credit Risk

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Abstract

This study examines how climate-related physical and transition risks affect credit risk. We develop a modular framework based on a threshold model for credit migrations, linking latent credit factors to key economic indicators to measure credit risk in bond markets. Using historical rating migrations, we estimate the model parameters and apply the framework to U.S. data to assess the implications of alternative climate policies. These policies generate projected paths for the credit cycle that differ markedly in direction, magnitude, and volatility. These differences translate into substantial variation in both expected losses and tail risks for diversified bond portfolios. Notably, high-quality bond cohorts are most sensitive to policy choices. Comparisons with a continuation of current policies show that orderly transitions (characterized by reduced physical damages and increased transition costs) entail higher initial expenses but deliver net savings by 2050. In contrast, disorderly transitions result in steep cost increases after 2030 and overall higher costs by 2050.

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1 Introduction

Risks from climate change can significantly affect financial institutions and financial markets. These risks can be split into physical and transition risks (see e.g., Acharya et al., 2023; BCBS, 2021). Physical risks arises from the adverse effects of greenhouse gas emissions, resulting in heightened vulnerability to physical damages. Transition risks emerge from actions taken to mitigate the impacts of global warming, and can take the form of changes in government policies, technological developments or changes in investor and consumer sentiment. Both risk types affect the risk profile of firms' cash flows, and hence the value and riskiness of financial assets. Importantly, they are not independent, but present a trade-off to some extent. Continuing current policies with limited effort to deal with climate change generates small transition risks but considerable physical risks, whereas other policies may lead to larger transition risks but smaller physical risks, with key differences arising from the timing with which they materialize or recede. Though the financial sector is well aware of these risks (Stroebel and Wurgler, 2021), their incorporation into banks' risk models still needs attention.[1] This holds in particular for the effects that the evolution of transition risks in different policies has on financial risk.

In this paper, we ask how the paths of physical and transition risks stemming from different climate change policies can be translated into financial risk. We investigate the impact that different transition policies have on the credit risk of corporate bonds with different ratings and on the loss distribution of bond portfolios, taking a systematic risk perspective. Though firms are heterogeneous in their exposure to climate risk such that threats to one firm may be opportunities for another, the systematic part remains present in the financial sector and should be reflected in capital reserves. The associated costs have to be eventually borne by society. Having better insight into these costs can be beneficial for evaluating the different policies and comparing, for example, a scenario in which CO_2 emissions reach net-zero in 2050 with one in which countries stick to nationally determined contributions. This systematic risk focus makes our methods generalizable to other assets and other financial risks.

To answer our research question, we propose a modular framework that links scenarios that follow from climate change policies via their macroeconomic consequences to credit risk. The first module consists of a factor model for migrations of bonds between different rating categories. It takes the form of the ordered probit model of CreditMetrics as in Gupton, Finger and Bhatia

[1] See ECB (2022) and the update in `https://www.bankingsupervision.europa.eu/press/blog/2025/html/ssm.blog20250711~6b58023889.en.html?` for the European, and FED (2024) for the US banking sector.

(1997) and Belkin, Suchower and Forest Jr. (1998), which generalizes the default-threshold model by Merton (1974) and Vasicek (2002). The second module is a dynamic linear model that relates the factors from the first module to key economic indicators. The third module combines the first two to assess the credit risk of a well-diversified portfolio of bonds in a through-the-cycle setting. Extending Vasicek (2002), we derive the asymptotic loss distribution of homogeneous bond portfolios, and show how simulations can generate the loss distribution of heterogeneous portfolios as in Miu and Ozdemir (2006) and Keijsers, Diris and Kole (2018). From the loss distribution, the economic capital that acts as a buffer for unexpected losses can be calculated.

We use this framework to determine the impact that different climate scenarios have on the loss distribution of US corporate bonds. Based on biannual rating transitions published by S&P Global over the period 2000 to 2024, we estimate the parameters and the credit cycle of the CreditMetrics module. The second module links the cycle to standard key economic indicators, such as economic growth, unemployment, inflation, interest rates, oil prices and equity returns. Module three uses the scenarios produced by the Network of Central Banks and Supervisors for Greening the Financial System (NGFS, 2024b) for the paths of these indicators up to 2050. The scenarios depend on the policies that are adopted as a response to climate change but also on the models for physical and transition risks. In particular, we study six policies that vary in ambition and timeline combined with three transition models. Two policies can be characterized as orderly transitions, where different countries and institutions take rapid and concerted actions to limit climate change. These policies combine small physical with small to moderate transition risks. The other scenarios are either less ambitious with moderate transition but large physical risks, or less timely and orderly with large transition risks as well as moderate to large physical risks. We use the paths of the key economic indicators in each scenario to predict the credit cycle and derive the loss distribution of various bond portfolios. This last step produces credit risk dynamics that are consistent with the overall economic developments in each scenario.

Our results show a credit cycle that is strongly but not perfectly related to key economic indicators. Differences in exposures to the factors underlying the cycle lead to mild heterogeneity over the cohorts formed by firms with the same credit rating. We establish that the resulting model has good predictive quality. Feeding the economic paths that follow from the different scenarios into our credit risk model produces paths for the credit cycle that vary substantially. The rapid and concerted actions of the orderly transition scenarios lead to a quick drop in the credit factor in each cohort, followed by a prolonged period in which they are either slightly

negative or positive. The two scenarios with limited actions lead to a hot-house world in which the credit cycle shows a steady worsening over time. In the remaining two scenarios, transitions are delayed and/or disorderly, and as a consequence the credit cycle remains favorable in the first five years, but exhibits large swings thereafter. Comparing the paths of the credit cycle shows that a reduction of physical risks translates into an upward level shift in the credit factor, whereas a reduction of transition risks dampens fluctuations.

Changes in the credit cycles affect the loss distribution of bond portfolios and the resulting capital requirements, where we focus on its expectation and 99%-quantile. The difference between these two gives the economic capital that financial institutions must hold as a buffer against unexpected losses. Though both the expected losses and quantiles are non-linear functions of the credit cycle, their paths in the different scenarios are qualitatively similar to the path of the cycle itself. We assess the change in capital requirements in the different scenarios relative to current policies, both for portfolios with bonds from one rating cohort and for more heterogeneous bond portfolios.

Our empirical results indicate that orderly transitions lead to short-term increases in capital requirements but ultimately reduce them by mitigating long-term physical risks. Across all investment-grade cohorts, we find that an orderly transition consistent with the Net Zero 2050 goals results in lower capital requirements than those predicted under current policies by the end of the 2040s. In contrast, delayed and disorderly transitions initially exhibit lower costs, followed by steep increases relative to the current-policies scenario. Notably, the largest relative increases in capital requirements occur among the highest-rated bonds, where requirements may rise by nearly 40 percent compared with current-policy predictions. This effect is amplified in the absence of an orderly transition, leading to an important and somewhat counterintuitive finding: investing in the highest-rated bonds may entail the greatest relative increase in capital requirements and opportunity costs once climate and transition risks are taken into account.

Our research contributes to three strands of literature. First, we propose a modular framework that generates risk measures that are consistent with the general macroeconomic consequences of a specific climate scenario. It extends the climate risk stress test methodology of the European Central Bank that also advocates the use of the NGFS scenarios (see ECB, 2022) by incorporating the impact of a climate scenario on the credit cycle through macroeconomic conditions. This integration is one of the challenges for the consequences of climate risk for banks discussed by Baudino and Svoronos (2021). The extension fits well with the Basel IV

guidelines prescribed by the Basel Committee on Banking Supervision, in which an asymptotic single risk factor model is used to determine capital requirements for credit risk (see also BCBS, 2005, 2017). It is also in line with the conceptual framework laid out in a survey article by Acharya et al. (2023) about climate stress testing. Their framework consists of three elements: (i) a set of future scenarios of climate changes and related policies with their effect on macro indicators, (ii) models that link these indicators to interest rate, market, credit or other forms of risk and give their effect on (portfolios of) financial assets, and (iii) the consequences for financial institutions in terms of their balance sheet, risk-weighted assets and capital reserves. Reinders, Schoenmaker and van Dijk (2025) propose a similar framework, with the additional step of a "satellite model" that links the macro indicators to financial ones (see also Roger and Vlcek, 2012). We show how to implement such a framework for credit risk. In a similar way, our framework shows how climate risk can be incorporated in the general macro stress test discussed by Borio, Drehmann and Tsatsaronis (2014). It complements studies that look at actual bank exposures like Jung, Santos and Seltzer (2023) or stress tests with more specific scenarios like Reinders, Schoenmaker and van Dijk (2023).

Second, we contribute to the literature about credit risk modeling. We extend the static framework of Gupton et al. (1997), Belkin et al. (1998) and Vasicek (1991) by introducing dependence of the credit cycle on contemporaneous economic indicators. Because the commonality in credit migrations is not necessarily fully driven by these economic indicators, our approach accommodates the presence of a frailty factor that has been widely documented for defaults, see e.g. McNeil and Wendin (2007), Koopman and Lucas (2008), Duffie, Eckner, Horel and Saita (2009), Koopman, Lucas and Schwaab (2012) and Schwaab, Koopman and Lucas (2016), and for credit migrations by Koopman, Lucas and Monteiro (2008). We deviate from the mixed-measurement models proposed by Creal, Schwaab, Koopman and Lucas (2014), Schwaab et al. (2016), and Keijsers et al. (2018), where probabilities of default and macro variables are all adapted to the same latent processes. Because of the direct link between the economic indicators and the credit risk factor, we can plug in the NGFS scenarios and straightforwardly determine the consequences for the factor.

Third, our research contributes to the larger field of climate finance by showing how different paths for physical and transition risks affect the risk profile of corporate bonds with different ratings. This result complements research into the valuation of fixed income instruments like Painter (2020), Javadi and Masum (2021) and Acharya, Johnson, Sundaresan and Tomunen

(2022), showing that physical risk is priced, and Seltzer, Starks and Zhu (2022) showing the pricing of transition risk. Our focus on corporate bonds complements Klusak, Agarwala, Burke, Kraemer and Mohaddes (2023), who show that climate change can lead to a substantial deterioration of sovereign credit ratings based on projections up to 2100. The different effects of physical and transition risks may require separate treatment in more structural models capturing the interplay between economic processes of consumption and production, asset prices and climate, like Bansal, Kiku and Ochoa (2019), Giglio, Kelly and Stroebel (2021), Giglio, Maggiori, Rao, Stroebel and Weber (2021) and Cosemans, Hut and Van Dijk (2021).

From a practical perspective our proposed framework and results contribute to the discussion on how to deal with climate change from a financial risk perspective. Orderly transitions with coordinated and timely actions can reduce physical risks with limited increases in transition risks. They initially bring larger costs but lead to net savings over the full period to 2050. Disorderly transitions lead to a smaller reduction of physical risk, and substantial transition risk, which produces a volatile and negative path for the credit factor. Though having lower costs at first, the net effect shows that delaying actions imposes larger costs on the financial sector and hence on society.

Our paper is organized as follows. Section 2 presents our modular framework and estimation. Section 3 presents the migration data, key economic indicators, and the NGFS scenarios. We present the in-sample results in Section 4 and turn to the out-of-sample results in Section 5. Section 6 presents the conclusion and discussion. We present additional results in an appendix.

2 Methodology

In this section, we present the model framework that we use to investigate how the transition policy impacts credit risk and the resulting economic costs for diversified bond portfolios of different credit quality. The central concept in our framework is a set of latent factors $\boldsymbol{F}_t$ that capture the credit cycle. All bonds are exposed to the credit cycle, so for each bond, the probability of a credit migration, of which default is one outcome, is adapted to $\boldsymbol{F}_t$. The actual exposures of a bond to the latent factors depend on its current credit rating, which we use to define cohorts. We relate the credit cycle to a set of key economic indicators. By combining these two parts, we can determine the impact of a transition policy on the credit cycle and consequently on the bonds in a particular cohort. We make this impact concrete by comparing the expected losses and economic capital required for bond cohorts and for diversified bond

portfolios under different transition policies.

2.1 The latent factor model for credit risk

The starting point of our methodology is the ordered probit model of CreditMetrics for credit rating transitions as in Belkin et al. (1998). This model generalizes the threshold view of default of Merton (1974) and Vasicek (2002), which states that default occurs when a firm's equity is completely depleted or, in other words, when the value of its assets falls below its liabilities.[2] The CreditMetrics model incorporates all types of credit migration, recognizing that default is just one specific outcome within the broader context of credit migration. In this model, the credit rating S_{it} of the firm i at time t is a categorical variable that reflects the probability that the firm will default through the cycle. We assume that there are q rating categories $j = 1, \ldots, q$, with 1 being the highest rating and q being the lowest, which indicates that the firm is already in default at time t. The final state $S_{it} = q$ is an absorbing state, so firms in default will remain so.

Because a firm's financial conditions changes over time, the credit rating of a firm's bonds can change. We assume that the rating follows a first-order Markov chain, that is, the rating distribution at time t depends only on the rating at $t-1$, $\Pr[S_{it} = j|S_{i,t-1}, S_{i,t-2}, \ldots] = \Pr[S_{it} = j|S_{i,t-1}]$. As in Belkin et al. (1998), this conditional probability reflects a latent variable Y_{it} that can be interpreted as a credit change indicator, with a low value indicating a worsening of a firm's credit position.

Next, we define sets of $q-1$ ordered thresholds $K_{1m} > K_{2m} > \ldots > K_{q-1,m}$ for $m = 1, \ldots, q-1$ to give the probability $p_{jm} = \Pr[S_{it} = j|S_{i,t-1} = m]$ of a transition from state $m = 1, \ldots, q-1$ to j as

$$p_{jm} = \begin{cases} \Pr[Y_{it} > K_{1m}|S_{i,t-1} = m] & \text{for } j = 1, \\ \Pr[K_{jm} < Y_{it} \leq K_{j-1,m}|S_{i,t-1} = m] & \text{for } j = 2, \ldots, q-1, \\ \Pr[Y_{it} \leq K_{q-1,m}|S_{i,t-1} = m] & \text{for } j = q. \end{cases} \tag{1}$$

Because the default state q is absorbing $p_{qq} = 1$, $p_{jq} = 0$ for $j \neq q$.

To capture that the economy exhibits a credit cycle in which periods of many downgrades and few upgrades alternate with periods of few downgrades and many upgrades, we follow Gordy

[2]This model abstracts from the actual event that triggers a default, i.e. arrears in payments or filing for default protection.

and Heitfield (2010); Pfeuffer, Nagl, Fischer and Rösch (2020) and assume that each firm is exposed to r common factors $\boldsymbol{F}_t$,

$$Y_{it} = \boldsymbol{\lambda}_i' \boldsymbol{F}_t + \sigma_i \varepsilon_{it}, \tag{2}$$

where $\boldsymbol{\lambda}_i$ gives the r-vector of factor loadings and ε_{it} is an idiosyncratic component. The idiosyncratic components for different firms are assumed to be independent. This formulation can be seen as a structural model for the credit change indicator, or as a factor model such as those that are widely used in finance and macro (see e.g. Cochrane, 2005; Stock and Watson, 2016). An important difference is that Y_{it} is latent, and hence identifying restrictions are needed. It is common in this literature to impose that all random variables Y_{it}, $\boldsymbol{F}_t$ and ε_{it} follow standard normal distributions. As a consequence, $-1 < \lambda_{ij} < 1$ for $j = 1, \ldots, r$, $\boldsymbol{\lambda}_i' \boldsymbol{\lambda}_i < 1$ and $\sigma_i = \sqrt{1 - \boldsymbol{\lambda}_i' \boldsymbol{\lambda}_i}$. Because of the normality for Y_{it}, the model for credit migrations in eq. (1) becomes an ordered probit model.

Next to these identification restrictions, the literature typically assumes that firms in the same cohort, defined by one or more characteristics, have the same exposure to the common factor. We group firms by initial credit rating $S_{i,t-1} = m$, so $\boldsymbol{\lambda}_i = \boldsymbol{\lambda}_j$ if $S_{i,t-1} = S_{j,t-1}$ and we consequently write $\boldsymbol{\lambda}_m$. Consequently, the model in eq. (2) can be rewritten as

$$Y_{it} = \boldsymbol{\lambda}_m' \boldsymbol{F}_t + \sqrt{1 - \boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m} \varepsilon_{it}. \tag{3}$$

The correlation ρ_m between two firms i and j in the same cohort equals $\mathrm{E}[Y_{it} Y_{jt}] = \boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m$. The correlation between tow firms i and j in different cohorts is equal to $\boldsymbol{\lambda}_i' \boldsymbol{\lambda}_j$, which is referred to as inter-cohort correlation (see Pfeuffer et al., 2020).

Latent factor models generally exhibit the property that the factors and loading are not uniquely defined (see Stock and Watson, 2016). In this case, the factors and loadings in eq. (3) can be replaced by $\boldsymbol{Q}\boldsymbol{F}_t$ and $\boldsymbol{\lambda}_m \boldsymbol{Q}'$ where $\boldsymbol{Q}$ is an orthogonal matrix. Because the product of factors and loadings is unique per cohort, it is convenient to write eq. (3) as a single factor model,

$$Y_{it} = \sqrt{\rho_m} Z_{mt} + \sqrt{1 - \rho_m} \varepsilon_{it}, \tag{4}$$

where $Z_{mt} = \boldsymbol{\lambda}_m' \boldsymbol{F}_t / \sqrt{\boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m}$, where the scaling ensures Z_{mt} has a standard normal distribution. So for each cohort, Z_{mt} is a unique factor that drives the cyclical variation in migrations.

We relate each factor Z_{mt} by a simple dynamic linear model to a set of k business cycle

indicators $\boldsymbol{X}_t$ and to its lagged realization

$$Z_{mt} = \boldsymbol{\beta}_m' \boldsymbol{X}_t + \phi_m Z_{m,t-1} + \psi_m \eta_{mt}, \quad \eta_{mt} \sim \mathrm{N}(0,1), \tag{5}$$

where $\boldsymbol{\beta}_m$ is a k-vector with coefficients, ϕ_m and ψ_m are scalar coefficients and η_{mt} is an innovation independent of $\boldsymbol{X}_t$, $Z_{m,t-1}$ and ε_{it} for all i. Because η_{mt} is common to all bonds in cohort m, but independent of the business cycle indicators, it can be interpreted as a frailty factor as in Duffie et al. (2009); Koopman and Lucas (2008); Koopman et al. (2012); Schwaab et al. (2016). Because Z_{mt} has unit variance by construction, the residual variance is restricted to $\psi_m^2 = 1 - \phi_m^2 - \boldsymbol{\beta}_m' \boldsymbol{\Sigma}_{\boldsymbol{X}} \boldsymbol{\beta}_m$, where $\boldsymbol{\Sigma}_{\boldsymbol{X}}$ contains the variance matrix of the macro variables, and as a result, $0 \leq \phi_m^2 + \boldsymbol{\beta}_m' \boldsymbol{\Sigma}_{\boldsymbol{X}} \boldsymbol{\beta}_m \leq 1$. This specification with a cohort-specific factor Z_{mt} as dependent variable corresponds with a linear model for $\boldsymbol{F}_t$, but is easier to interpret as the factors are not uniquely identified.

2.2 Implications for risk management

The credit risk of a portfolio of bonds can be analyzed in the point-in-time (PIT) or the through-the-cycle (TTC) setting.[3] In the PIT setting, the common factors are treated as given or predicted, whereas in the TTC setting, they are averaged out (see e.g. Carlehed and Petrov, 2012; Yang, 2014). We will use the NGFS scenarios to create paths of the predicted probability of default at each point in time, which we will then use to derive risk measures for portfolios of bonds. This approach can be seen as hybrid, as we use the effect of the NGFS scenarios as given, but we do not make further assumptions about the state of the business cycle. We consider two types of portfolio, one with infinitely many bonds of the same cohort, in which case we derive closed-form expressions for the risk measures, and one with a fixed number of bonds of different cohorts, in which case we revert to simulations. Aggregation over the paths gives an indication of the TTC implications of the difference scenarios.

With information about the common factors, the probability of a transition of a bond from rating cohort m to j during time t becomes $p_{jm}(\mathcal{I}_t) = \Pr[S_{i,t} = j | S_{i,t-1} = m, \mathcal{I}_t]$. $\mathcal{I}_t$ is the

[3] Accounting regulations in IFRS9 prescribe the use of forward-looking PIT probability of default to determine expected losses, see `https://www.ifrs.org/issued-standards/list-of-standards/ifrs-9-financial-instruments.html/`. The Basel Framework prescribes the use of 1-year TTC probabilities of default to calculate unexpected losses to determine required capital reserves, see `https://www.bis.org/baselframework/BaselFramework.pdf`.

information set that contains Z_{mt} or $\boldsymbol{X}_t$ and $Z_{m,t-1}$. This probability is derived from eq. (1),

$$p_{jm}(\mathcal{I}_t) = \begin{cases} 1 - \Phi((K_{jm} - \mu_{mt})/\sigma_m) & \text{for } j = 1, \\ \Phi((K_{j-1,m} - \mu_{mt})/\sigma_m) - \Phi((K_{jm} - \boldsymbol{\mu}_{mt})/\sigma_m) & \text{for } j = 2, \ldots, q-1, \\ \Phi((K_{j-1,m} - \mu_{mt})/\sigma_m) & \text{for } j = q, \end{cases} \tag{6}$$

where we use that the distribution of Y_{it} conditional on $S_{i,t-1}$ and $\mathcal{I}_t$ follows a normal distribution $\mathrm{N}(\mu_{mt}, \sigma_m^2)$ with $\Phi(\cdot)$ denoting its standard cdf. The parameters μ_{mt} and σ_m^2 depend on the information set

$$\left(\mu_{mt}, \sigma_m^2\right) = \begin{cases} \left(\sqrt{\rho_m} Z_{mt}, 1 - \rho_m\right) & \text{if } \mathcal{I}_t = Z_{mt} \\ \left(\sqrt{\rho_m}(\boldsymbol{\beta}_m' \boldsymbol{X}_t + \phi_m Z_{m,t-1}), 1 - \rho_m(1 - \psi_m^2)\right) & \text{if } \mathcal{I}_t = \{\boldsymbol{X}_t, Z_{m,t-1}\}. \end{cases} \tag{7}$$

The variance in the second case follows as $\mathrm{Var}[Y_{it}|S_{i,t-1} = m, \boldsymbol{X}_t, Z_{m,t-1}] = \mathrm{Var}[\sqrt{\rho_m}\eta_{mt} + \sqrt{1-\rho_m} \cdot \varepsilon_{it}|\boldsymbol{X}_t, Z_{m,t-1}] = \rho_m\psi_m^2 + 1 - \rho_m = 1 - \rho_m(1-\psi_m^2)$. Since $0 \leq \psi_m^2 \leq 1$, the variance of the second case exceeds that of the first case and the difference reflects the additional uncertainty due to Z_t being predicted instead of given.

We are interested in the risk of a portfolio bonds. We assume that at the start of period t the portfolio consists of N_{mt} bonds with rating m, which we gather in the vector $\boldsymbol{N}_t$ of size $q-1$. For each bond with rating m, γ_{im} denotes the exposure at default and λ_{im} the loss given default as a proportion of the exposure at default, which we assume to be deterministic or independent from the common factor, from each other and from other bonds.[4] The loss at the end of period t, $L_t(\boldsymbol{N}_t)$ is a random variable given by

$$L_t(\boldsymbol{N}_t) = \sum_{m=1}^{q-1} \sum_{i=1}^{N_{mt}} \gamma_{im}\lambda_{im} I(Y_{imt} \leq K_{q-1,m}), \tag{8}$$

where $I(\bullet)$ denotes the indicator function.

The expected loss of this portfolio conditional on the information set $\mathcal{I}_t$ follows directly as

$$\mathrm{E}[L_t(\boldsymbol{N}_t)|\mathcal{I}_t] = \sum_{m=1}^{q-1} \sum_{i=1}^{N_{mt}} \gamma_{im}\lambda_{im} p_{qm}(\mathcal{I}_t), \tag{9}$$

where the probability of default $p_{qm}(\mathcal{I}_t)$ is given in eq. (6). To determine the economic capital,

[4] Evidence in Frye (2000); Keijsers et al. (2018); Schuermann (2004) shows larger LGDs during economic downturns, but given the paucity of data, we leave inclusion of this dependence for future research.

which is defined as the difference between the Value-at-Risk with confidence level α and the expected loss of the portfolio, the α-quantile of $L_t(\boldsymbol{N}_t)$ is required. In the asymptotic setting of Vasicek (1991, 2002), this quantile can be derived in closed form, and otherwise simulations can be used. We will discuss both.

In the setting of Vasicek (1991, 2002), it is assumed that $\gamma_{im} = \lambda_{im} = 1$. Under these assumptions, the percentage loss of a bond portfolio consisting solely of bonds with rating m is calculated as

$$\delta(N_{mt}) = L_t(N_{mt})/N_{mt} = \sum_{i=1}^{N_{mt}} I(Y_{imt} \leq K_{q-1,m})/N_{mt}. \tag{10}$$

We show in appendix A that the distribution of the percentage loss $\delta_{mt} = \lim_{N_{mt}\to\infty} \delta(N_{mt})$ follows as

$$\Pr[\delta_{mt} \leq v|\boldsymbol{X}_t, Z_{m,t-1}] = \Phi\left(\frac{\sqrt{1-\rho_m}\Phi^{-1}(v) + \mu_{mt} - K_{q-1,m}}{\sqrt{\rho_m}\sigma_\eta}\right). \tag{11}$$

This result extends Vasicek (1991) to the case where the common factor is predicted. The α-quantile of the distribution of δ_{mt} follows from inverting $\Pr[\delta_{mt} \leq v|\mathcal{I}_t] = \alpha$,

$$v_{mt}(\alpha; \boldsymbol{X}_t, Z_{m,t-1}) = \Phi\left(\frac{\sqrt{\rho_m}\sigma_\eta\Phi^{-1}(\alpha) - \mu_{mt} + K_{q-1,m}}{\sqrt{1-\rho_m}}\right). \tag{12}$$

Hence the economic capital at confidence level α for this asymptotic portfolio at time t equals

$$EC_\alpha^{\text{as}}(m; \boldsymbol{X}_t, Z_{m,t-1}) = v_{mt}(\alpha; \boldsymbol{X}_t, Z_{m,t-1}) - p_{qm}(\boldsymbol{X}_t, Z_{m,t-1}). \tag{13}$$

This expression for economic capital corresponds with a limiting portfolio consisting solely of bonds of one rating category. The result can hence be interpreted as an upper bound on the effect of a particular scenario at time t on a portfolio of bonds with credit rating m. In this portfolio all idiosyncratic effects have been diversified, so the portfolio risk is completely driven by the systematic component. Comparing the different rating categories by this risk measure can then show which cohorts are most sensitive to climate risk.

In reality, banks do not hold portfolios consisting of infinitely many bonds of the same rating category. If not all idioysncratic risk has been diversified or loans are heterogeneous in credit quality, the close-form expressions above can be replaced by simulations to evaluate the loss distribution in eq. (8). For a given information set, simulate a realization for the credit

indicator for each bond in the portfolio as $\tilde{Y}_{imt} = \mu_{mt} + \tilde{e}_{imt}$, where

$$\tilde{e}_{imt} = \begin{cases} \sqrt{1-\rho_m}\tilde{\varepsilon}_{imt} & \text{if } \mathcal{I}_t = Z_{mt} \\ \psi_m \boldsymbol{\lambda}_m' \tilde{\boldsymbol{u}}_t + \sqrt{1-\rho_m}\tilde{\varepsilon}_{imt} & \text{if } \mathcal{I}_t = \{\boldsymbol{X}_t, Z_{t-1}\}, \end{cases}$$

and $\tilde{\varepsilon}_{imt}$ and $\tilde{\boldsymbol{u}}_t$ are independently drawn from the standard univariate and r-variate normal distribution. In the second case, defaults are correlated, which is accounted for by the draw $\tilde{\boldsymbol{u}}_t$ which is common to all bonds in all cohorts. The simulated loss follows as $\tilde{L}_t(\boldsymbol{N}_t) = \sum_{m=1}^{q-1}\sum_{i=1}^{N_{mt}} \gamma_{im}\lambda_{im} I(\tilde{Y}_{imt} \leq K_{q-1,m})$. Repeating this procedure many times gives the distribution of $L_t(\boldsymbol{N}_t)$ from which the α-quantile can then be calculated.

2.3 Estimation

The estimation procedure consists of four steps. First, we use a sample of credit transitions observed over T periods to consecutively estimate the thresholds K_{jm}, the factor loadings $\boldsymbol{\lambda}_m$, and factor realizations $\boldsymbol{F}_t$. We then use these realizations to construct the implied $Z_m t$ series and estimate the parameters $\boldsymbol{\beta}_m$ and ϕ_m in the dynamic linear model in eq. (5) for each cohort.

Let D_{jmt} give the number of bonds migrating from rating m to j during period t. Because the default state q is absorbing, m runs from 1 to $q-1$. $\boldsymbol{D}_t$ denotes the set of all migrations during period t. Conditional on $\boldsymbol{F}_t$, the set of migrations $\{D_{jmt}\}_{j=1}^{m}$ from a given cohort m follow a multinomial distribution, parametrised by the q transition probabilities $p_{jm}(Z_t)$. They are a function of the thresholds K_{jm} in eq. (6) and the factor loadings $\boldsymbol{\lambda}_m$ in eq. (3). The probability mass function for $\boldsymbol{D}_t$ follows as

$$\Pr[\boldsymbol{D}_t|\boldsymbol{F}_t; \boldsymbol{\Lambda}, \boldsymbol{K}] = \prod_{m=1}^{q-1} N_{mt}! \prod_{j=1}^{q} \frac{(p_{jm}(\boldsymbol{F}_t))^{D_{jmt}}}{D_{jmt}!}, \tag{14}$$

where $N_{mt} = \sum_{j=1}^{q} D_{jmt}$ gives the number of firms in cohort m at the start of t, $\boldsymbol{\Lambda}$ is the $q-1 \times r$ matrix with factor loadings, and $\boldsymbol{K}$ the $q-1 \times q-1$ matrix with thresholds K_{jm}. It is the product of $q-1$ multinomial pmfs because conditional on $\boldsymbol{F}_t$, transitions from different cohorts are independent. The unconditional probability at t follows as

$$\Pr[\boldsymbol{D}_t; \boldsymbol{\Lambda}, \boldsymbol{K}] = \int_{\mathbb{R}^r} \Pr[\boldsymbol{D}_t|\boldsymbol{F}_t; \boldsymbol{\Lambda}, \boldsymbol{K}) \, \mathrm{d}\Phi_r(\boldsymbol{F}_t),, \tag{15}$$

where $\boldsymbol{\Phi}_r$ denotes the r-variate standard normal density.

We estimate $\boldsymbol{K}$ by a method of moments estimator as in Gordy and Heitfield (2010) and Belkin et al. (1998). This estimator uses the result that the unconditional distribution of each firm's credit change indicator Y_{it} in a particular cohort m follows a standard normal distribution as given by eq. (3). Combining this result with eq. (1) means that the unconditional transition probabilities p_{jm} satisfy

$$p_{jm} = \begin{cases} 1 - \Phi(K_{1m}) & \text{for } j = 1, \\ \Phi(K_{jm}) - \Phi(K_{j-1,m}) & \text{for } j = 2, \ldots, q-1, \\ \Phi(K_{qm}) & \text{for } j = q. \end{cases}$$

Estimating the unconditional probabilities by the average rates $\bar{p}_{jm} = \frac{1}{T}\sum_{t=1}^{T} D_{jmt}/N_{mt}$ and inverting the above equation leads to the estimator

$$\hat{K}_{jm} = \Phi^{-1}\left(1 - \sum_{k=1}^{j} \bar{p}_{km}\right) \quad \text{for } j = 2, \ldots, q-1. \tag{16}$$

Gordy and Heitfield (2010) show that this estimator has negligible bias, also for small realistic sample sizes.

To calculate the likelihood, we need to integrate over the latent factor realizations $\boldsymbol{F}_t$ which follow a standard normal distribution. We approximate this integral by taking S draws $\boldsymbol{F}_s$ from an r-variate standard normal distribution, yielding the approximate likelihood for observations t

$$\mathcal{L}_t(\boldsymbol{D}_t, \boldsymbol{N}_t; \boldsymbol{\Lambda}, \boldsymbol{K}) = \frac{1}{S}\sum_{s=1}^{S} \Pr[\boldsymbol{D}_t | \boldsymbol{F}_s; \boldsymbol{\Lambda}, \boldsymbol{K}). \tag{17}$$

The log likelihood to optimize then follows as

$$\ell(\boldsymbol{\Lambda}, \boldsymbol{K}) = \sum_{t=1}^{T} \log \mathcal{L}_t(\boldsymbol{D}_t; \boldsymbol{\Lambda}, \boldsymbol{K}) = C + \sum_{t=1}^{T} \log \sum_{s=1}^{S} \prod_{m=1}^{q-1} \prod_{j=1}^{q} p_{jm}(\boldsymbol{F}_s)^{D_{jmt}}, \tag{18}$$

where we suppressed the dependence of ℓ on the series $\boldsymbol{D}_t$ to ease the notation, and C collects the constant terms. The estimator $\hat{\boldsymbol{\Lambda}}$ maximizes this expression,

$$\hat{\boldsymbol{\Lambda}} = \arg \max_{\boldsymbol{\lambda}_m : \boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m < 1} \ell(\boldsymbol{\Lambda}, \hat{\boldsymbol{K}}), \tag{19}$$

with $\hat{\boldsymbol{K}}$ as in eq. (16). Because the loadings are identified up to a rotation by an orthogonal matrix, we impose that all $q-1$ cohorts load on the first factors, only $q-2$ cohorts load on the

second factor, and so on. [5]

For given values of $\boldsymbol{\Lambda}$ and $\boldsymbol{K}$, one way to determine $\hat{\boldsymbol{F}}_t$ is to maximize the log likelihood at each point in time t as a function of $\boldsymbol{F}_t$, i.e.

$$\hat{\boldsymbol{F}}_t = \arg\max_{\boldsymbol{F}_t} \sum_{m=1}^{q-1} \sum_{j=1}^{q} D_{jmt} \log p_{jm}(\boldsymbol{F}_t). \tag{20}$$

This maximization differs from the one in Belkin et al. (1998), who propose to estimate the factor realization as the solution to a weighted least-squares problem. Their approach is less appealing because it ignores the multinomial distribution of credit migrations.

In the final step, we create the cohort-specific factor realizations $\hat{Z}_{mt} = \hat{\boldsymbol{\lambda}}_m' \hat{\boldsymbol{F}}_t$ and use a linear regression to estimate the parameters $\boldsymbol{\beta}_m$ and ϕ_m in eq. (5), treating the realizations as observed. To impose the restriction $\mathrm{E}[Z_{mt}] = 0$, we demean all variables in $\boldsymbol{X}_t$ as is common in the factor model literature (see e.g., Stock and Watson, 2016).

3 Data

3.1 Credit migrations

We use historical semi-annual corporate transition matrices from Standard & Poor's Credit Market Services Limited (S&P) to estimate latent systemic factors. We restrict our attention to firms in the United States that are classified as corporate institutions, excluding financial and insurance institutions. The dataset covers transitions from January 2000 to June 2024 and is publicly available on the website of the European Securities and Markets Authority (ESMA).[6],[7]

S&P distinguishes nine performing rating cohorts (AAA to C), three default cohorts (Default, Selective Default, Regulatory Supervision), and the categories "Non-rated" and "Withdrawals". We exclude bonds in these last two categories from our analysis. Next, we merge the three default cohorts and some of the performing cohorts to ensure a sufficient number of assets and transitions between the different cohorts. We merge the performing cohorts that have the same risk weight according to the EU's Capital Requirement Regulation (see appendix B for more information), that is AAA and AA, as well as B, CCC, CC and C (denoted as AAA–AA and

[5] The probability $\Pr[D_{1mt}, \ldots, D_{qmt} | Z_s] = N_{mt}! \prod_{j=1}^{q} \frac{(p_{jm}(\boldsymbol{F}_s))^{D_{jmt}}}{D_{jmt}!}$ can fall below numerical precision for certain values of Z_s, in which case we remove that particular draw. For our sample, this happens in less than 1% of the draws.

[6] ESMA (2024): "Central Repository of Ratings (CEREP) for publishing the rating activity statistics and rating performance statistics of credit rating agencies". `https://registers.esma.europa.eu/cerep-publication/`

[7] We label the data matrices by the mid-points of the 6-month period, *i.e.*, April 1 and October 1.

B–C). As shown in table 1, the AAA–AA cohort is smallest with an average number of 47 bonds, whereas the B–C cohort is largest (868 bonds). The cohort sizes show substantial variation in their sizes over time. In each cohort, the number of bonds tend to increase as time goes by.

Table 1: Cohort sizes and credit migrations

Initial				End-of-period cohort					
Cohort	Min.	Av.	Max.	AAA–AA	A	BBB	BB	B–C	Default
AAA–AA	29	47	131	95.39	4.13	0.46	0.008†	0.008†	0.008†
A	222	280	367	0.25	96.26	3.39	0.045	0.029	0.022
BBB	454	520	615	0.032	1.23	96.64	1.83	0.219	0.047
BB	331	427	500	0.010	0.028	1.84	93.28	4.73	0.11
B–C	513	868	1191	0.001†	0.036	0.036	1.99	96.46	1.47

This table presents the size of each cohort at the start of the period (minimum, average and maximum number of bonds), and the average relative frequency (in %) of migrations. Migrations are measured semi-annually during the period January 2000 to June 2024 ($T = 49$). AAA–AA and B-C denote the merged cohorts of AAA and AA, and B, CCC, CC and C. A † indicates that no migration has been observed over the sample period. In that case we calculate the average migration frequency by replacing the zero by 1/2 for the period with maximum cohort size.

The unconditional migration probabilities in table 1 highlight that transitions within 6-month periods are generally rare. The relative frequency of assets migrating to a lower rating are below 5 percent, and less than 2 percent of assets enter default. The cohort subject to the most transitions is the BB rating, in which around 6.7 percent of assets tend to migrate. The low frequency of transitions emphasizes the importance of maintaining a large cross-section of assets to obtain accurate estimates of the underlying factor structure.

3.2 Economic indicators

The economic indicators consist of macroeconomic variables retrieved from the FRED Database of the Federal Reserve Bank of St. Louis and equity market returns taken from Kenneth French's data library.[8] The macroeconomic variables consist of the growth rate of GDP, the unemployment rate, the inflation rate, the change in the oil price of Brent crude, and the 10-year real interest rate. Equity market returns are measured based on the value-weighted portfolio of all common stocks on the NYSE, AMEX, and NASDAQ. These data account for various effects arising from macro, monetary and financial shocks.

The nature of corporate debt data introduces a subtle timing puzzle with respect to economic indicators. We do not observe the exact timing of credit migration between cohorts; rather, we observe end-of-period summaries of the transitions that occurred. We generally expect economic

[8]Available at `https://fred.stlouisfed.org/` and `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

indicators to lead. For example, low GDP growth reduces firms' expected future cash flows, which may trigger a credit downgrade. Though the bankruptcy of a large firm or downgrades of a few large firms may have economy-wide consequences, we do not account for this possibility. As such, we lag the economic indicators by a quarter, meaning that we relate the credit cycle factor corresponding with the first half of year t with the economic indicators observed over the last quarter of year $t-1$ and the first quarter of year t. We present summary statistics and graphs of the time series in Appendix B.2.

3.3 Climate policies and economic scenarios

The Network of Central Banks and Supervisors for Greening the Financial System (NGFS) constructs scenarios "to provide a common starting point for analysing the impact of climate risks on the economy and financial system" (NGFS, 2024b). They reflect different paths that depend on the evolution of climate change, transition policies, technological and macro-financial developments, and are internally consistent. We use their scenarios, released as NGFS Phase V in November 2024, as predictions for the economic indicators presented in the previous section.[9]

The NFGS distinguishes six different sets of policy ambition, measures and timing, and consequent technological changes, which we will refer to as policies. We present their names, description, and risk characterization in table 2. The *Net Zero 2050* and *Below* $2\,^{\circ}C$ scenarios can be seen as *orderly* transitions with low physical risk and limited transition risk. The *Delayed Transition* scenario is *disorderly* with a high degree of transition risks and intermediate degree of physical risks. The scenarios *Current Policies* and *NDCs* are characterized as *hot house world* with high physical but low transition risks. The *Fragmented World* scenario is *too little, too late* with high risks in both dimensions.

To determine the impact of these different policies, the NGFS combines models for acute and chronic physical risks with models for transition risks. These latter take the form of so-called Integrated Assessment Models (IAMs), that determine the impact on a wide array of economic activities, land uses, and emissions. The NGFS considers three different IAMs, being REMIND-MAgPIE (REMIND), Global Change Analysis Model (GCAM) and MESSAGEix-GLOBIOM (MESSAGEix), to which we refer by their short name in parentheses. These model share a common goal of modeling the interaction between the economy and the environment, in particular the energy system and land use, but differ with respect to assumptions, granularity,

[9]The scenarios are available at www.ngfs.net.

Table 2: Overview of policy scenarios and their descriptions.

Scenario Name	**Description**	**Risk characterization**		
		P	T	Type
Below 2 °C	Increasingly strict policies give approximately a 67% chance of keeping warming below 2 °C, and countries with net-zero targets achieve 80% of their goals.	-	-	Orderly
Net Zero 2050	Forceful action and innovation will limit global warming to 1.5 °C, with net-zero CO_2 emissions reached around 2050.	--	□	Orderly
Delayed Transition	Policy action is postponed until 2030, after which decisive measures limit warming to below 2°C.	-	+	Disorderly
Fragmented World	Current policies are maintained until 2030, after which countries with net-zero targets partially meet them by 2050, while countries without such targets continue current policies with no further action.	+	++	Too little, too late
Current Policies	Only currently implemented policies are preserved.	++	--	Hot house world
NDCs	Beyond current policies, all pledged targets are met.	+	-	Hot house world

This table reports for each policy scenario its name, description, and a risk characterization with regard to its physical risk (P) and transition risk (T), and the resulting combination (under "Type"). The risk categorization labels are very high (++), high (+), intermediate (□), low (-) and very low(--). The information in this table has been taken from NGFS (2024b, p. 8–9).

equilibrium type and solution method, see NGFS (2024a). The macro-financial consequences of physical and transition risks are taken from the National Institute Global Econometric Model (NiGEM).[10] We use the predictions from all three IAMs.

The predictions provided in NiGEM correspond with annual effects on economic variables in the different scenarios. We add these affects to the baseline predcitions of these variables, also produced by NiGEM. To align these out-of-sample data with the semi-annual estimates from the in-sample period, we interpolate the annual series using cubic splines. From the levels of the economic variables, we compute the changes to obtain series that are analogous to those used in the in-sample data.

Table 3 shows the means of the economic indicators resulting from the different scenarios and IAMs. The means in the baseline scenarios show no or only small differences between the IAMs, meaning that differences between the other scenarios reflect differences in the impact of climate change and policies in the IAMs. The means are also in line with the historical averages over the 2000-2024 period reported in table 8. In all policies and IAMs, incorporating climate change leads to small decreases in the average economic growth and equity market return, and

[10]Created by the National Institute of Economic and Social Research, `https://niesr.ac.uk/`.

small increases in inflation and the long-term real interest rate. The reaction of the oil price varies widely over the scenarios and IAMs.

Table 3: Mean of the economic indicators in the NGFS scenarios

		g	u	π	p	i	r
GCAM	Baseline	3.12	4.47	4.25	0.50	1.22	6.68
	Below 2°C	2.56	4.43	4.63	11.41	1.69	5.54
	Current Policies	2.40	4.34	4.61	0.50	1.22	6.01
	Delayed transition	2.41	4.47	4.78	17.06	1.57	6.30
	Fragmented World	2.34	4.44	4.77	10.00	1.46	6.11
	Nationally Determined Contributions (NDCs)	2.36	4.41	4.70	5.27	1.41	6.02
	Net Zero 2050	2.61	4.46	4.65	19.98	1.86	5.54
MESSAGEix	Baseline	3.39	4.47	4.25	0.50	1.22	6.68
	Below 2°C	2.80	4.39	4.62	2.91	1.50	5.84
	Current Policies	2.67	4.33	4.61	0.50	1.22	5.92
	Delayed transition	2.68	4.41	4.74	2.95	1.47	6.24
	Fragmented World	2.70	4.35	4.63	−3.20	1.30	5.98
	Nationally Determined Contributions (NDCs)	2.70	4.39	4.68	0.28	1.42	6.22
	Net Zero 2050	2.84	4.45	4.64	11.54	1.95	5.27
REMIND	Baseline	3.14	4.47	4.25	0.50	1.22	6.68
	Below 2°C	2.55	4.39	4.59	4.98	1.40	6.18
	Current Policies	2.30	4.32	4.66	0.50	1.22	5.86
	Delayed transition	2.39	4.48	4.76	15.71	1.53	6.59
	Fragmented World	2.34	4.38	4.70	5.98	1.31	6.21
	Nationally Determined Contributions (NDCs)	2.36	4.43	4.72	8.03	1.53	6.38
	Net Zero 2050	2.78	4.37	4.41	15.68	1.70	5.89

This table reports the means of the economic indicators collected from the NGFS data library for the seven scenarios and three Integrated Assessment Models. Variables are annual and expressed in percent. We denote GDP growth by g, unemployment by u, inflation by π, oil price changes by p, long-term interest rates by i, and equity market returns by r. The data runs from 2024 to 2051.

More interesting and probably more relevant are the variations over time resulting from the scenarios and IAMs. The first three rows fig. 1 show considerable differences in the impact that the policies have on GDP growth, inflation and unemployment. Particularly the scenarios *Delayed Transition* and *Fragmented World*, which impose substantial transition risks, lead to dips in GDP growth and inflation and a bump in the unemployment rate after 2030. The GDP growth rate and unemployment rate slowly revert back, but inflation goes up and remains higher for several years after. The orderly scenarios *Net Zero 2050* and *Below* $2\,^{\circ}C$ in which immediate transitions take place show the opposite picture with lower GDP growth but higher inflation and unemployment in the years up to 2030. After 2030, the ranking reverses, and these scenarios have among the highest GDP growth, lowest inflation and unemployment rate. The variation in impact between the scenarios is lowest in GCAM, followed by MESSAGEix and REMIND.

The different scenarios have a pronounced and stable effect on the long-run real interest rate. The orderly transitions in *Net Zero 2050* and *Below* $2\,^{\circ}C$ lead to quick technological advances

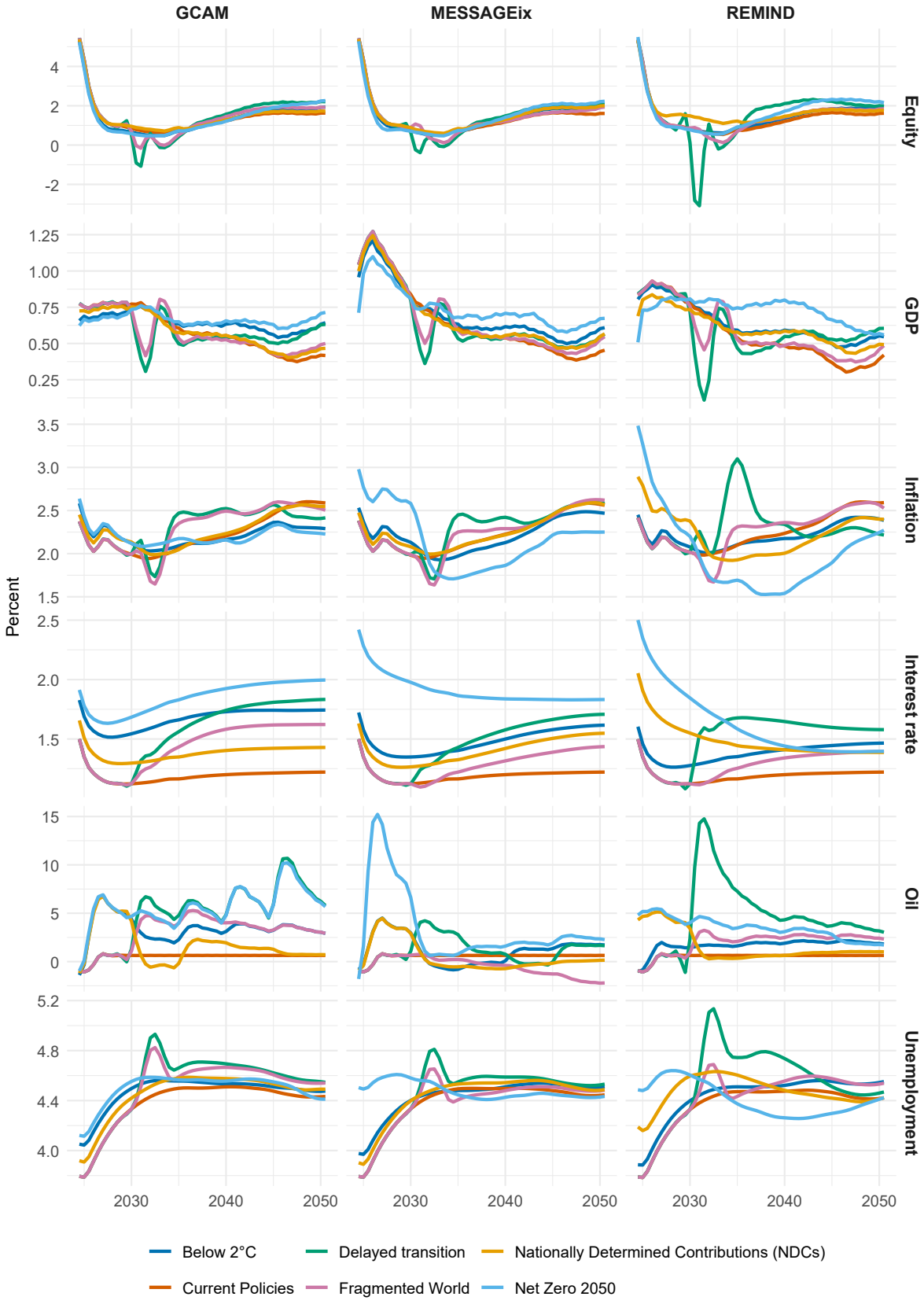


Figure 1: Predictions of the economic indicators in the NGFS scenarios

The figure presents predictions of the in the six different climate policies between 2024 and 2050. The rows correspond with the different economic indicators and the columns with the different IAMs; GCAM, and MESSAGEix and REMIND.

reflected in high rates. In the *Delayed Transition* scenario, measures are postponed until after 2030, after which the real rate catches up with the former two. In the Hot house world of *NDCs* and *Current Policies*, physical risks remain high with a detrimental effect on productivity and technological advances, as signaled by a relatively low long-term real rate. The *Fragmented World* scenario shows a low rate until 2030 and modest increases thereafter. In GCAM and MESSAGEix real rates remain different over the complete out-of-sample period, whereas they move closer together in REMIND.

The scenarios differ little in their effect on the equity market return. The *Delayed Transition* scenario leads to a dip in stock returns lasting a few years after 2030. In particular in the REMIND predictions this dip is sizeable, but it is followed by higher returns after 2035. The predictions for the relative changes in the oil price vary considerably over the scenarios and the IAMs as shown in (fig. 1). MESSAGEix predicts large increases in the early years of the *Net Zero 2050* scenario with stable prices after 2032. REMIND predicts large and prolonged price increases in the *Delayed Transition* scenario after 2030. Whereas the differences between the scenarios become smaller in the predictions by MESSAGEix and REMIND toward the end of the out-of-sample period, they remain large in the GCAM predictions.

Together, the scenarios indicate quite different paths for the economy. On the one end, the orderly transitions of *Net Zero 2050* and *Below* $2\,^{\circ}C$ lead to early pain in the form of lower economic growth, higher unemployment and inflation and rising oil prices, but after 2035 the benefits dominate. The *Delayed Transition* scenario is disorderly, with sharp dips in the GDP growth and the equity market and upticks in the unemployment rate. The inflation first dips but then picks up. The *Fragmented World* scenario shows similar but less extreme effects. In the Hot house world scenarios of *NDCs* and *Current Policies* measures are more limited, and consequently, all indicators show stable behavior with a downward trend in economic growth and low long-term real interest rates.

The figures reveal that while the three models tend to deliver estimates that are qualitatively similar with respect to these economic variables, the magnitude of the effects can vary substantially. In particular, they provide very different assessments of the magnitude of effects from a delayed transition. The REMIND model tends to indicate more extreme effects. Furthermore, the effect on oil price changes (fig. 1) vary greatly over the models.

In all, the models and scenarios in the NGFS data provide a wide range of possible paths for the economic indicators. The differences across the scenarios in the economic variables of

interest are substantial and indicate very different economic conditions. However, contrasting the transition risk models highlights some ambiguity regarding how severe the effects are expected to be in different scenarios. We do not take a stance on the likelihood or accuracy of these assessments but present results across all models.

4 Estimation results

We first present the estimates based on historical data. We begin with the estimates of the latent factors that captures commonalities in credit migrations. We then relate these factors to the economic indicators observed during the period and construct a linear model to track their changes.

4.1 Estimates of the latent credit factor

From the unconditional transition probabilities summarized in table 1, we obtain an estimate of the threshold matrix $\boldsymbol{K}$ as in eq. (16). We then proceed to estimate the factor exposures and the latent factors. We assume that credit cycle is well approximated by a two-factor model. This specification is flexible enough to allow the cycle to vary across cohorts, while remaining suitably parsimonious relative to the available sample.

The estimation results are in table 4. By construction, the thresholds are decreasing over the destination cohort, that is, over the columns, indicating that a more negative realization of Y_{im} leads to a larger downgrade. They are increasing over the departure cohorts, that is, over the rows, which means that for a downgrade of, for example, a BBB-rated bond to B a less negative realization of Y_{im} is needed than for an A-rated bond, as the threshold is -3.100 for A and -2.034 for BBB. This pattern in the data corresponds with economic logic, and does not arise by construction.

The estimates for the factor exposures show that the first factor can be interpreted as a level factor and the second one more as a curvature factor. The joint effect of the common factors is given by the intra-cohort correlation $\rho_m = \sqrt{\boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m}$, reported in the last column. These correlation parameters show a U-shape where the effect of the common factors is highest in the extreme cohorts AAA-AA and B–C. Since the variance of the latent credit indication Y_{it} equals 1, the intra-cohort correlation also indicate how much of its variation is explained by the common factors. For the AAA-AA cohort this is largest at 6.6% and lowest for the A-cohort at 3%. For identification, we impose that λ_2 equals zero for the BBB cohort, as this is one of

cohort	AAA-AA	A	BBB	BB	B–C	λ_1	λ_2	ρ_m
AAA–AA	−1.684	−2.588	−3.499	−3.606	−3.782	0.170	0.193	0.066
A	2.806	−1.813	−3.100	−3.283	−3.511	0.150	0.090	0.030
BBB	3.417	2.237	−2.034	−2.787	−3.307	0.209	0	0.044
BB	3.726	3.367	2.079	−1.661	−3.062	0.181	0.125	0.048
B–C	4.299	3.378	3.184	2.040	−2.178	0.096	0.236	0.065

Table 4: Estimation results for the CreditMetrics model with 2 factors

This table shows the estimates for the thresholds, the factor exposures and the resulting intra-cohort correlations in the CreditMetrics model specified in eqs. (1), (3) and (4). The columns labeled with a cohort give the estimates for the thresholds as in eq. (16). The columns labeled with λ_1 and λ_2 give the estimates for the factor exposures as in eq. (19). The intra-cohort correlations follow from the factor exposures, $\rho_m = \sqrt{\boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m}$. To identify the factors, we impose that λ_2 equals zero for the BBB cohort.

the bigger cohorts. Varying the identification restriction alters the exposure estimates ($\boldsymbol{\lambda}_m$) but does not affect the intra-cohort correlations (ρ_m).

We proceed to estimate the latent factors $\boldsymbol{F}_t$ and determine their joint effect $\lambda_m \boldsymbol{F}_t / \sqrt{\boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m}$ for each cohort. Whereas the factors depend on the identification restriction, their joint effect is uniquely determined. Figure 2 reveal states of the corporate bond market that vary over time intuitively. We plot the number of upgrades and downgrades in each period on the secondary vartical axis. The credit cycle was low in the early 2000s, coinciding with the period of the dot-com bubble and its aftermath. It recovered until the financial crisis of 2008, which marked the lowest point in our sample. Following the financial crisis, we observe a period of better credit states, ultimately interrupted by the COVID-19 pandemic.

All cohort-factors are constructed such that they have approximately a mean of zero and variance equal to 1, and follow the actual pattern in upgrades and downgrades quite closely. The graphs show mild heterogeneity over the cohorts. For example, the lowest cohort B–C seems more strongly affected by the financial crisis of 2008, but less by the COVID-19 pandemic. Government support during the pandemic may have prevented defaults but not downgrades of higher rated firms. Surprisingly, the BBB-cohort was not strongly affected by the financial crisis, as reflected by the small number of downgrades and consequently small negative values for the factor. This feature may be explained by the stickiness of the BBB-cohort as the lowest investment grade cohort.

4.2 Relating changes in the factor to economic indicators

Using the economic indicators, we fit linear models to track changes in the latent cohort-factors. Table 5 presents the OLS estimates of the parameters in eq. (5) and table 6 the correlations

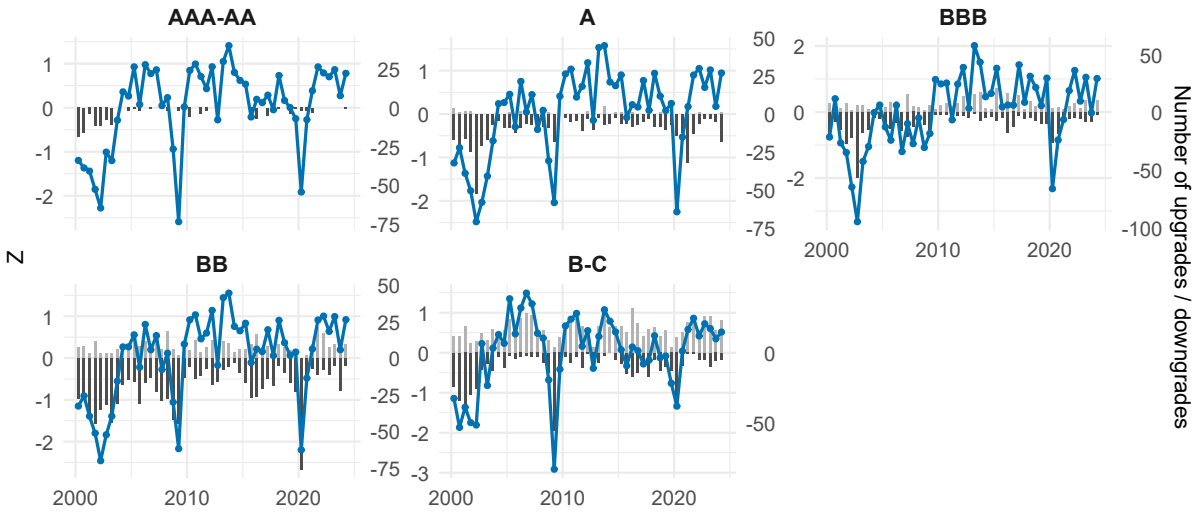


Figure 2: Joint effect of the latent factors estimates per cohort

The figure presents the estimated latent factors per cohort together with the upgrades and downgrades in each half-year period. We set the number of latent factors equal to 2. For each cohort, the joint effect of the latent factors follow as $Z_{mt} = \boldsymbol{\lambda}_m' \boldsymbol{F}_t / \sqrt{\boldsymbol{\lambda}_m' \boldsymbol{\lambda}_m}$ with estimates for $\boldsymbol{\lambda}_m$ reported in table 4. The factor estimates follow from eq. (20). The bars give the number of upgrades (light grey, positive) and downgrades (dark grey, negative) with the scale indicated on the secondary vertical axis.

of the dependent and independent variables. Most coefficients for the GDP growth rate and the inflation rate are positive, indicating a positive relation with the credit cycle. A rise in the unemployment rate is associated with an improving credit cycle, which may indicate that firms are cutting costs by laying off staff. Real interest rates have a strong and negative effect on the credit cycle, as higher rates increase the cost of borrowing (in real terms) and dampen economic growth. Part of the strength may be due to the negative correlation with GDP growth, inflation and unemployment in table 6. Equity market returns are positively related with the credit cycle. Changes in oil prices hardly have an effect on the credit cycle.

In the dynamic models, the AR coefficients tend to be substantial with values between 0.37 and 0.58, indicating that shocks to the credit cycle take several periods to disappear. The inclusion of the AR term dampens the effect of inflation and the real interest rate, and makes the effect of the unemployment rate stronger. Coefficients for the other variables are not much affected.

The values for the adjusted R^2 ranging from 0.24 to 0.39 for the static models indicate that the economic indicators explain a substantial part of the variation of the credit cycle. They also indicate that the joint fit of the variables is good, even though the standard errors are relatively large and indicate that some estimates are insignificant. Introducing an AR component leads to large increases in R^2-values up to 0.65 and lower standard errors.

Table 5: Linear macro-finance models per cohort

	AAA–AA		A		BBB		BB		B–C	
g	0.28	0.30	0.19	0.20	−0.01	−0.01	0.21	0.22	0.36	0.37
	(0.17)	(0.10)	(0.16)	(0.11)	(0.18)	(0.15)	(0.17)	(0.11)	(0.15)	(0.09)
r	0.22	0.21	0.28	0.25	0.33	0.28	0.27	0.25	0.12	0.15
	(0.08)	(0.14)	(0.08)	(0.12)	(0.15)	(0.14)	(0.08)	(0.13)	(0.10)	(0.16)
i	−0.31	−0.01	−0.45	−0.13	−0.60	−0.38	−0.43	−0.10	−0.12	0.09
	(0.17)	(0.09)	(0.16)	(0.08)	(0.17)	(0.10)	(0.16)	(0.08)	(0.21)	(0.12)
π	0.17	0.02	0.11	0.00	−0.01	−0.05	0.13	0.00	0.22	0.08
	(0.11)	(0.14)	(0.12)	(0.12)	(0.19)	(0.17)	(0.12)	(0.12)	(0.13)	(0.16)
u	0.09	0.16	0.01	0.08	−0.13	−0.09	0.02	0.10	0.17	0.22
	(0.14)	(0.08)	(0.17)	(0.08)	(0.18)	(0.11)	(0.17)	(0.07)	(0.09)	(0.07)
p	−0.14	−0.01	−0.12	−0.02	−0.08	−0.02	−0.13	−0.01	−0.13	−0.03
	(0.13)	(0.10)	(0.14)	(0.12)	(0.21)	(0.20)	(0.14)	(0.11)	(0.12)	(0.09)
Z_{t-1}		0.59		0.55		0.38		0.56		0.54
		(0.07)		(0.08)		(0.12)		(0.08)		(0.06)
R^2	0.34	0.65	0.38	0.61	0.32	0.41	0.38	0.62	0.24	0.55
R^2_{LOO}	0.24		0.29		0.18		0.29		0.08	

The table reports estimates from linear regressions of each latent cohort factor Z_k onto economic variables and, for the dynamic specification, the first lag of the same factor. All economic indicators are centered and the coefficients associated with the economic variables are scaled such that they represents the change in the dependent variable resulting from a one-standard deviation increase in the corresponding predictor. Newey–West standard errors are reported in parentheses. R^2 denotes the in-sample adjusted R^2. R^2_{LOO} gives the leave-one-out error variance and is not available for the dynamic specifications.

In small samples, overfitting can be a significant concern. To obtain an approximate estimate of the out-of-sample fit, we compute the linear fit of the economic variables using a leave-one-out approach.[11] Unsuprisingly, the values for the leave-one-out R^2 are lower than for the in-sample adjusted R^2 but not much. Together the results show that a linear combination of the economic indicators provides an empirically relevant prediction of the credit cycle for each cohort. This holds in particular for the AAA–AA, A and BB cohorts, and is a bit weaker for the BBB and B–C cohorts.

5 Scenario analysis

In this section we combine the model for the credit cycle of the previous section with the NGFS scenarios. We use the scenarios to make predictions of the credit cycle up to 2050 and use them to investigate the consequences for the risk profile of portfolios of bonds that vary with respect to their credit rating. To keep the exposition of the results clear, we focus our discussion on the risk management implications of the credit cycles obtained from the REMIND model. The results from the GCAM and MESSAGEix models are presented in Appendix B.3. This choice

[11] Specifically, when we leave out the observation for time s and cohort m, we first construct the estimate $\hat{\boldsymbol{\beta}}_{ms}$ without this observation, and then construct the leave-one-out residual as $\hat{u}_{ms} = Z_{ms} - \hat{\boldsymbol{\beta}}'_{ms}\boldsymbol{X}_s$. The corresponding R^2_{LOO} for cohort m follows as $1 - \sum_{s=1}^{T} u^2_{ms}$, where we use that all cohort-factors have unit variance.

Table 6: Correlation between latent factor estimates and economic indicators

	$\hat{Z}_{AAA-AA}$	$\hat{Z}_A$	$\hat{Z}_{BBB}$	$\hat{Z}_{BB}$	$\hat{Z}_{B-C}$	r	i	g	π	u	p
$\hat{Z}_{AAA-AA}$	1.00										
$\hat{Z}_A$	0.94	1.00									
$\hat{Z}_{BBB}$	0.64	0.86	1.00								
$\hat{Z}_{BB}$	0.96	1.00	0.83	1.00							
$\hat{Z}_{B-C}$	0.92	0.74	0.29	0.78	1.00						
r	0.41	0.42	0.35	0.42	0.33	1.00					
i	−0.46	−0.55	−0.57	−0.54	−0.28	−0.16	1.00				
g	0.47	0.39	0.18	0.41	0.49	0.46	−0.14	1.00			
π	0.30	0.21	0.02	0.23	0.36	0.16	0.00	0.58	1.00		
u	0.15	0.17	0.16	0.17	0.11	0.16	−0.41	−0.18	−0.26	1.00	
p	0.24	0.17	0.03	0.19	0.28	0.46	0.02	0.56	0.55	0.10	1.00

The table reports lower-triangular correlations between five estimated latent factors $\hat{Z}_{AAA-AA}, \ldots, \hat{Z}_{B-C}$ and economic indicators during the in-sample period. We denote equity market returns as r, long-term interest rates as i, GDP growth as g, inflation as π, unemployment as u, and oil price changes as p.

does not mean that we consider the results from the REMIND models as more reliable.

5.1 Climate policies and the credit cycles

We present the credit cycle for each cohort that is consistent with a particular NGFS scenario in fig. 3. The predictions follow from eq. (5), starting from the last estimation for the factor realization Z_{mT}. Because the AR-coefficients are substantial and the estimates for the last realization are positive for all cohorts, as shown in fig. 2, the first prediction of the credit cycle, corresponding with the first half of 2025, is positive for all scenarios and cohorts. As of the second prediction, the predictions diverge across scenarios and cohorts. Two periods are particularly critical: (1) the early period ending in 2030, during which orderly transitions incur greater transition-related damages, and (2) the period from 2030 to 2040, when disorderly transition scenarios incur greater damages.

The majority of investment-grade bonds are in cohorts A, BBB, and BB. fig. 3 shows that the policy scenarios' impacts on the cycles in these cohorts are qualitatively similar. For these cohorts, economic damages arising from transition risk in the orderly transition scenarios cause a rapid reversion from the high initial states. The impacts under the *Net Zero 2050* policy are especially severe, and the credit factor remains negative until 2035. The magnitude of transition risk related damages for BBB-rated bonds is particularly large. However, following the early-period damages, the credit cycles recover and, from 2035 onward, are predicted to be higher than those under the other scenarios. In contrast, under disorderly transitions, the credit cycles remain high initially but deteriorate rapidly and severely after 2030. In the final 10 years of the

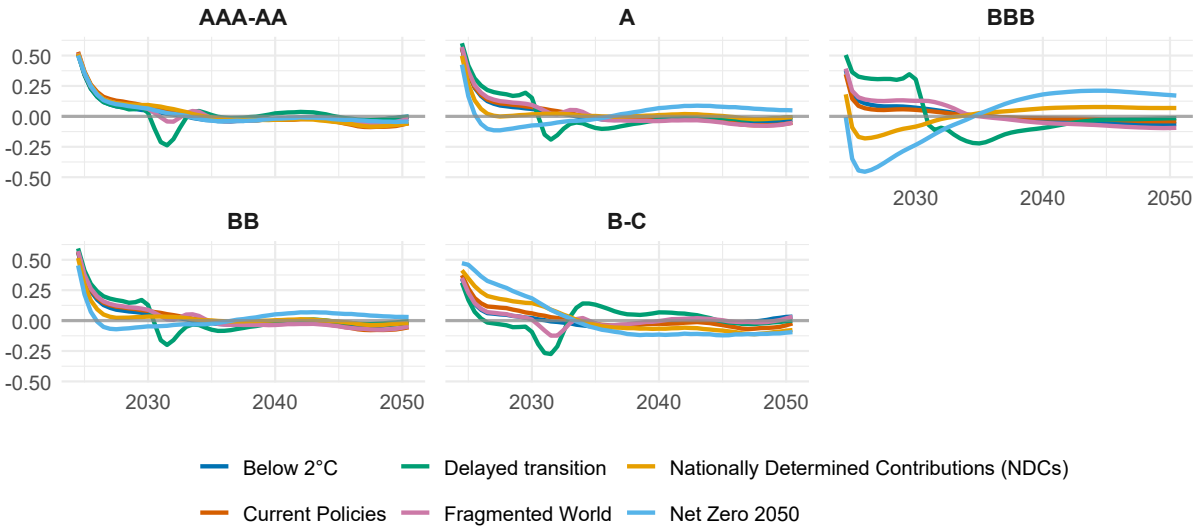


Figure 3: Predictions for the credit cycle from July 2024 to July 2050

The figure presents the predicted values of the credit cycle for the different cohorts under six different climate policies. The scenarios are generated by the REMIND model. Predictions are formed based on the model in eq. (5) with parameter estimates in table 5. The predictions take the estimates for the last factor realization Z_{mT} as a staring point.

prediction period, the positive effects of reduced physical risk under orderly transitions result in higher states of the credit cycle than those observed under disorderly transitions and the hot-house-world scenarios.

We find different predictions for the highest rated bonds, which fall into the AAA–AA cohort. The credit cycle in this cohort is much more homogeneous across policy scenarios than what we observe in the other investment grade cohorts. Whereas the *Net Zero 2050* policy scenario tends to cause large disruptions in the early years of the credit cycle for most cohorts, the AAA–AA credit cycle is far more robust and largely unaffected by transition risk under the orderly transition scenarios. The exception arises under the *Delayed Transition* policy, where large transition damages lead to a substantial deterioration in the credit cycle.

Lastly, turning to the bonds in the lowest-grade cohort, B–C, we find that the heterogeneity captured by the two-factor model generates markedly different outcomes compared with investment-grade bonds. In this cohort, despite the transition damages incurred under orderly transition policies, the cycles remain elevated throughout the first 10 years of the out-of-sample period. The source of this deviation is likely related to the distinct role of long-term real interest rates. Table 5 shows that all cohorts except this one are conditionally negatively related to real interest rates. In contrast, these high-yield bonds are positively related to rates, which are high during the initial period of the *Net Zero 2050* policy.

5.2 Economic capital requirements

Changes in the credit cycles affect the economic capital requirements that banks must meet. When the credit cycle deteriorates, downgrades and defaults are expected to rise across cohorts. We examine these requirements for well-diversified portfolios of bonds within a single cohort. We determine the predicted time series of required capital in each cohort relative to the initial requirements at the start of the prediction period in Figure 4, as well as the magnitude of the requirements relative to the scenario in which current policies are maintained in Figure 5. Since the opportunity costs associated with capital requirements change proportionally, the resulting percentages difference can directly be interpreted as increases or decreases in costs.

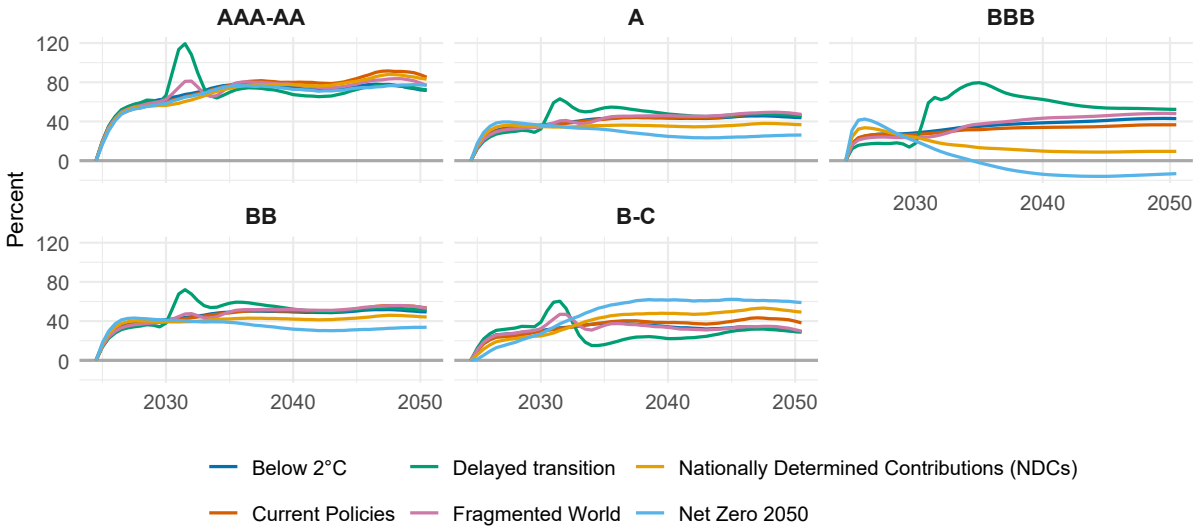


Figure 4: Relative change in economic capital

The figure presents the development of the predicted economic capital requirements up to July 2050 relative to the initial level of July 2024 in percentages. The economic damages are generated using the REMIND model.

Figure 4 shows the evolution of capital requirements relative to the initial values for each cohort and policy scenario. The initially elevated credit cycles imply low capital requirements, which subsequently rise as the cycle reverts to its mean. Across cohorts, and largely independent of the policy scenarios, the increase is largest for the highest grade bonds (AAA–AA). However, the *Delayed Transition* scenario generates a sharp increase in the early 2030s, exceeding all other policy alternatives. The peak approaches 120 percent of the initial level – roughly 40 percentage points higher than in other scenarios at that time. Although this shock fades later in the sample, the two hot-house-world scenarios *Current Policies* and *NDCs* ultimately produce the largest increases.

The remaining investment-grade cohorts A, BBB, and BB exhibit similar dynamics. Trans-

ition risk under both orderly and disorderly pathways leads to short-term increases in capital requirements. As transition related damages subside, however, the reduction in physical risk in the later part of the sample translates into lower requirements. For BBB-rated bonds, this reduction is strong enough to push predicted capital requirements below their initial levels. In contrast, the adverse effects of the *Delayed Transition* scenario are substantial, and requirements in this cohort do not return to the levels observed under the *Fragmented World* scenario by the end of the prediction period. Only in the B–C cohort do we find that an orderly transition meeting the *Net Zero 2050* targets fails to offset the transition damages incurred early in the prediction period.

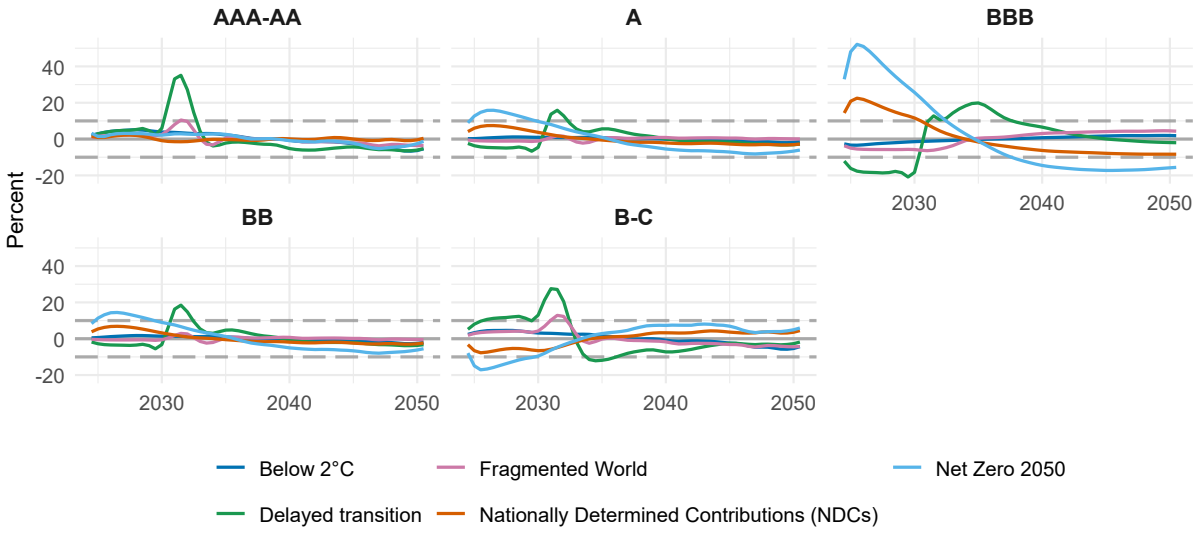


Figure 5: Economic capital of the different policies relative to *Current Policies*
The figure presents the development of the predicted economic capital requirements in the different policies as the percentage change relative to the Current Policy scenario level from July 2024 to July 2050. The economic damages are generated using the REMIND model. The dashed (gray) line provide reference lines at 10 and -10 percent.

Figure 5 presents the economic capital in each policy scenario as the percentage change of the economic capital in the *Current Policies* scenario, offering a direct comparison of capital requirements across policy scenarios. For the AAA-AA cohort, the *Delayed Transition* scenario increases requirements by almost 40 percent at the time of transition relative to maintaining current policies. Across all cohorts, the damages incurred during a delayed transition exceed those under current policies by at least 10 percent. As these damages decline, the requirements eventually converge to those in the *Current Policies* scenario illustrating that a disorderly late transition leads to costs for capital reserves that will not be recovered.

Orderly transitions also entail costs. For BBB-rated bonds, the *Net Zero 2050* policy generates damages that elevate capital requirements by more than 40 percent relative to current

policies. Nonetheless, by the end of the prediction period, reduced physical risk offsets these early damages sufficiently that requirements fall to more than 10 percent below those predicted in *Current Policies* scenario. By 2050, the *Net Zero 2050* pathway is predicted to reduce capital requirements across all investment-grade cohorts.

In sum, our results highlight that transition risk increases capital requirements and thereby raises the opportunity costs for banks holding well-diversified portfolios of bonds within a single cohort. At the same time, physical risk from climate change generate persistent damages which, if left unmitigated, lead to even higher opportunity costs by the end of the 2040s. Thus, while all policy pathways entail costs, our results indicate that over a 25-year horizon most bond cohorts benefit from an orderly transition aligned with the Paris Agreement.

6 Conclusion

In this paper, we assess how different climate policy scenarios affect the credit risk of corporate bonds. We propose a two-factor framework directly linked to key economic variables, allowing us to trace credit cycles through 2050 using predictions from the NGFS. The latent risk factors driving credit cycles across bond cohorts govern rating migrations and have immediate implications for risk management and capital requirements of institutions holding these financial instruments.

We apply our framework to evaluate capital requirements on well-diversified portfolios within a single cohort. We find that economic damages arising from physical and transition risks generate different effects across cohorts. Orderly climate transitions tend to cause short-term disruptions in the credit cycle for most cohorts, yet they mitigate the physical damages that otherwise lead to deterioration in the credit cycles. Delayed and disorderly transitions similarly lead to substantial transition-related deterioration and greater volatility due to the abrupt adjustments required. Insufficient mitigation of physical risk produces hot-house-world scenarios in which credit cycles are persistently weakened by the severe physical damages projected under such pathways.

Differences in credit-cycle dynamics translate directly into differences in the capital requirements investors must satisfy to maintain a well-diversified corporate bond portfolio. Restricting attention to single-cohort portfolios, we find that variation in predicted credit cycles produces sizable differences in required economic capital and, consequently, in the opportunity costs faced by investors. Because capital requirements follow the credit cycle, our results highlight a clear

trade-off: orderly transitions generate short-term increases in opportunity costs but ultimately reduce them through lower long-term physical risk. Over a 25-year horizon, the orderly transition aligned with the Net Zero 2050 pathway more than compensates for early transition damages, leaving investors with lower capital requirements by the end of the 2040s compared with a continuation of current climate policies.

Our results further show that the largest relative increases in capital requirements occur in the cohort of highest-rated bonds, an effect that is further amplified in scenarios that do not involve an orderly transition. This leads to an important, and somewhat counterintuitive, result: seeking safety by investing in the highest-grade bonds may actually result in the greatest relative increase in opportunity costs when climate and transition risks are taken into account.

Our study has several limitations. We focus exclusively on the impact of climate-related economic damages on the systemic risk of credit markets and the associated capital requirements, omitting channels through which credit market dynamics may themselves influence the broader economy. Such interactions could amplify the effects of climate and transition risk. Moreover, we do not quantify the uncertainty surrounding our estimates of capital requirements and opportunity costs. A full treatment of this uncertainty is beyond the scope of this paper, particularly because we take the NGFS projections as given.

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Supplementary Material

A Derivation of the asymptotic portfolio loss distribution

To derive eq. (11), we first write the probability of default as a function of η_t for given values of $\boldsymbol{X}_t$ and Z_{t-1},

$$p_{qm}(\eta_t; \boldsymbol{X}_t, Z_{t-1}) = \Pr[Y_{imt} \leq K_{q-1,m} | \eta_t, \boldsymbol{X}_t, Z_{t-1}] = \Phi\left(\frac{K_{q-1,m} - \mu_{mt} - \sqrt{\rho_m}\sigma_\eta \eta_t}{\sqrt{1-\rho_m}}\right), \quad \text{(A.1)}$$

with $\mu_{mt} = \sqrt{\rho_m}(\boldsymbol{\beta}_m' X_t + \phi Z_{t-1})$ following the second case in eq. (7). Consequently, the distribution of the percentage loss $\delta_{mt} = \lim_{N_{mt}\to\infty} \delta(N_{mt})$ follows as

$$\begin{aligned}\Pr[\delta_{mt} \leq v] &= \Pr[p_{qm}(\eta_t; \boldsymbol{X}_t, Z_{t-1}) \leq v] = \Pr[\eta_t \geq p_{qm}^{-1}(v; \boldsymbol{X}_t, Z_{t-1})] \\ &= \Phi(-p_{qm}^{-1}(v; \boldsymbol{X}_t, Z_{t-1}) = \Phi\left(\frac{\sqrt{1-\rho_m}\Phi^{-1}(v) + \mu_{mt} - K_{q-1,m}}{\sqrt{\rho_m}\sigma_\eta}\right), \quad \text{(A.2)}\end{aligned}$$

where p_{qm}^{-1} denotes the inverse of $p_{qm}(\eta_t; \boldsymbol{X}_t, Z_{t-1})$ as a function of η_t, treating $\boldsymbol{X}_t, Z_{t-1}$ as parameters, which is a monotonically decreasing. This result differs from Vasicek (1991), as some conditional information of the realization of the common factor is known, leading to an additional term μ_{mt} in the numerator and a reduction of the denominator by a factor σ_η.

B Additional data analysis

B.1 Capital Requirement Regulation

The Capital Requirements Regulation (CRR) is a key EU regulation that sets prudential requirements for banks. It is closely linked to the Capital Requirements Directive and is the EU's direct implementation of the Basel framework. Under the standardised approach for credit risk, the regulation assigns risk weights to corporate debt exposures based on their external credit ratings (Table 7).[12]

B.2 Macroeconomic data

The macroeconomic series, along with the equity market returns, are presented in Figure B.1.

[12]This mapping is based on the European Banking Authority's mapping of External Credit Assessment Institutions to the credit quality steps defined in the CRR as of January 1, 2025. `https://www.eba.europa.eu/activities/single-rulebook/regulatory-activities/external-credit-assessment-institutions-ecai/overview-ecais-mapping-under-standardised-approach`

Table 7: Mapping of S&P credit ratings to credit quality steps and risk weights.

	S&P rating									
	AAA	AA	A	BBB	BB	B	CCC	CC	C	$R/SD/D$
Risk weight (%)	20	20	50	75	100	150	150	150	150	150

The table reports the risk weights assigned by regulation to the respective cohorts that we observe in our data. Cohorts with the same risk weights are merged in the empirical analysis.

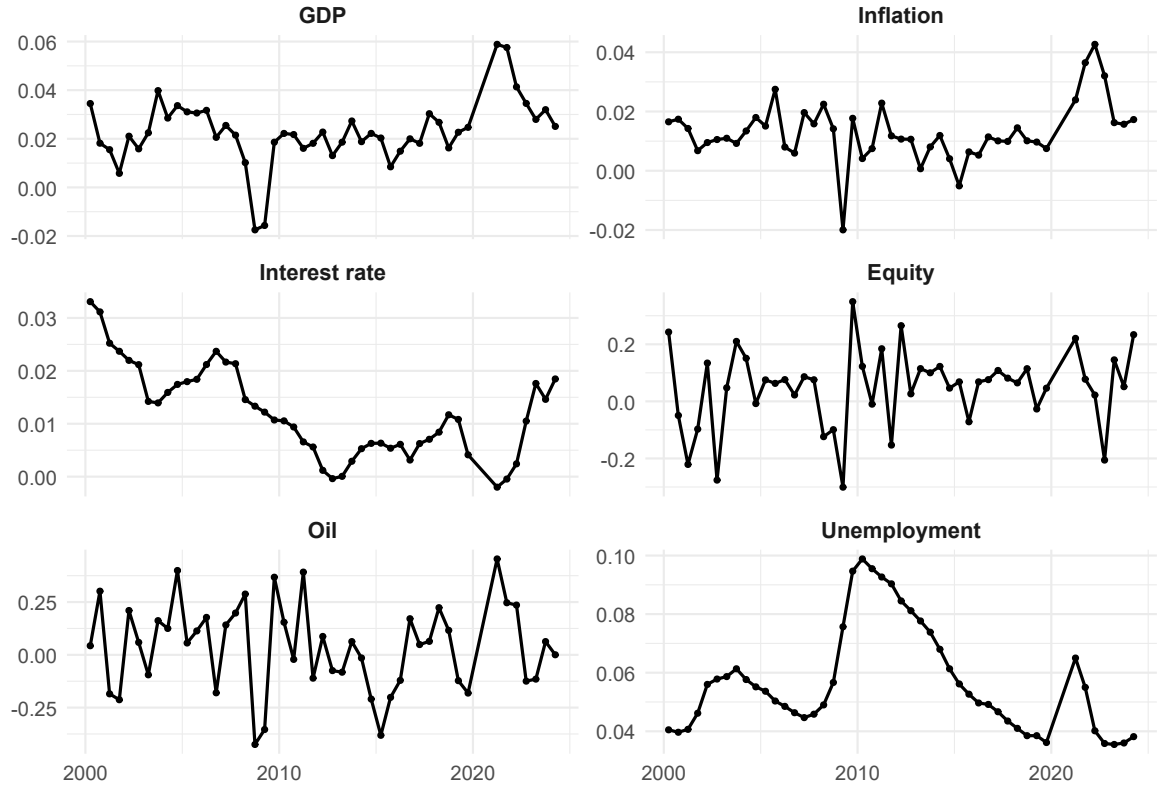


Figure B.1: Macroeconomic conditions (January 1999 - July 2024)

The figure presents macroeconomic conditions in the US during the in-sample period. The equity returns are computed using the market factor obtained from Kenneth French's data library, all other data are collected from FRED St. Louis FED. *GDP growth*, *Inflation*, and *Oil prices* are measured by log differences, the *10 year Interest rate* is the level of the long-term rates, and *Equity returns* denote average monthly returns.

Table 8: Descriptive statistics of the economic indicators

Variable name	Mnemonic	Transformation	Abbrev.	Mean	Std. Dev.	Min.	Median	Max.
GDP growth rate	GDP	log. dif.	g	2.27	1.33	-1.75	2.22	5.85
Unemployment rate	UNRATE	rolling mean	u	5.66	1.81	3.55	5.27	9.88
Inflation rate	CPIAUCSL	log. dif.	i	1.30	1.00	-1.99	1.14	4.27
Oil price	POILBREUSDM	log. dif.	p	3.72	20.79	-42.46	5.90	45.43
10-year real interest rate	REAINTRATREARAT10Y	rolling mean	r	1.21	0.85	-0.20	1.08	3.31
Equity return	-	rolling mean	e	0.73	2.27	-5.41	1.22	5.17

The table reports the economic indicators with their mnemonic, the transformation applied to the raw data, their abbreviations, and summary statistics of the transformed series. The first five variables are retrieved from the FRED Database of the Federal Reserve Bank of St. Louis. The equity market returns are taken from Kenneth French's data library. In the column Transformation "log. dif" means that the first difference of the natural logarithm of the data is taken with a half year frequency; "rolling mean" means the average over a six-month period is taken;, "sum" means that the sum over a six-month period is taken. The six-month periods correspond with October 1 to March 31, and April 1 to September 30. The summary statistics are reported in percentages. The means, standard deviations and medians have been annualized. The data ranges from April 2000 to March 2024.

B.3 Alternative Integrated Assessment Models

B.3.1 GCAM

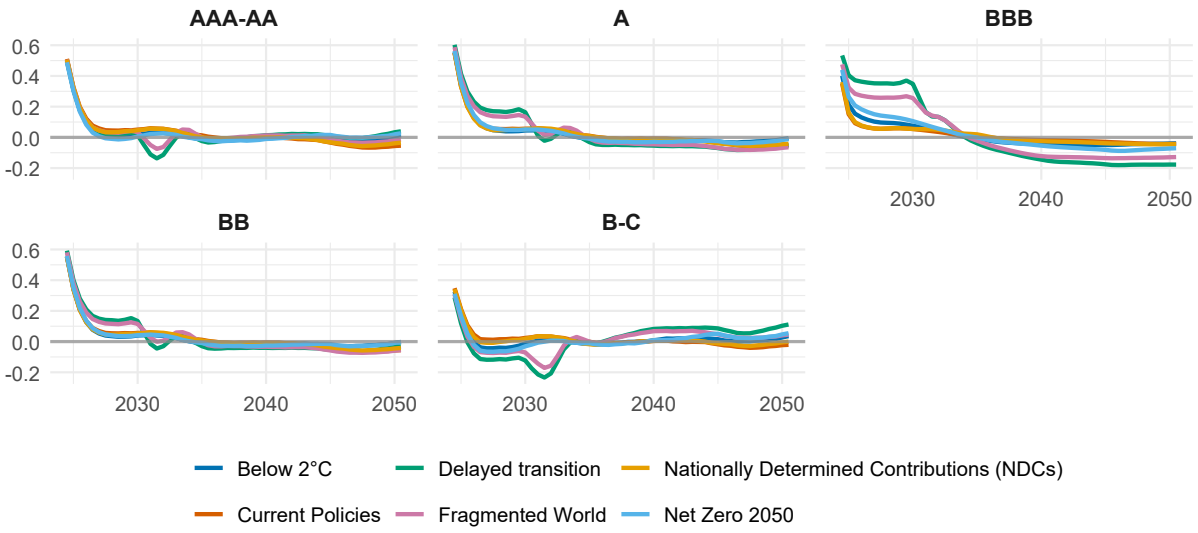


Figure B.2: Predictions for the credit factor from July 2024 to July 2050

The figure presents the predicted values of the latent factor under six different climate policy transitions. Economic damages are generated by the GCAM model. Predictions are formed based on the model in eq. (5) with parameter estimates in table 5 and the initial values of the cohorts are the last estimates from the in-sample data.

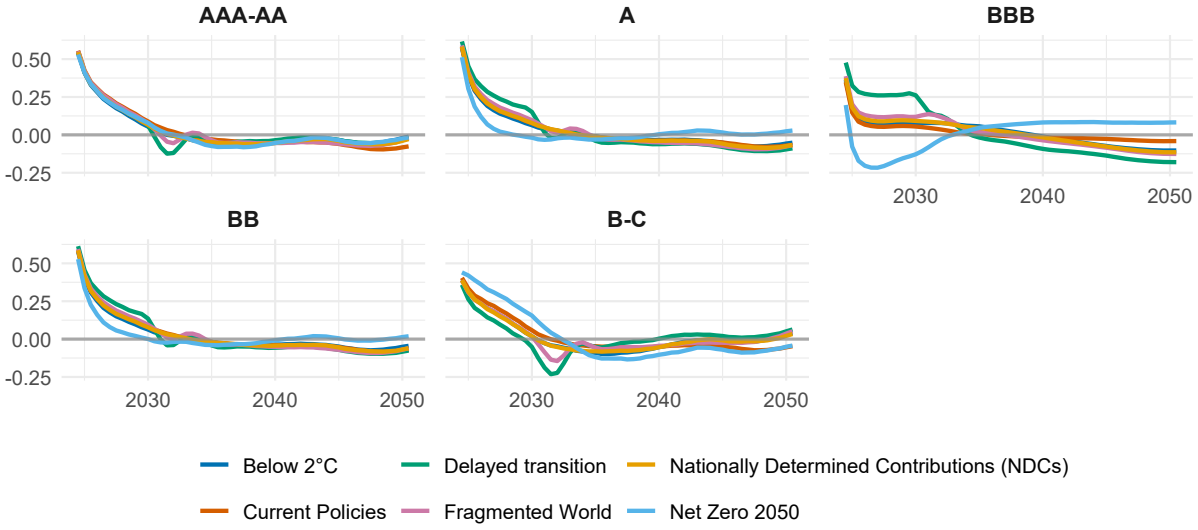


Figure B.3: Predictions for the credit factor from July 2024 to July 2050

The figure presents the predicted values of the latent factor under six different climate policy transitions. Economic damages are generated by the MESSAGEix model. Predictions are formed based on the model in eq. (5) with parameter estimates in table 5 and the initial values of the cohorts are the last estimates from the in-sample data.

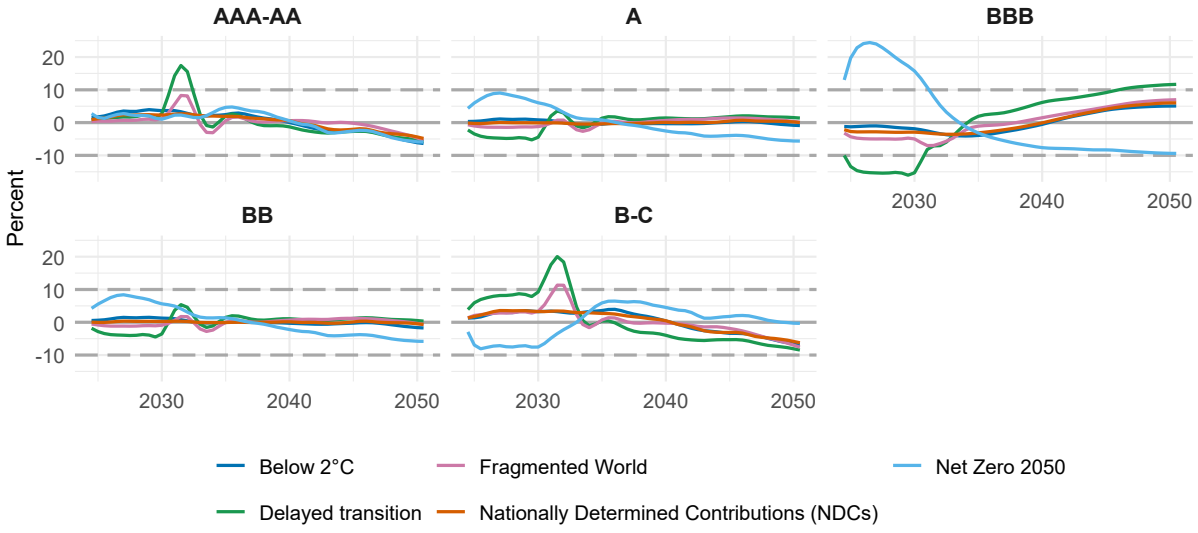


Figure B.4: Economic capital July 2024 to July 2050

The figure presents ... in the six different climate policies between January 2024 and July 2050. The economic damages are generated using the MESSAGEix model. $(EC_t^P / EC_t^{Current} - 1) \times 100$

B.3.2 MESSAGEix

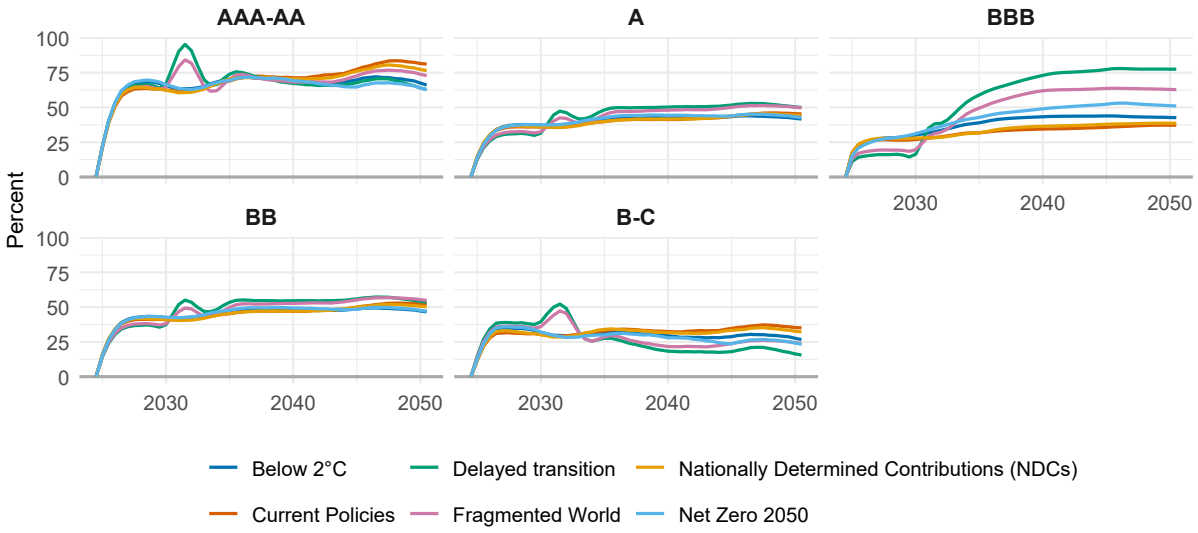


Figure B.5: Economic capital July 2024 to July 2050

The figure presents the development of the required economic capital $(EC_t/EC_0 - 1) \times 100$. The economic damages are generated using the GCAM model.

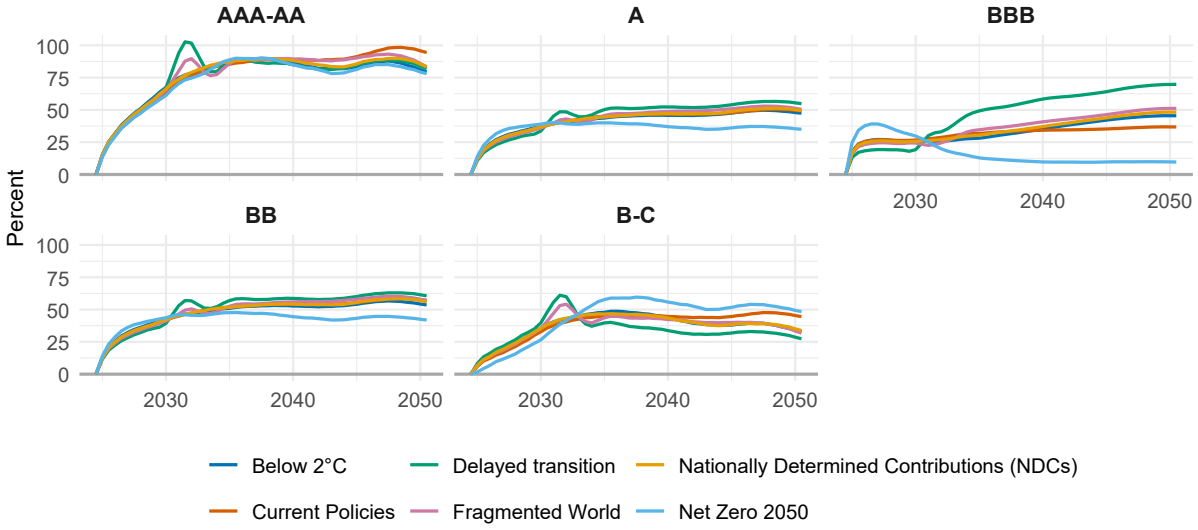


Figure B.6: Economic capital July 2024 to July 2050

The figure presents the development of the required economic capital $(EC_t/EC_0 - 1) \times 100$. The economic damages are generated using the MESSAGEix model.

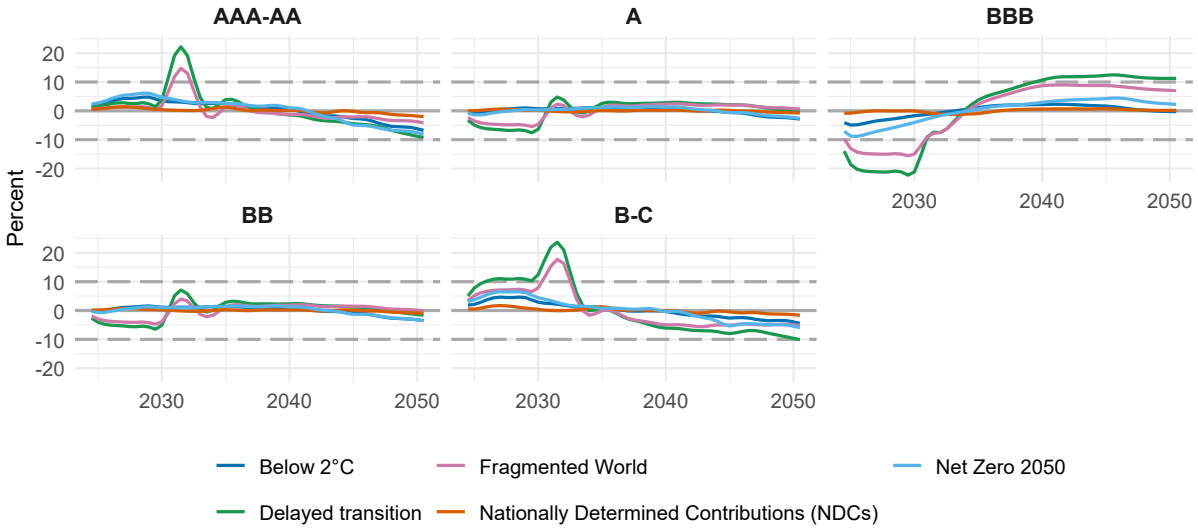


Figure B.7: Economic capital July 2024 to July 2050

The figure presents ... in the six different climate policies between January 2024 and July 2050. The economic damages are generated using the GCAM model. $(EC_t^P / EC_t^{Current} - 1) \times 100$