The risks of climate tipping points for financial investors

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ABSTRACT

Financial investors increasingly recognize the economic threats of climate change, yet most assessments of financial risk do not account for climate tipping points. Here, we combine advances in integrated assessment modeling of tipping points with dividend discount modeling to quantify risks of climate change damages for major stock indices. For the MSCI World and the MSCI Emerging Markets, two globally diversified indices, climate-related losses vary considerably by index and damage function; under RCP4.5, the expected loss ranges between 1–15%, and the 95% Value-at-Risk, a common risk measure, between 4–26%. Risks are highest in emerging markets with extensive coastal areas. Tipping points increase expected losses and Values-at-Risk by over 10%, primarily due to permafrost thaw and ice sheet disintegration. Unlikely but potentially catastrophic tipping points, such as the Atlantic meridional overturning circulation's collapse, exacerbate tail risks. Therefore, tipping points should be integrated into climate scenario analyses in the financial sector.

Introduction

Climate change is projected to hamper economic prosperity in many regions[1–7] through channels such as labor productivity and human capital losses[8], agricultural impacts[9], or the destruction of existing capital stocks[10]. Since the economic damages of climate change will decrease firms' profitability, climate change poses risks to financial investors, who will face lower returns and, due to the forward-looking nature of markets, might see their assets devalued in return[11–14]. As a response, financial investors have become increasingly alert to such physical climate risks over the past years[15], with hazard exposure increasingly reflected in asset prices[13,16]. In addition, forward-looking assessments of climate change's impacts on investor portfolios and banks have become increasingly common in academia and among financial institutions[11,13,14,17–24], leveraging well-established climate scenarios and modeling outputs for broader top-down assessments and asset- and impact-specific bottom-up approaches.

Past and current assessments of physical risks of climate change to banks and investors, however, do not account for climate tipping points, that is, climatic subsystems that may switch into a persistently different state due to minor perturbations[25], such as the disintegration of the Antarctic ice sheet[26]. The impacts of such tipping points on societies and economies are highly uncertain but potentially severe[26–31], might be triggered at global warming levels as low as 1.5°C[32] and, in the worst case, could trigger each other, resulting in a cascade of tipping elements[33]. Therefore, current assessments of physical risks for financial investors are likely to underestimate the exposure of assets to physical climate change risks. However, a systematic assessment of this potential omission is missing.

Here, we use an established framework to translate scenario-dependent economic damage projections into financial risk[11], measured in terms of a portfolio's average losses and Value-at-Risk (VaR), a typical risk measure in finance based on loss distribution quantiles[17]. We apply this framework to the META integrated assessment model, which represents annual impacts from warming and sea level rise and accounts for multiple climate tipping points based on a meta-analysis of the extant economic literature[27]. We advance the META model with recently developed region-specific damage functions that account for various bottom-up climate change impacts[34]. By doing so, we derive the first country-specific estimates of physical risks to stock investors due to climate tipping points based on the latest evidence on the economic impacts of climate change. Combining these estimates with data on the composition of major stock indices, we derive financial loss distributions for these indices under different climate change scenarios with and without accounting for climate tipping points. Our approach is applicable to any generic international stock portfolio and, in principle, could incorporate damage estimates of any climate-economy model with country-level resolution.

Importantly, building on the META model[27] our analysis only covers some tipping points[31], primarily those with more gradual effects[35], and addresses their impact primarily through the lens of additional warming and sea level rise. In addition, our treatment of tipping points abstracts from direct effects on local economies, non-market impacts, intra-country heterogeneities, potential ripple effects (e.g., climate-related famine or conflicts), and additional feedback from financial losses onto the economy. Therefore, our assessment of tipping points' financial risks is conservative and remain subject to deep uncertainties regarding the physical feedbacks underlying climate tipping points and their socio-economic impacts[31]. It nevertheless constitutes an important advancement in the assessment of climate-induced financial risk.

Results

Estimating lost dividends based on integrated assessment modeling outputs

While the short-term evolution of individual stock prices is highly uncertain, the trajectory of dividend growth (and hence stock prices over the long run) is driven by overall economic development[36,37]. Based on this fundamental concept of dividend discount modeling, our methodological framework[11] links climate change-induced shifts in overall gross domestic product (GDP) to changes in future stock dividends. Fig. 1 illustrates the steps of this approach. First, the META model translates different scenarios of socio-economic developments and emissions into temperature shifts and sea level rise with or without accounting for climate tipping points, with the latter increasing warming and sea level rise (Fig. 1a–b) before converting them into impacts on GDP (for an overview of META's climate and socio-economic model dynamics, see Supplementary Fig. S4 and S5, respectively). Notably, through Monte Carlo analysis, META explicitly accounts for the stochastic nature of several climate tipping points, which might or might not be triggered for a given Monte Carlo run. For each Monte Carlo run, META also samples key model parameters, such as the climate sensitivity or the damage function parameters, from calibrated distributions to account for climate and socio-economic uncertainties[27]. Based on our framework's assumption that the resulting GDP impacts affect dividend growth proportionally—which is unlikely to hold for a single year and stock but reasonable for all publicly listed companies in a country combined in the long run[11]—, we translate the GDP losses projected by META into dividend losses for each market (Fig. 1c; example values for the United States, the world's largest stock market). Using growth data from the Shared Socio-economic Pathways (SSPs) and empirical estimates for investor discount rates and country risk differences (see Experimental procedures), we then project the present value of future dividends in the absence of climate change and the country-specific present value loss due to climate change damages with and without accounting for climate tipping points (Fig. 1d).

Finally, we aggregate the country-specific losses to globally diversified stock indices based on granular data on their current composition. For our main results, we use three indices covering all large-cap and mid-cap stocks in different categories of stock markets: i) the MSCI World, which covers all well-developed stock markets; ii) the MSCI Emerging Markets (EM), which covers less developed stock markets in terms of size, liquidity, and accessibility; and iii) the MSCI Frontier Emerging Markets (FEM), which covers even less developed stock markets. These indices cover approximately 85% of the total stock market in each constituent country and, due to their broad coverage and diversification, are most compatible with dividend projections based on economy-wide shocks from climatic shifts. Globally diversified stock indices, such as the MSCI World, are widely used as benchmark indices for actively managed portfolios of financial practitioners, including major pension and sovereign wealth funds[38], and for exchange-traded funds used extensively by retail investors. Notably, the increasing awareness of financial investors about climate change risks means that some future dividend losses might already be reflected in current index valuation. However, a recent literature review finds that physical climate risks are not fully priced yet[13], which aligns with surveyed expert beliefs on climate risk pricing[39]. Therefore, investors have already suffered some of the losses quantified in this paper, while others will be due in the future once asset prices adjust further. Importantly, climate tipping points, in particular, are unlikely to be priced in since the systematic understanding of their economic impacts is relatively nascent[27,31] and they have been absent from extant risk assessments by practitioners and academics[11,12,14,17–23].

Implications for diversified stock indices

Fig. 2a shows the expected loss (i.e., the mean reduction in the present value of future dividends) and the 95% VaR (i.e., the 95th percentile of the loss distribution) under RCP4.5 for the ten largest developed, emerging, and frontier markets, respectively. Climate change is projected to generate losses for all markets, albeit more pronounced for emerging markets and lower-latitude frontier markets than developed markets—with the notable exception of Australia and the Netherlands for which the 95% VaR reaches almost 6.5%, due to high initial temperatures and exposure to sea level rise. For the largest market in each country category (the US, China, and the Philippines), the expected loss amounts to 1.5% (95% VaR: 3.3%), 1.6% (95% VaR: 3.7%), and 4.4% (95% VaR: 10.3%), respectively.

Fig. 2b displays the implications of these country-level losses for the respective stock indices. For the MSCI World, even under a mitigation scenario compatible with the Paris Agreement (RCP3-PD/2.6), the expected present-value loss in future dividends when including climate tipping points averages 0.9% of the index's current valuation, while the 95% VaR amounts to 2.1%. Under RCP4.5, expected losses and the 95% VaR increase to 1.5% and 3.4%, respectively. For RCP8.5, the expected loss and 95% VaR nearly double. Given the predominant role of US stocks for globally diversified portfolios focusing on developed markets (see Supplementary Fig. S11), losses for the MSCI World closely track the results for the US stock market. For the

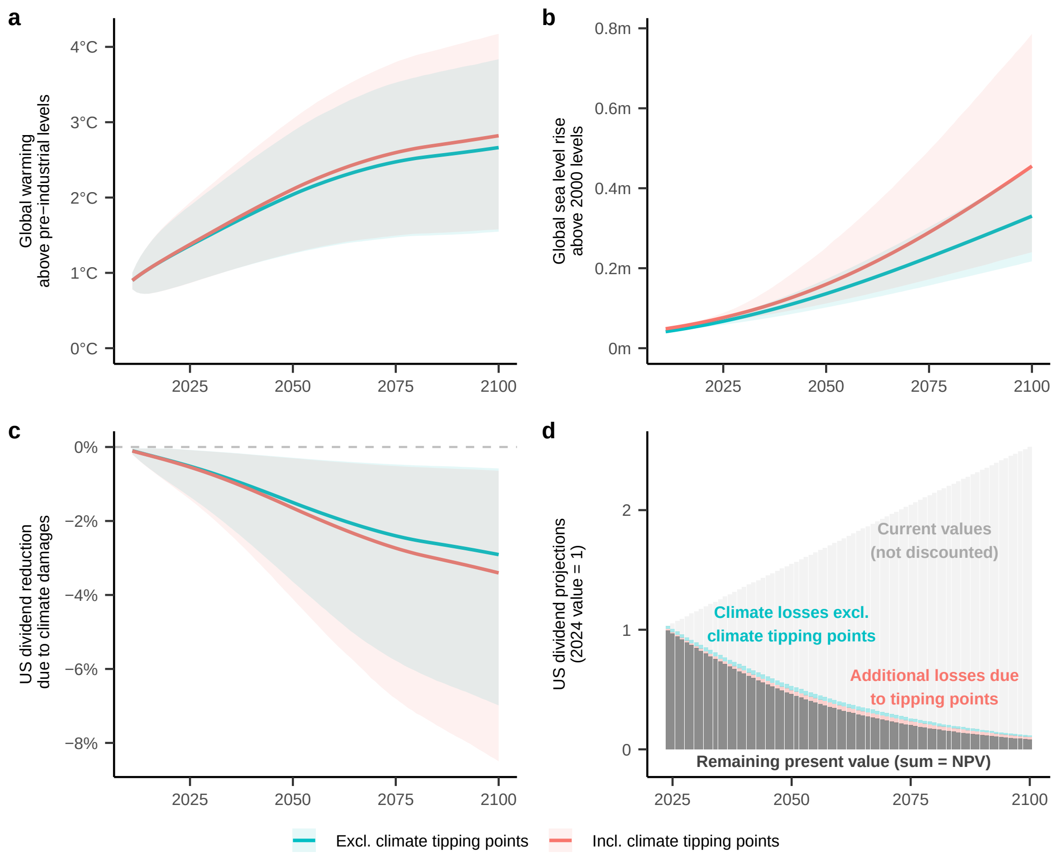

Figure 1. Steps to convert integrated assessment model outputs into index-specific dividend impacts. **(a)** Increase in global mean surface temperature based on Monte Carlo runs of the META integrated assessment model under RCP4.5 with and without climate tipping points. Line and shaded area denote the Monte Carlo mean and the 2.5th–97.5th percentile, respectively. **(b)** Same as Panel a but for global sea level rise. **(c)** Same as Panel a but for dividend losses of an example market (United States) based on GDP loss projections by META. **(d)** Projected dividends from US stocks under RCP4.5-SSP2 in current and present value, gross and net of climate change-related losses excluding and including climate tipping points. Grey transparent bars denote the current value prior to discounting, colored bars the reduction of discounted dividends due to climate damages excluding tipping points (blue) and the additional reduction due to tipping points (red). Note that given the conceptual nature of the figure, the bars for climate losses have been magnified for the sake of readability and do not represent actual model results. For the unmodified chart version, see Supplementary Fig. S12.

MSCI EM, the high losses of key markets, such as India, South Africa, and Thailand, translate into higher relative losses at the index level, averaging 2.5% under RCP4.5 with a 95% VaR of 5.9%. Under RCP8.5, the 95% VaR increases to 9.2%. While the index size of the MSCI FEM is minor compared to the other two indices, its expected losses and 95% VaR in relative terms are the highest due to substantial losses in the Philippines, Vietnam, and Morocco particularly. Under RCP4.5 and RCP8.5, the 95% VaR of the MSCI FEM amounts to 7.5% and 11.9%, respectively.

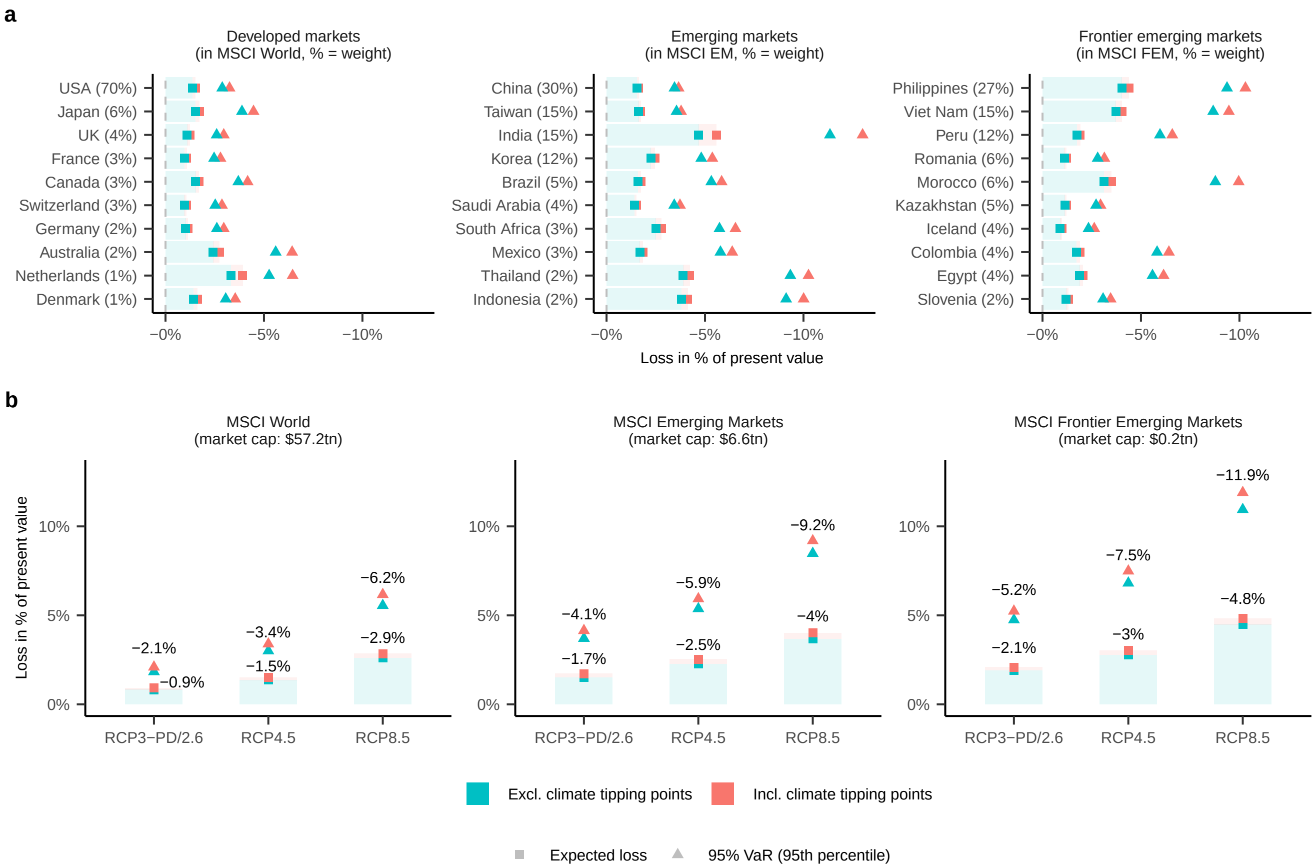

Figure 2. Expected loss and 95% VaR for major stock indices with and without accounting for climate tipping points. **(a)** Expected loss and 95% VaR by country under RCP4.5. Countries displayed are the ten largest stock markets in each MSCI market category (developed, emerging, and frontier emerging), with the weight in the respective stock index in parentheses. Blue bars denote the expected loss excluding climate tipping points, red bars denote the additional increase in the expected loss due to including tipping points. **(b)** Same as Panel a but for MSCI World, MSCI Emerging Markets (EM) and MSCI Frontier Emerging Markets (FEM) indices under RCP3-PD/2.6, RCP4.5, and RCP8.5. Value labels in % denote the expected loss (squares) and 95% VaR (triangles) including climate tipping points.

Loss distributions by damage function specification

A 95% VaR of around 2–12% of indices' current valuation might seem low compared to estimates that climate change may reduce global GDP on average by 7–14% at the end of this century under RCP8.5[2,3,34], with some studies indicating even higher damages[1,6]. This discrepancy is partially driven by the fact that our method emulates the high discount rates used by financial investors, which reflect the high volatility (and hence risk) of the overall stock market and, particularly, the higher risk of investing in emerging markets, where most climate damages will occur[1,2,6,34]. As a result, dividend losses from years far into the future play a reduced role in the overall present value from an investor perspective (compare Fig. 1d). In addition, the MSCI World is dominated by Northern Hemisphere countries, especially the United States, where economic climate impacts are likely smaller[34].

More pertinently, our loss distributions strongly depend on the assumed effects of temperature shifts and sea level rise on economic output and the persistence of these impacts (i.e., whether the economy bounces back after an adverse shock or persistently follows a lower growth trajectory). For the GDP-temperature relationship, the results presented above use the

COACCH damage functions by ref.[34] calibrated on bottom-up impact models for agriculture, riverine floods, energy demand, labor and energy supply, and road infrastructure. These damage functions produce results that align with a recent meta-analysis of global cost estimates of climate change[40], and, importantly, do not imply damage persistence. To evaluate the range of losses under different damage function specifications, Fig. 3 illustrates the loss distribution for the MSCI World and the MSCI EM under RCP4.5 using two alternative damage specifications: i) the main specification by ref.[1] combined with sampling the damage persistence from a uniform distribution between 0–100%, which is the default setting of the META model[27] due to mixed empirical evidence[1,2,4–6,41,42] (Fig. 3b,e); ii) the same dose-response function of ref.[1] paired with the full persistence assumption by ref.[1] in their own GDP loss projections (Fig. 3c,f).

In line with the heterogeneous estimates of climate change's economic costs[43], the loss distributions differ substantially by damage specifications. For the MSCI World (Fig. 3a–c), the expected loss across damage specifications, when including climate tipping points, ranges between 0.8–4.2%; for the MSCI EM (Fig. 3d–f), losses average between 2.3–15.0%. Allowing for some or full damage persistence widens the distribution substantially, with the 95% VaR reaching up to 17.1% for the MSCI World and 25.8% for the MSCI Emerging Markets. Notably, when using the damage function by ref.[1], a considerable share of the loss distribution for the MSCI World implies index-level dividend gains, driven by economic benefits to colder, high-latitude countries, whereas the COACCH damage functions are more pessimistic for the Northern Hemisphere (see Supplementary Fig. S1). Despite these differences in magnitude and sign, the effect of including tipping points is fairly consistent across specifications and increases the expected loss and the 95% VaR by roughly a tenth or more (Fig. 3a–f), except a somewhat smaller VaR increase for the MSCI World under full persistence (+5%; Fig. 3c). This is because the main underlying drivers of tipping points' financial risks in our model are additional warming and sea level rise, which, in relative terms, have similar implications across damage specifications.

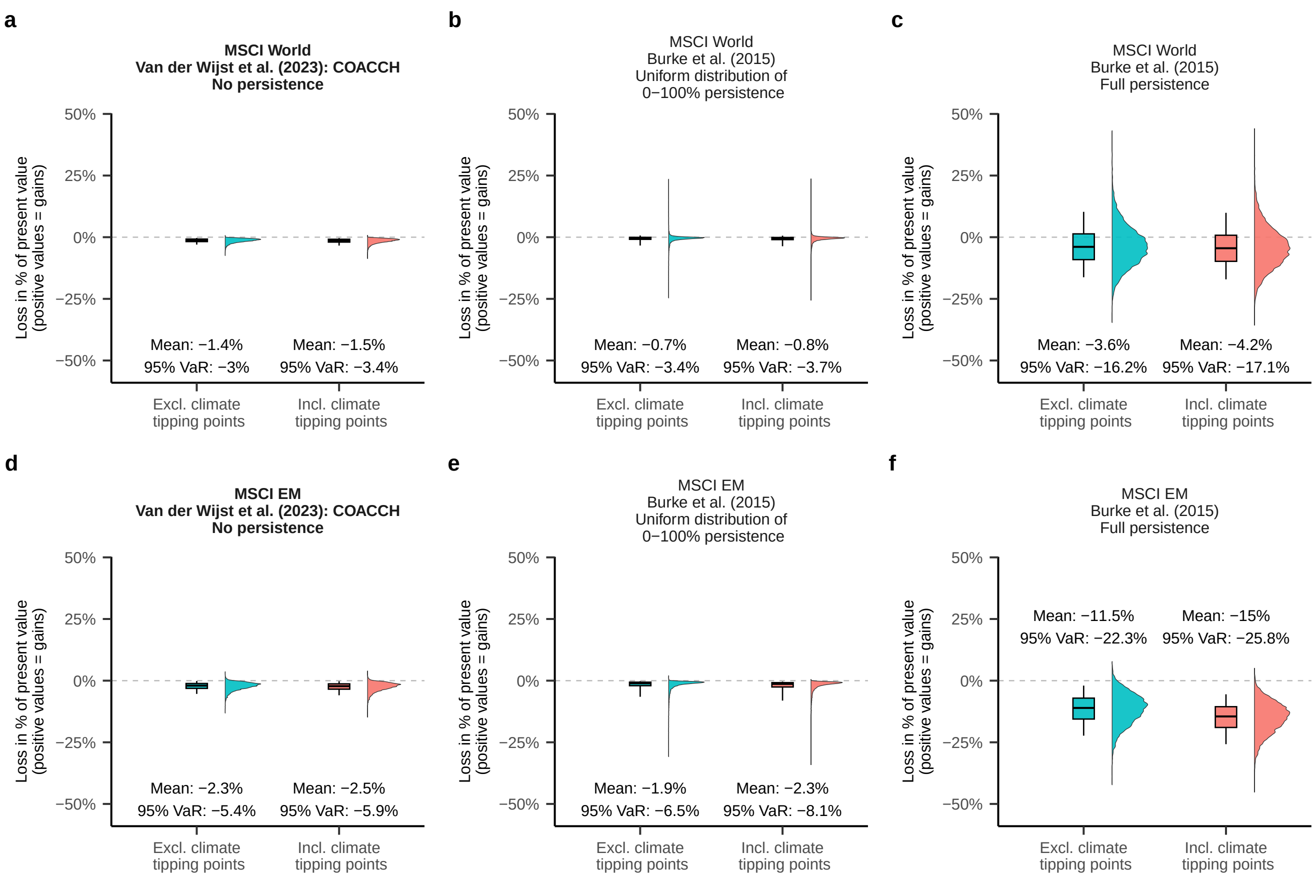

Figure 3. Loss distribution for the MSCI World and the MSCI Emerging Markets (EM) under RCP4.5 by GDP-temperature damage function and persistence of GDP damages assumed. The box and whiskers denote the 25th, 50th and 75th percentile, and the 5th and 95th percentile (i.e., the 95% VaR), respectively. For details on the damage specifications, see Experimental procedures and Supplementary Note 1.

Risk increases due to climate tipping points

When assessing losses and their tipping point-related increase separately for each market using our main COACCH damage specification (Fig. 4a–b), India exhibits the highest expected loss among major stock markets (5.6%, 95% VaR: 13.0%) and the highest tipping point-related increase in the expected loss (+19% increase), primarily due to the impacts of the region-specific summer monsoon. Losses are also particularly high for African developing countries, such as Mauritius (95% VaR: 11.6%), Côte d'Ivoire (95% VaR: 10.7%) and Senegal (95% VaR: 10.6%) and for Southeast Asian markets like Malaysia (95% VaR: 10.7%) or Indonesia (95% VaR: 10.0%). Tipping point-related increases in the expected loss are higher for OECD countries like the Netherlands (+18%), Australia (+14%), or Japan (+13%). The impact of tipping points is lower but still substantial in Latin America (+9% for Brazil), the Middle East (+7% for Saudi Arabia), or China (+6%). For the entire MSCI World index, tipping points increase the expected loss by 11% and the 95% VaR by 13%.

When considering the different climate tipping points in the META model in isolation, additional warming due to permafrost thawing dominates the effect on all markets alike (Fig. 4c and Supplementary Fig. S13). Sea level rise due to the disintegration of the Greenland and West-Antarctic Ice Sheets also plays an important role, particularly for developed markets—in line with previous findings on tipping point impacts on the social cost of carbon[27]. For the MSCI EM, the Indian summer monsoon increases the expected loss by over 3%. By contrast, Amazon dieback risks have little effect on the loss distribution, primarily because the META model only accounts for warming-related impacts of this tipping point through additional CO_2 emissions from forest diebacks (and not for the potentially devastating socio-economic ripple effects on local and regional economies[27,30,31]). Therefore, these results are particularly conservative and should be taken with caution.

To explore how the risk increase due to climate tipping points is related to investors' patience and time horizons, Fig. 4d displays the expected loss and the 95% VaR for the MSCI World with and without climate tipping points (red and blue lines) for different equity risk premiums used in the investor discount rate (see Experimental procedures). The figure also shows the relative increase of both risk measures due to tipping points (red error bars) for our default equity risk premium of 5% (dashed vertical line), akin to the return expectation of institutional investors like pension funds, and other example values up to 15%, in the range of high return expectations of actors like buyout or venture capital funds. Both the expected loss and the 95% VaR decrease sharply in the discount rate deployed. However, the additional risk due to tipping points remains important for all discount rates considered and, in relative terms, decreases from +11% to +7% for the expected loss and from +13% to +9% for the 95% VaR. As a result, additional physical risks due to climate tipping points are most material for "patient" investors, such as pensions funds, but can apply to investors with higher discount rates as well. In addition, these risks increase for simulated investment horizons starting in 2034 or 2044 instead of 2024 (Fig. 4e) since physical damages of climate change increase over time. Therefore, tipping point-related risks are poised to become more material in future assessments. The same findings hold for the MSCI EM and the MSCI FEM (Supplementary Fig. S14).

The possibility of catastrophic tipping point impacts

While our main results align with recent estimates of additional tipping point-related warming[35], they do not capture the possibility of unlikely but catastrophic impacts[33]. To explore this possibility, we model a shutdown of the Atlantic meridional overturning circulation (AMOC) following ref.[28] as an additional tipping point, which is unlikely through the 21st century[32,44] but, if triggered, gradually harms global GDP by up to 15% (see Experimental procedures). Unlike other tipping points in META, such a stylistic impact assumption lacks geophysical foundations[27] but is a useful worst-case scenario. Compared to our main results under RCP4.5 using the COACCH damage specification, the possibility of a catastrophic AMOC collapse increases the expected loss from 1.5% to 1.6% (+6%) for the MSCI World, with much more moderate effects for emerging and frontier markets as an AMOC collapse shifts the climate primarily in the North Atlantic (Fig. 5a). While the AMOC remains stable for a large majority of Monte Carlo runs, the tails of the loss distribution for the MSCI World increase substantially. The 95% VaR rises from 3.4 to 3.7% and the 99% VaR (i.e., the 99th percentile of the loss distribution) from 4.7 to 5.7%, with worst-case losses reaching almost 15%. When considering the dividend loss distribution by year for the United States under RCP4.5 and RCP8.5 (Fig. 5b), annual expected losses in the near-term future are largely the same whether an AMOC collapse is introduced or not. By contrast, the tails of annual losses rise sharply and, for the 99th percentile under RCP4.5, may even be comparable to the corresponding percentile under RCP8.5 without an AMOC collapse. The reason is that such a climate catastrophe can introduce substantial tail risks over the next decades if a collapse occurs earlier than thought, which remains unlikely but possible[32,44].

Discussion

Our results show that the physical risk increase due to climate tipping points for diversified stock portfolios is secondary to overall climate change damages but remains material across a wide range of stock indices, investor preferences, and damage specifications. Since markets are unlikely to have already priced in the economic impacts of climate tipping points entirely, this suggests potential overvaluations in regions where tipping points add to overall risks, albeit to a very heterogeneous

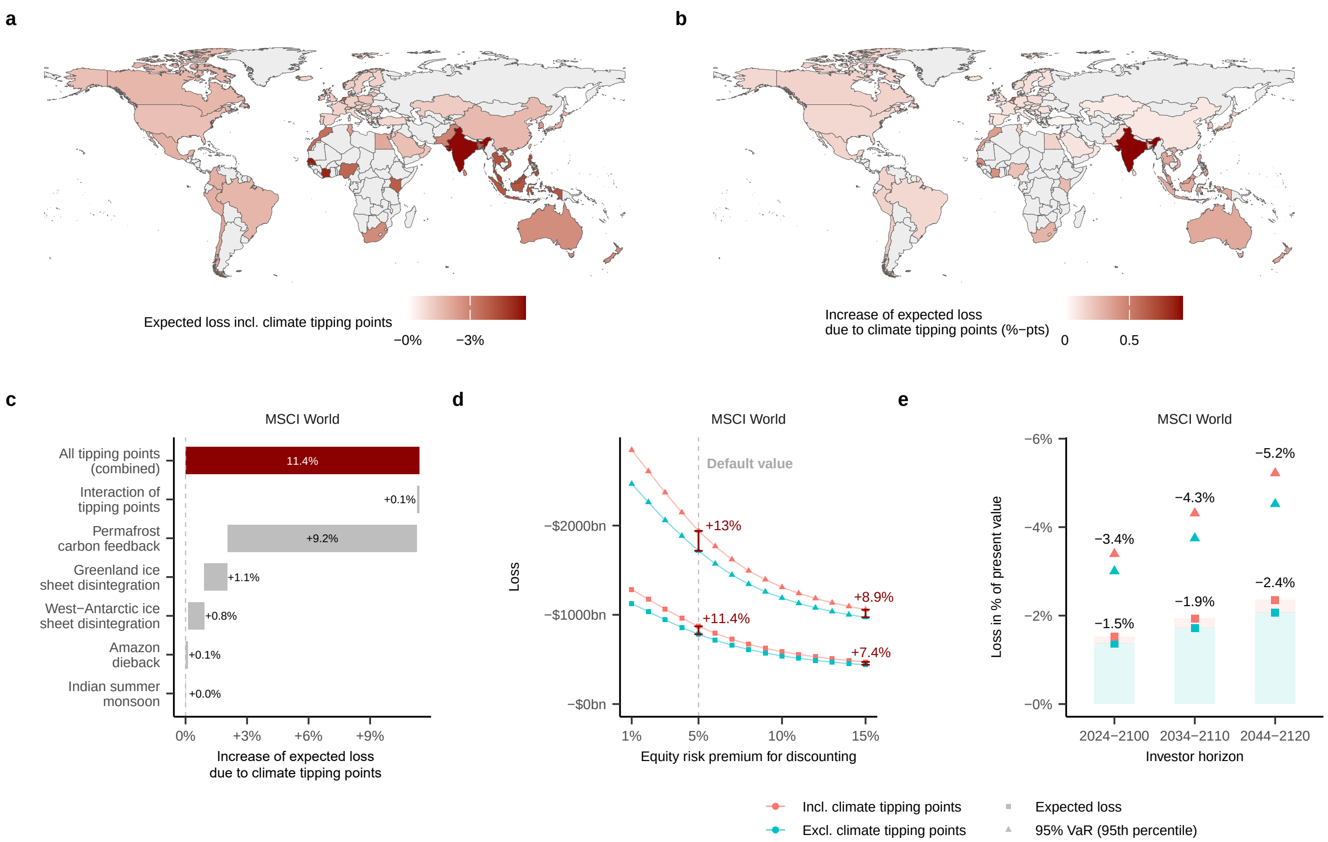

Figure 4. Losses and tipping-related loss increases under RCP4.5 by tipping points and investor preferences. **(a)** Expected loss due to climate damages including climate tipping points for all countries featured in the MSCI World, EM or FEM (for detailed values, see Supplementary Table S4). **(b)** Increase in the relative country-level expected loss due to tipping points. **(c)** Contribution of each climate tipping point to the overall relative increase in the expected loss (+11.2%), calculated as the difference between the expected loss excluding tipping points and a model specification that features only the tipping point in question. “Interaction of tipping points” is the residual between the summed individual contributions and the expected loss increase of all tipping points combined. **(d)** Expected loss and 95% VaR (expressed in current USD) for different equity risk premiums used in the investor discount rate (see Experimental procedures) with and without accounting for climate tipping points. Dark red error bars and value labels denote the relative increase in both risk measures due to tipping points for example values of the equity risk premium (5%, 10%, 15%). **(d)** Expected loss and 95% VaR for different investment horizons. Blue bars denote the expected loss excluding climate tipping points, red bars denote the additional increase in the expected loss due to including tipping points.

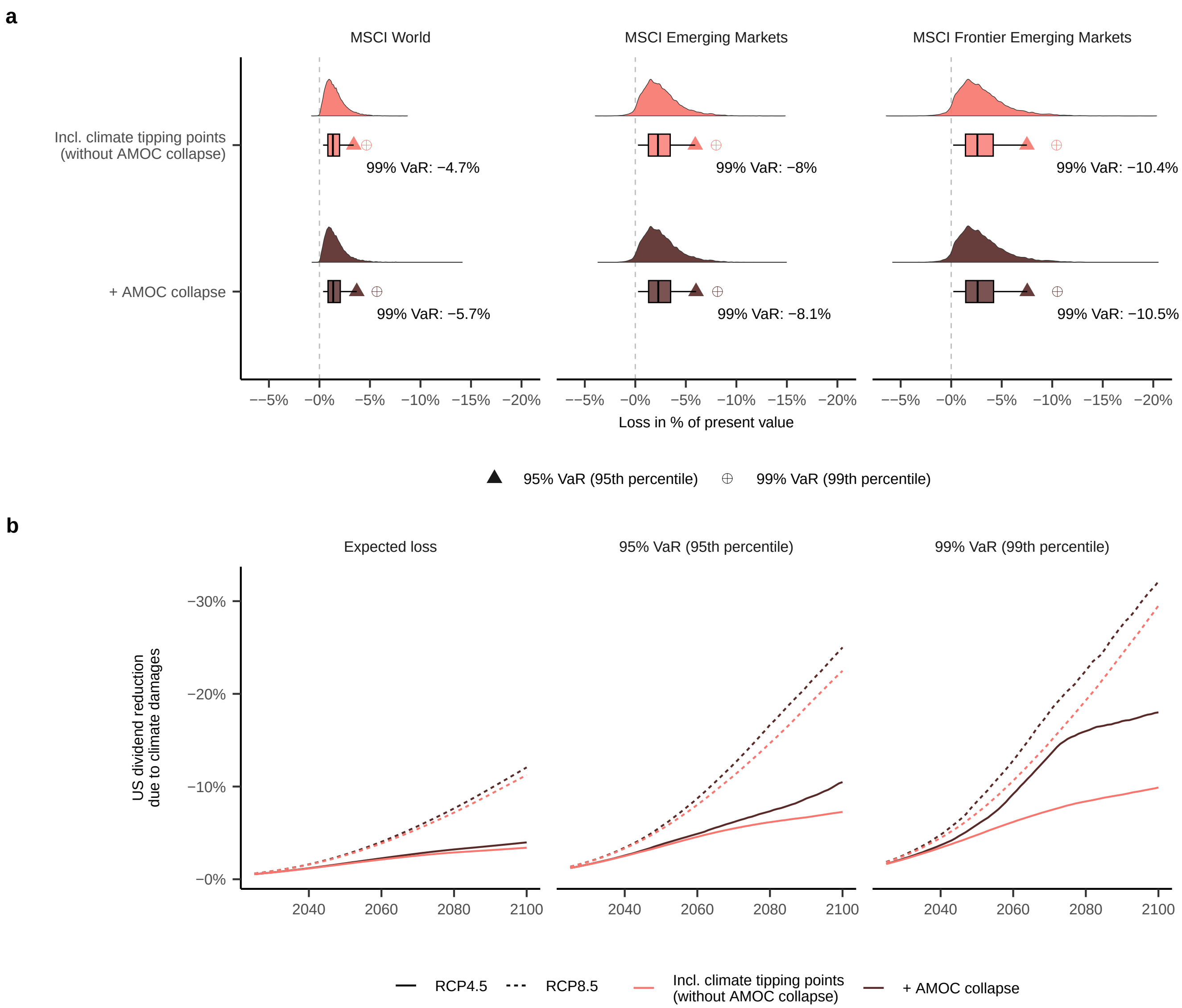

Figure 5. The impacts of a catastrophic AMOC collapse on the loss distribution. **(a)** Loss distribution by stock index under RCP4.5 with and without the possibility of a catastrophic AMOC collapse (calibrated following ref.[28]). **(b)** Monte Carlo mean and percentiles (95th and 99th) of annual dividend reduction due to climate change damages for the United States with and without the possibility of a catastrophic AMOC collapse under RCP4.5 and RCP8.5.

extent. Therefore, financial investors and regulators should integrate tipping points into their climate scenario analyses and stress tests. Specifically, risk assessments should prioritize the effects of ice sheet disintegration and permafrost thawing, and potential regional tipping points, such as monsoon shifts, in the case of geographically concentrated portfolios. Risk magnitudes are highly sensitive to the damage function and persistence assumed, illustrating the need for careful sensitivity checks or meta-analyses to capture the full distribution of potential losses. Unlikely but potentially catastrophic tipping point impacts strongly affect the tails of the loss distribution, meaning that too conservative assumptions can easily result in underestimated VaRs.

Indeed, there are many reasons why the numbers presented here may provide a lower bound of tipping point-related risks rather than a central estimate[27]. The science of modeling the economic impacts of climate tipping points is in its infancy and subject to deep uncertainties[31], such that updating the structural modeling of tipping points to the most recent literature can affect results considerably (see Supplementary Note 2). In addition, the META model deployed here encapsulates the consequences of such events through the lens of additional warming and sea-level rise alone. Severe regional impacts of specific tipping points, such as the dieback of the Amazon rain forest[30], are not covered, nor are non-market effects (e.g., on health or biodiversity), as presumably financial investors do not consider them directly in their valuations. Several suspected tipping points, such as Boreal forest ecosystem shifts, coral reef die-offs, or changes in the West African monsoon, are not represented in our model but could inflict substantial impacts on societies[31,35]. In addition, the damage functions deployed abstract from intra-country heterogeneities and potential ripple effects of climatic shifts via climate-related famine, conflicts, or the propagation of shocks through supply chains[45]. Assuming that GDP losses are spread evenly across a country's stocks abstracts from more concentrated climate disasters triggering bankruptcies of individual firms, which could increase investor losses further. In addition, stochastic parameters in the Monte Carlo runs of the META model are assumed to be independently distributed[27], which can lead to underestimated tail risks[46].

As such, the figures presented here are conservative and should be seen as conditional on avoiding an all-out climate catastrophe (similar to how financial risk analysis often abstracts from other low-likelihood catastrophes, such as global nuclear war). However, their magnitude aligns with previous estimates of climate change's impacts on investor cash flows[11] and suggests that climate change impacts are, from today's investors' perspective, an important but not an overwhelming risk to globally diversified portfolios—unless impacts on the economy and stocks persist over time. This is primarily because global stock portfolios are concentrated in the Global North and because investors apply high discount rates, particularly to investments located in developing countries, thus assigning lower weights to these countries' long-term future in valuations. As a result, investors' short-termism may result in inefficient capital allocation if long-term damages are not appropriately taken into account. At the same time, our results suggest that a reallocation in response to such risks might remove capital from (and increase risk premiums for) low-income countries with high exposures to sea level rise—where finance for mitigation and adaptation is already scarce[43,47]. Therefore, stringent public policies are key to ensure that capital allocation accounts for the physical risks of climate change without depriving the most vulnerable countries of much-needed capital.

In interpreting the results of this study, additional caveats warrant consideration. First, our approach treats each market as homogeneous, thereby not capturing business-specific, sectoral, and subnational dynamics, and treats future GDP growth deterministically in line with the SSPs. Second, applying climate change-related GDP shifts of a country to equities located there abstracts from the global dispersion of operations and supply chain. This assumption, however, is, on average, conservative since there is more market capitalization in companies headquartered in the Global North (where GDP impacts are lower) and with substantial economic activity in the Global South (where GDP impacts are higher) than vice-versa (see Supplementary Table S6). Therefore, accounting for the geographic scope of operations would rather increase than decrease the numbers presented here. Finally, while the methodological framework employed here is well-rooted in financial theory and allows for comprehensive scenario analysis regarding dividends[11], it should not be misconstrued as a forecast given the volatile and unpredictable nature of stock prices[48].

Overall, our results assess the importance of climate tipping points' physical risks for stock investors and highlight the key drivers and mechanisms. In addition, our approach can be easily extended to any globally diversified stock portfolio of interest. Future research could build on our work by including additional tipping points[31,32], accounting for GDP growth uncertainty[49], and replacing the economy-wide projections deployed here with more granular impact projections and asset data to allow for asset- and location-specific assessments[12]. This could involve modeling impacts based on supply chain structures[45] and more granular damage functions that better capture structural and climatic heterogeneities across regions[6,7]. Given the conservative nature of our approach, we expect such work to strengthen further our call for the inclusion of tipping points in financial risk assessments.

Experimental procedures

Climatic and GDP projections We use the recently developed META integrated assessment model[27] to derive climatic and GDP impact projections with and without considering climate tipping points under different RCP-SSP scenarios. META covers the 2010–2200 period in annual time steps for 180 countries and uses the Finite Amplitude Impulse Response (FaIR) model as a climate module[50]. Country-level warming and global sea level rise calculated by the climate module for the respective emission scenario are translated into economic impacts using damage functions based on ref.[1] and ref.[51], respectively. META covers seven potential climate tipping points as well as their interactions with each other, with the calibration based on a meta-analysis of the extant literature: i) Greenland Ice Sheet disintegration, ii) West-Antarctic Ice Sheet disintegration, iii) Amazon rain forest dieback, iv) shifts in the Indian summer monsoon, v) permafrost thawing, vi) ocean methane hydrate dissociation, vii) slowdown of the Atlantic meridional overturning circulation. In addition, META explicitly represents the surface albedo feedback in its climate module[52]. However, based on the latest state of climate science and to avoid double counting, we do not use the tipping point modules for vi) and vii), which combined has a conservative effect as it reduces the impact of tipping points on dividend present values (see Supplementary Note 2 for a detailed discussion). To account for the climatic and socio-economic uncertainties involved, META uses Monte Carlo draws for a wide range of model parameters, such as the climate sensitivity, the GDP-temperature damage function coefficients, or the parameters used to calibrate the different tipping points. Since some tipping points in the model are stochastic, sampling a large distribution of Monte Carlo runs provides a more accurate representation of the risks involved. An overview of META's climate and socio-economic modules and our modifications to the original model version by ref.[27] can be found in Supplementary Fig. S4 and S5.

For our main results, we couple RCP3-PD/2.6, RCP4.5, and RCP8.5 with the "middle-of-the-road" scenario SSP2 to isolate the effect of climatic shifts (since varying SSPs would also alter economic growth projections and hence the projected future dividends in the absence of climate change). However, using SSP5 instead, which is more compatible with RCP8.5[53], produces somewhat higher losses across different RCPs and model specifications but does not alter our conclusions regarding the effects of climate tipping points (see Supplementary Table S3). Using $N = 10{,}000$ Monte Carlo runs of META for each scenario s and model specification m following ref.[27], we calculate the overall impact of climate change on GDP in country i and year t for each Monte Carlo run as follows:

$$\gamma^{CC}_{i,t,s,m} = GDP^{CC}_{i,t,s,m} / GDP^{SSP}_{i,t,s} \tag{1}$$

where GDP^{SSP} denotes GDP as per the SSP scenario in the absence of climate change, which does not vary across model specifications m, and GDP^{CC} denotes the GDP remaining after market damages due to climate change.

For model specifications m, we vary the following three settings in META:

- The tipping points included (all, none, all including a potential AMOC collapse, or individual tipping points separately—with the latter option being used for Fig. 4c and Supplementary Fig. S13 only)
- The GDP-temperature damage function deployed to estimate GDP^{CC}, for which we use region-specific COACCH damage functions provided by ref.[34] (main approach) or the main function from ref.[1]. For more information and mathematical expressions for the damage functions, see Supplementary Note 1.
- The persistence of GDP-temperature damages, that is, whether economies rebound after a climate shock or are persistently pushed to a lower growth path[5,54]. We run META with three different specifications: no persistence following ref.[52] (main approach), full persistence following ref.[1], or drawing the share of persistent damages from a uniform distribution between 0–100% following ref.[27]. For details on how damage persistence is implemented in META, see ref.[27].

Notably, we trim 35 Monte Carlo runs from the total distribution of $10{,}000$ runs because they produce NA values in META's climate module due to inconsistent or implausible combinations of parameter draws. These trimmed runs are not featured in any of the results presented in this paper. In addition, we impute $\gamma^{CC}_{i,t,s,m}$ for Taiwan, whose damages are currently not captured in META, with the values for Hong Kong due to a similar latitude and exposure to sea level rise impacts and the fact that both territories are covered by the same region-specific COACCH damage function.

Financial losses for national stock markets We use the dividend discount modeling framework developed by ref.[11] to translate GDP projections from integrated assessment models into financial losses due to physical climate change impacts, assuming that the initial dividends from all stocks in a given market grow at the same rate as the respective economy. Therefore, in the absence of climate change, the present value of future dividends from country i for a given SSP can be written as follows:

$$PV^{SSP}_{i,s} = \sum_{t=2024}^{T} \left(D_{i,2024} \prod_{k=2025}^{t} \frac{1+g^{SSP}_{i,k,s}}{1+r_i} \right) \tag{2}$$

where $D_{i,2024}$ is the initial dividends received in the base year 2024, $g^{SSP}_{i,t,s}$ is the respective country's GDP growth rate in year t as per the SSP scenario s, and r_i represents a country-specific investor discount rate (see next subsection). In the base year $t = 2024$, dividends simply amount to $D_{i,2024}$ and are not discounted. As a time horizon under consideration, we cap T at 2100 but note that years late in the century are subject to high discount factors and hence have a low weight in the overall present value.

This approach assumes that the current valuation of stocks in country i is based on the discounted value of expected future dividends[36,55] and hence abstracts from the excess volatility of stocks[48] and the possibility of capital gains not rooted in dividend expectations[37], for instance through share buybacks. These simplifications notwithstanding, dividend discount modeling has been found to identify potential excess returns[37], is a common approach to assess climate physical risks[11,12], and can reproduce the actual market capitalizations of most major stock markets reasonably well (see Supplementary Note 4). Notably, ref.[12] also assume a linear relationship between output shifts and dividends, while equating dividend and GDP growth is a common long-term assumption in dividend discount modeling[37] and aligns with empirical evidence based on dividend growth in developed financial markets since World War II (see Supplementary Note 5).

Assuming that dividends are affected proportionately by the climate change-related reduction in overall GDP, the present value of future dividends from country i under climate change is then

$$PV^{CC}_{i,s,m} = \sum_{t=2024}^{T} \left(D_{i,2024} \prod_{k=2025}^{t} \frac{1+g^{SSP}_{i,k,s}}{1+r_i} \right) \gamma^{CC}_{i,t,s,m} \tag{3}$$

Lastly, the relative present-value loss is

$$L^{CC}_{i,s,m} = 1 - PV^{CC}_{i,s,m}/PV^{SSP}_{i,s} \tag{4}$$

Since $D_{i,2024}$ is a constant, it cancels out when dividing $PV^{CC}_{i,s,m}$ by $PV^{SSP}_{i,s}$, such that the relative loss $L^{CC}_{i,s,m}$ is independent of the initial dividends' absolute magnitude[11]. Repeating the calculation in Equation (4) for the different values of $\gamma^{CC}_{i,t,s,m}$ for each Monte Carlo draw of META input parameters then provides us with a loss distribution, reflecting the climatic and socio-economic uncertainties and, more importantly, the stochastic nature of the tipping points involved. Notably, ref.[11] refers to the loss term $L^{CC}_{i,s,m}$ as the "climate VaR", whereas in financial analysis, VaR describes percentiles of the loss distribution[56]. To avoid misunderstandings, we, therefore, use the term "loss" throughout the paper and use the VaR term only for the 95th and the 99th percentile of the Monte Carlo distribution of $L^{CC}_{i,s,m}$.

Investor discount rate Dividends are discounted to present values using a country-specific, inflation-adjusted investor discount rate r_i, which we calibrate based on the widely-used capital asset pricing model[57,58] paired with a country risk premium[47]:

$$r_i = \frac{1 + r_{rf} + r_{crp,i} + \beta \times ERP}{1+\pi} - 1 \tag{5}$$

where r_{rf} denotes the nominal return on a risk-free asset, $r_{crp,i}$ is a country-specific risk premium, ERP denotes the overall equity risk premium of the stock market, β denotes the volatility of the asset in question relative to the overall market, and π is the expected annual inflation rate in USD, the currency of our results. Following extant studies[47,59], we take country risk premiums from the Damodaran database[60], and use an equity risk premium of $ERP = 5\%$ and $\beta = 1$ since we model broadly diversified investments in the overall stock market[37]. Lastly, we calibrate the risk-free rate r_{rf} based on the 10-year geometric mean of the US treasury bond rate between 2014-2023 (1.5%[60]) and use the corresponding 10-year geometric mean of the US Consumer Price Index (1.8%[61]) for π. Therefore, dividends from "risk-free" countries with $r_{crp,i} = 0$ are discounted at an annual rate of $\frac{1+0.015+0.05}{1+0.018} - 1 \approx 4.6\%$. Country risk premiums for each market are displayed in Supplementary Table S5. Notably, this calibration aims to reproduce discount rates that financial investors typically apply, not determine which rates they *should* use, as the *social* discount rate supported by expert surveys generally is much lower[62]. To test the robustness of our findings to alternative discount rates, we further vary the assumed value of ERP between 1–15% (Fig. 4d).

Financial losses for globally diversified stock indices To calculate present value losses for globally diversified stock indices, we obtain data on their market capitalization and specific composition as of 31 August 2023 from MSCI, a commercial provider of financial indices. Summing up the market capitalization of all equities in index p listed in country i and dividing it by the overall index's market capitalization provides us with country weights $w_{i,p}$ in the current valuation of the respective index (weights are listed in Supplementary Tables S7–S9). Notably, the methodological framework by ref.[11] assumes that current valuations of stocks reflect the present value of expected dividends[36,37]. Under this assumption, the share of a country in the present value of the entire index's future dividends must equal its share in the index's current market capitalization. Then, the relative present-value loss of the entire index p simply equals the weighted average of the relative loss of each market i in index p, weighted by $w_{i,p}$:

$$L^{CC}_{p,s,m} = \sum_i w_{i,p} L^{CC}_{i,s,m} \tag{6}$$

Lastly, we can convert relative present-value losses based on Equation (6) to *absolute* losses in current USD (used in Fig. 4d) by multiplying $L^{CC}_{p,s,m}$ by the index's market capitalization (as of 31 August 2023 to ensure consistency with our weights $w_{i,p}$). Note that this step rests on the simplifying assumption that climate change damages are currently not priced in. If investors have already priced in at least some damages (such that current market capitalization is already lower than the market capitalization in the absence of climate change), this means that we underestimate the index value in the absence of climate change and hence also the financial loss due to climate change impacts in absolute terms.

Impacts of a catastrophic AMOC collapse Following ref.[28], we model the probability of an AMOC collapse for a given year t as

$$p_{AMOC,t} = 1 - exp\left(-b_{AMOC} \times max\{0, \Delta T_{global,t} - 1\}\right) \tag{7}$$

where $b_{AMOC} = 0.00063064$. By subtracting one and using the *max* operator, this approach ensures that at +1°C of global warming, the probability of an AMOC collapse is zero. At +1.5°C, +3°C, and +4°C of global warming, Equation (7) yields an annual tipping probability of 0.03%, 0.13%, and 0.19%, respectively. Over our modeling horizon of 2010–2100, these probabilities translate to a cumulative probability of no AMOC shutdown throughout the 21st century of 84–97%, calculated via $(1 - p_{AMOC})^{91}$. Therefore, an AMOC shutdown in this calibration is unlikely in line with recent IPCC assessments[32,44], but it remains a possibility. Interactions of the likelihood of an AMOC collapse with other tipping points are modeled based on the calibration by ref.[27] for tipping point interactions of a strong AMOC slowdown (for details, see Supplementary Information section 2.1.9 of ref.[27]).

Regarding the economic impacts of an AMOC collapse, the central specification of ref.[28] assumes that impacts increase linearly over a 50-year period until reaching the maximum of 15% of global GDP. We follow their approach, but given the country-level resolution of META, we assume that national losses are proportional to how strongly reductions in AMOC alter country-level temperatures in META's AMOC module[27]. For compatibility with ref.[28], we further require the global GDP-weighted loss to equal 15% (using each country's share in META's global GDP in the 2010 base year). Mathematical expressions for how we calibrate country-level impacts of an AMOC collapse are provided in Supplementary Note 3.

Resource availability

Lead contact Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Paul Waidelich (paul.waidelich@gess.ethz.ch).

Materials availability This study did not generate new unique materials.

Data and code availability MSCI index composition data can be obtained commercially from MSCI. The META integrated assessment model version used in this study is available under https://github.com/pwaidelich/META-2021. Financial data used to calibrate the country risk premiums, the risk-free interest rate, and the equity risk premium can be obtained from the NYU Damodaran database[60]. US Consumer Price Index data are available at the World Bank's World Development Indicators database[61]. All additional data required to replicate the analysis and to create the figures in this study will be deposited and made publicly available upon acceptance. All original code will be deposited and made publicly available upon acceptance.

Acknowledgements

The authors thank Felix Schaumann, Chris Smith, James Rising, Lorenz Wieshammer, participants at EGU24 and EAERE 2024, and particularly Stefano Battiston for valuable comments. This work was supported by the European Union's Horizon 2020 research and innovation program, European Research Council (ERC) under grant agreement no. 948220, project GREENFIN and received funding from the Swiss State Secretariat for Education, Research and Innovation (SERI) (contract number: 22.00541).

Author contributions

All authors conceived the study and developed the methodology. P.W. collected the data, performed the model runs and the portfolio simulations, analyzed and visualized the results, and wrote the manuscript. All authors reviewed and edited the manuscript.

Declaration of interests

Lena Klaaßen is a co-founder of CCRI GmbH, a company providing data on sustainability aspects of cryptocurrencies and blockchain systems. To our knowledge, cryptocurrencies and blockchain systems do not play a decisive role in the present study. The other authors declare no competing interests.

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Supplementary Information of: The risks of climate tipping points for financial investors

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Supplementary Note 1: GDP-temperature damage functions

COACCH damage functions Ref.[1] develop and deploy region-specific damage functions that account for the economic impacts of climate change on agriculture, river floods, energy demand, labor and energy supply, and road infrastructure, each estimated via bottom-up impact models. Impact model outputs are fed through a computable general equilibrium (CGE) model to account for general equilibrium effects and market-based adaptation. Region-specific joint impacts on gross domestic product (GDP) are regressed on global temperature increases, resulting in the following damage function

$$a_i\left(b_{i,1}\Delta T_{global,t,1986-2005}+b_{i,2}\Delta T^2_{global,t,1986-2005}\right) \tag{S1}$$

where $\Delta T_{global,t,1986-2005}$ is the global temperature increase vis-a-vis the 1986–2005 average (which we calculate as 0.7765°C using annual anomaly data from Berkeley Earth based on land and ocean using air temperature above sea ice[2]), and a_i, $b_{i,1}$, and $b_{i,2}$ are region-specific parameters estimated via quantile regression to capture the range of GDP impacts returned by the CGE model for region i. We use the COACCH function specification that excludes sea level rise impacts (which are already captured by a separate, sea level rise-specific damage function in META[3,4]), for which parameters are publicly available at https://zenodo.org/records/5546264. Damage function uncertainties are captured via the a_i parameter, for which $a_i = 1$ represents the central value. Since the COACCH function repository does not publish the full distribution for a_i, we estimate Gaussian distributions for a_i based on the available percentiles in the repository, requiring the distribution mean to equal the central value of $a_i = 1$. The COACCH damage functions deployed are displayed in Fig. S1 below, with grey dotted lines indicating the range between the 2.5th and the 97.5th percentile as per the original repository values and the shaded area indicating the corresponding percentiles as per our Gaussian distribution estimates, which we use for Monte Carlo runs of the META model. Overall, the tails of our distribution are slightly more conservative than the repository percentiles, except in Latin America ("Laca"), where the published repository values indicate a highly non-symmetric distribution that the Gaussian distribution does not fully capture. Unfortunately, estimates for a_i, $b_{i,1}$ and $b_{i,2}$ are provided only at the resolution of major integrated assessment models (WITCH, REMIND, IMAGE) and not at the country level resolution used in META. Therefore, we apply the same estimate for a_i, $b_{i,1}$ and $b_{i,2}$ to all countries located in the respective region of the IMAGE model, using matching files from ref.[5].

Notably, the COACCH functions take global temperatures as input and account for differences in how local temperatures shift with global warming through the region-specific damage function parameters a_i, $b_{i,1}$, and $b_{i,2}$. However, META's module for a slowdown of the Atlantic meridional overturning circulation (AMOC) returns country-level temperature shifts (since the effect of such a slowdown on temperatures is very heterogeneous across countries[6–8]); for details, see section 2.1.7 of the Supplementary Information of ref.[3]. We do not include an AMOC slowdown in our main results for reasons provided in Supplementary Note 2, but it is featured in a robustness check in Supplementary Note 2. Therefore, using the COACCH damage functions in combination with the AMOC slowdown module requires "translating" the country-specific temperature shifts due to a slowdown into corresponding global temperature shifts. To do this, we calculate the global temperature shift that would have the equivalent effect on the national temperature of a country i in year t as follows:

$$\Delta T^{AMOC}_{global,i,t} = \Delta T^{AMOC}_{i,t}/\psi_{i,t} \tag{S2}$$

where $\Delta T^{AMOC}_{i,t}$ is the national temperature shift returned by META's AMOC slowdown module and $\psi_{i,t}$ is the country- and year-specific pattern scaling relationship between global mean surface temperature in year t and the national temperature of country i (calculated in META's "Pattern Scaling" component; see section 2.3.2 in the Supplementary Information of ref.[3]). For instance, if the AMOC slowdown module indicates that a country i's national temperature would decrease by -1.5°C due to the slowdown and the pattern scaling relationship is such that global warming of +1°C increases national temperatures of country i by +1.5°C (i.e., $\psi_{i,t} = 1.5$), then a global temperature shift of $\Delta T^{AMOC}_{global,i,t} = -1$°C would have the equivalent effect on the national temperature of country i. This country-specific AMOC slowdown-induced shift in global temperature is then added to the COACCH damage function:

$$a_i\left(b_{i,1}(max\{0,\Delta T_{global,t,1986-2005}+\Delta T^{AMOC}_{global,i,t}\})+b_{i,2}(max\{0,\Delta T_{global,t,1986-2005}+\Delta T^{AMOC}_{global,i,t}\})^2\right) \tag{S3}$$

Here, the *max* operator floors the global temperature increase over the 1986–2005 average at 0°C since the COACCH damage functions are not well-defined for decreases of global temperatures below baseline levels. As a result, the GDP gains of an AMOC slowdown can mitigate the otherwise adverse economic effects of global temperature increases but cannot lead to GDP levels that are *higher* than in a counterfactual world without climate change.

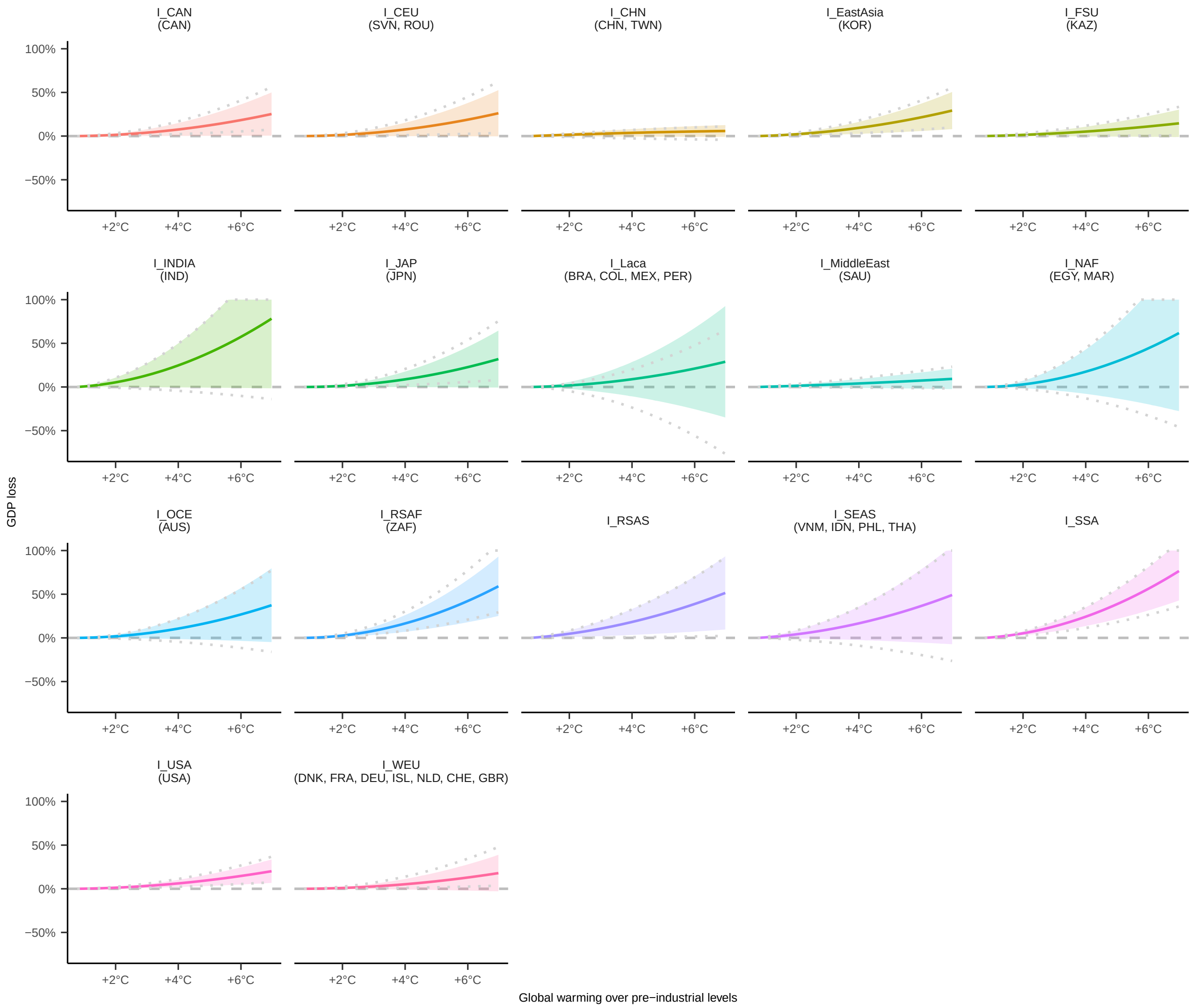

Figure S1. Region-specific GDP-temperature damage functions from the COACCH project[1] used in our main results. Solid lines and shaded areas indicate the distribution mean and the range between the 2.5th and the 97.5th percentile, respectively, based on our estimated Gaussian distributions. Dotted grey lines denote the corresponding percentiles based on the original percentile values for a_i in the COACCH repository. Negative values indicate GDP gains due to climate change. For the ten most important markets in the MSCI World, MSCI Emerging Markets, and MSCI Frontier Emerging Markets, respectively, we add the ISO3 code in parentheses to their respective COACCH region (e.g., FRA for France in Western Europe WEU). Some COACCH regions, such as Sub-Saharan Africa (SSA), do not feature any of the top 10 markets in either index. Note that the x-axis starts at the baseline warming level for the COACCH functions (0.7765°C).

Burke et al. (2015) damage function Following ref.[9], we implement the damages based on their main specification as

$$\beta_1 \left(T_{i,t} - T_{i,base}\right) + \beta_2 \left(T_{i,t}^2 - T_{i,base}^2\right) \tag{S4}$$

where $T_{i,t}$ is the average temperature of country i in year t, $T_{i,base}$ is the average temperature during a baseline period, and β_1 and β_2 denote the regression coefficients estimated by the main specification of ref.[9]. For our Monte Carlo analysis, we sample β_1 and β_2 from a bivariate Gaussian distribution with the respective coefficient estimates by ref.[9] as means ($\beta_1 = 0.0127$ and $\beta_2 = -0.0005$) and the variance-covariance matrix estimated by their main specification. As a baseline period for $T_{i,base}$, the META model uses 1981–2000[3].

Supplementary Note 2: Modifications of the climate tipping point modules in the META model

Overall, our calibration of the climate tipping point modules in the META model closely follows the main specification by ref.[3], which uses the following calibrations:

- **Permafrost carbon feedback:** Calibration based on ref.[10]
- **Amazon dieback:** Calibration based on ref.[11]
- **Greenland Ice Sheet disintegration:** Calibration based on ref.[12]
- **West-Antarctic Ice Sheet disintegration:** Calibration based on ref.[13]
- **Indian summer monsoon variability:** Calibration based on ref.[14] following ref.[15]

However, the main specification of ref.[3] also features three additional tipping point modules, namely:

- **Surface albedo feedback due to Arctic sea ice loss:** Calibration based on ref.[16]
- **Slowdown of the Atlantic meridional overturning circulation (AMOC):** Calibration based on ref.[7]
- **Dissociation of ocean methane hydrates:** Calibration based on ref.[17]

For these three elements, we depart from the main specification by ref.[3] due to different reasons laid out below.

Surface albedo feedback META's modeling of the surface albedo feedback stems from ref.[16] and takes into account that a loss of sea ice and snow cover on land leads to higher solar absorption in cold, high-latitude regions and, hence, higher temperatures. Therefore, this module primarily corrects how greenhouse gas emissions and concentrations are translated into mean surface temperature changes and does not cover any explicit tipping dynamics or elements. Indeed, the latest scientific understanding suggests that Arctic sea ice decline during summer is not a tipping element and is likely reversible, although a threshold-dependent tipping element may exist for sea ice loss during winters[18]. In any case, the surface albedo feedback module in META constitutes a definitive refinement of the FaIR-based climate module that translates emissions into temperature shifts, not a module capturing a potential tipping point. For this reason and following the recommendation of the META model developers, we include it in *all* of our model runs, including those excluding climate tipping points. As a result, META's surface albedo feedback module does not contribute to the joint effect of climate tipping points on expected losses and the Value-at-Risk (VaR) in any of our results.

AMOC slowdown The main calibration used by ref.[3] implies a reduction of 27% in AMOC strength and captures the temperature-altering effects of such a slowdown, which lowers national temperatures in many regions, most pertinently in the North Atlantic[7,8]. Importantly, the probability of such a slowdown occurring in year t in META ($p_{AMOC,t}$) is modeled as

$$p_{AMOC,t} = 1 - exp\left(-b_{AMOC}\Delta T_{global,t}\right) \tag{S5}$$

where $\Delta T_{global,t}$ denotes the increase in global mean surface temperature over pre-industrial levels and b_{AMOC} represents a hazard rate following the modeling of tipping points in ref.[11]. Therefore, the more the global mean surface temperature increases, the more likely the AMOC slowdown (and other tipping events in META) become. Importantly, as with all other tipping events in the model, the AMOC slowdown is irreversible, so $p_{AMOC,t} = 1$ for all years after the tipping is triggered. If an AMOC slowdown occurs in the model, this gradually alters country-level temperatures, most notably through a cooling effect on countries adjacent to the North Atlantic, such as the United States and Western Europe[7]. The maximum effect on country-level temperature in the main specification of ref.[3], which is reached 35 years after the slowdown begins, is displayed in Fig. S2.

In the main specification of ref.[3], b_{AMOC} is set to 0.54, which by Equation (S5) implies an *annual* probability of occurrence of 56%, 66% and 80% at +1.5°C, +2°C, and +3°C of global warming, respectively. Therefore, the occurrence of the slowdown over several decades is virtually certain in all model runs. Such a high likelihood of an AMOC slowdown is in line with recent IPCC assessments reporting a considerable decline in AMOC strength in climate models participating in the Coupled Model Intercomparison Project's (CMIP) 5th and 6th phase throughout the 21st century, which is more pronounced in high-emission scenarios[6,19]. However, META's climate module derives national temperatures by taking the global mean surface temperature returned by the simple climate model FaIR and scaling it down to the country level based on country-specific

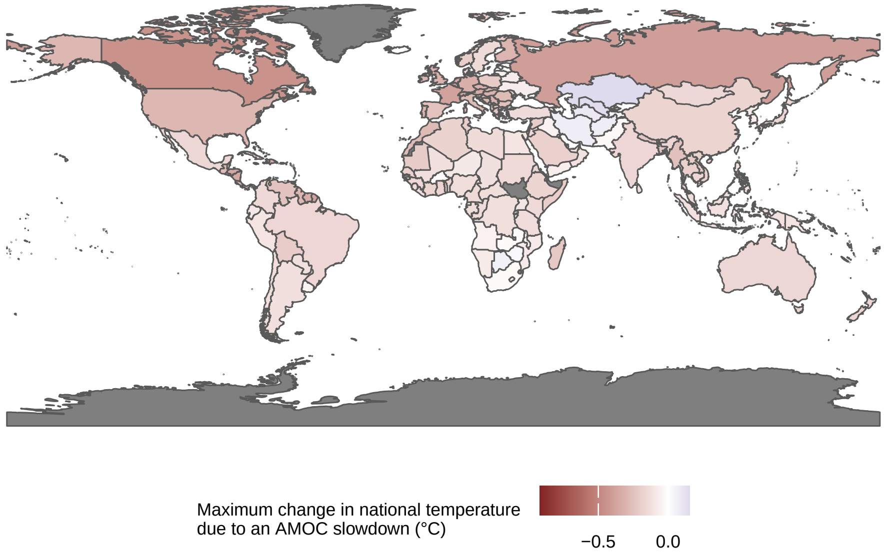

Figure S2. Maximum country-level temperature shifts due to an AMOC slowdown by 27% in the META model's main specification used by ref.[3] ("IPSL" calibration).

statistical relationships between global and national temperatures in CMIP5 model outputs (for details, see section 2.3.2 in the Supplementary Information of ref.[3]). Since an AMOC slowdown is widely present in these CMIP5 model runs, the estimated relationship between a country's national temperature and the global mean surface temperature implicitly accounts for AMOC slowdown-related temperature shifts. Therefore, adding the temperature effect of an AMOC slowdown to country-level temperatures that were pattern-scaled based on CMIP5 (or CMIP6) risks double-counting the temperature-altering effect of an AMOC slowdown, particularly since such a slowdown is near-certain in the main specification by ref.[3] and ubiquitous in CMIP model runs. To avoid such double counting, we do not include the AMOC slowdown module in any of the results in our paper.

Importantly, the reasoning above does not apply to a full *collapse* of the AMOC during the 21st century, which occurs in virtually none of the CMIP model runs[6,19] and, therefore, comes with no comparable risk of double counting climatic shifts and their socio-economic impacts.

Ocean methane hydrates The main specification by ref.[3] features a calibration of the ocean methane hydrates based on ref.[17] that releases up to 50 Gt of methane over 20 years. However, recent climate science indicates that ocean methane hydrates are only projected to release small amounts of methane throughout the 21st century[20], with ref.[18] modeling them with 5.91 Mt of methane released per year between 2000–2100 under SSP5-8.5. This much more conservative calibration translates to a cumulative release of approximately 0.6 Gt of methane throughout the 21st century, two orders of magnitude less than the calibration by ref.[17]. Indeed, the Global Tipping Points Report 2023[21] concluded: "While there is potential for methane hydrate deposits in ocean sediments to be destabilised by warming, which could eventually have very large impacts on global temperature due to increases in atmospheric methane concentrations, current evidence and understanding suggests timescales of centuries to millennia for substantial impacts[18]." For this reason, we omit the ocean methane hydrate module in the main specification.

Net effect of modifications to tipping point modules Fig. S3 below shows our main index-level results if we use the main specification of ref.[3] for all tipping point modules (i.e., include the AMOC slowdown and the ocean methane hydrates in our main specification including climate tipping points and treat the surface albedo feedback as a climate tipping point). In this case, climate tipping points would increase the expected loss for the MSCI World under RCP4.5-SSP2 from 1.4% to 2.0% (a +44% increase), while the expected loss for the MSCI Emerging Markets and the MSCI Frontier Emerging Markets would increase by +75% and +85%, respectively. Expected losses and 95% VaRs when using all tipping point modules from the main specification of ref.[3] are considerably higher than our main results in Fig. 2. The primary reason is that releases of methane in META's ocean methane hydrates module cause substantial near-term warming (Fig. S9) that strongly affects investor present values. By contrast, including the AMOC slowdown module and its effect on national temperatures reduces dividend losses, particularly in North America and Europe, which is why the increase of the expected loss due to climate tipping points in Fig. S3 is much less pronounced for the MSCI World than for the other two indices. Compared to the other two elements, the impact of the surface albedo feedback on expected losses is less pronounced. However, comparing Fig. S3 to our main results clearly shows that, overall, our modifications of META's tipping point modules are conservative by decreasing the estimated impact of climate tipping points considerably.

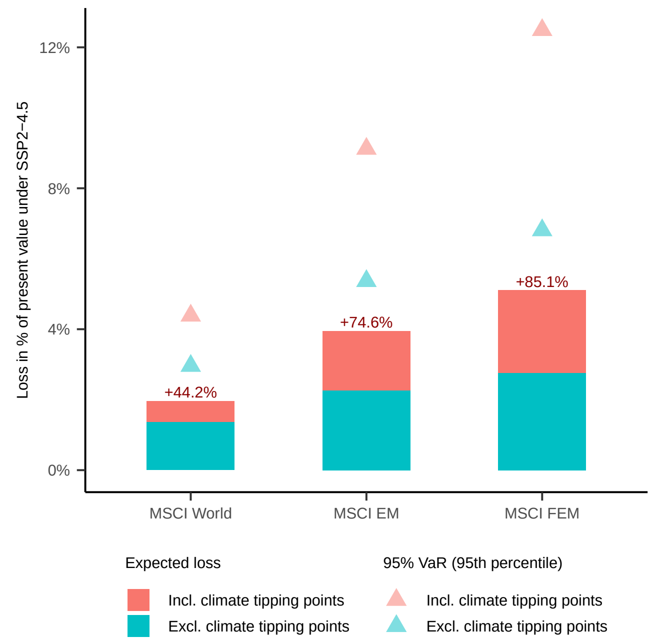

Figure S3. Expected loss and 95% VaR under RCP4.5-SSP2 when using the main specification of ref.[3] for climate tipping points (i.e., including ocean methane hydrates and the AMOC slowdown and switching off the surface albedo feedback in the specification excluding climate tipping points). Text labels in dark red denote the relative increase in the expected loss due to climate tipping points (i.e., the increase by adding the red to the blue bar).

Visual overview of our META modifications Figures S4 and S5 illustrate the climatic and economic parts of the META model by ref.[3], respectively. All modifications for the present study are highlighted by dashed red boxes and the text annotations in bold. Modifications include the climate tipping point adjustments explained above and the new COACCH damage functions for GDP-temperature damages explained in Supplementary Note 1. The output variables from META that feed into our present value calculations of future dividends with and without climate change's economic impacts are:

- A country's GDP in a given year in the absence of climate change, as per the respective SSP
- A country's GDP in a given year in the presence of climate change, that is, net of GDP losses due to (i) national temperature damages, (ii) sea level rise, and, specifically for India, (iii) the Indian Summer Monsoon

For a more detailed explanation of the META model, we refer readers to Section 2 of the Supplementary Information of ref.[3].

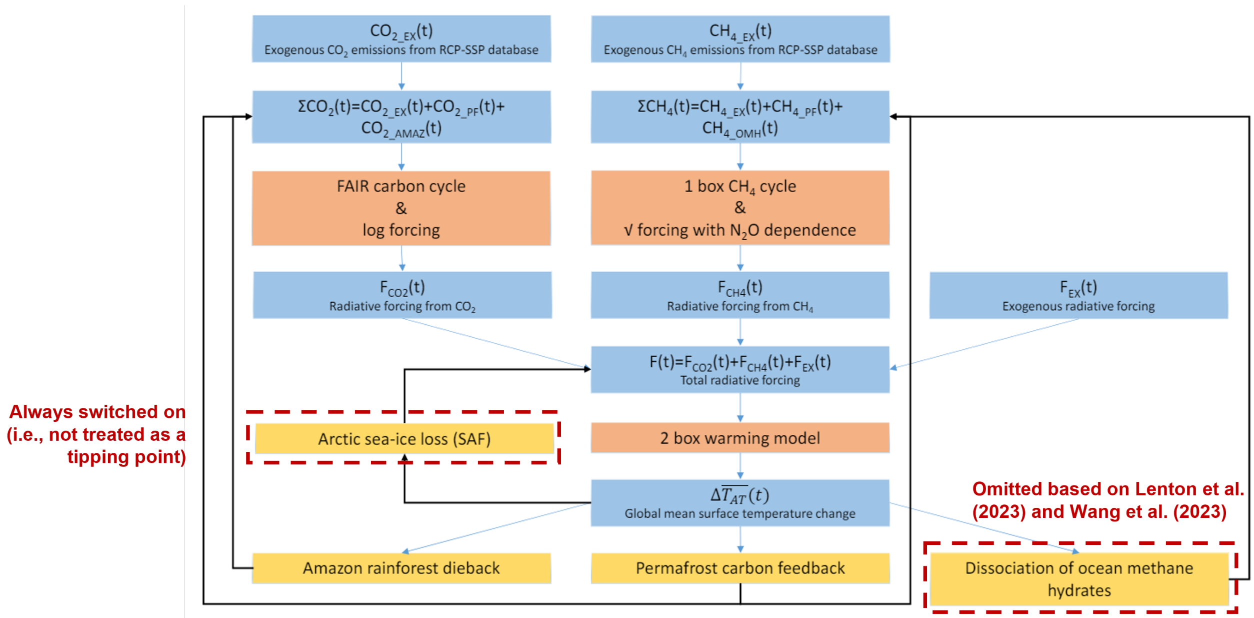

Figure S4. Overview of META's climate module with blue boxes indicating model variables, yellow boxes indicating tipping point modules, and orange boxes indicating other modules in META. Dashed red boxes and bold text denote our modifications to the original model. Source: Adapted from ref.[3], Figure 4 in their Supplementary Information.

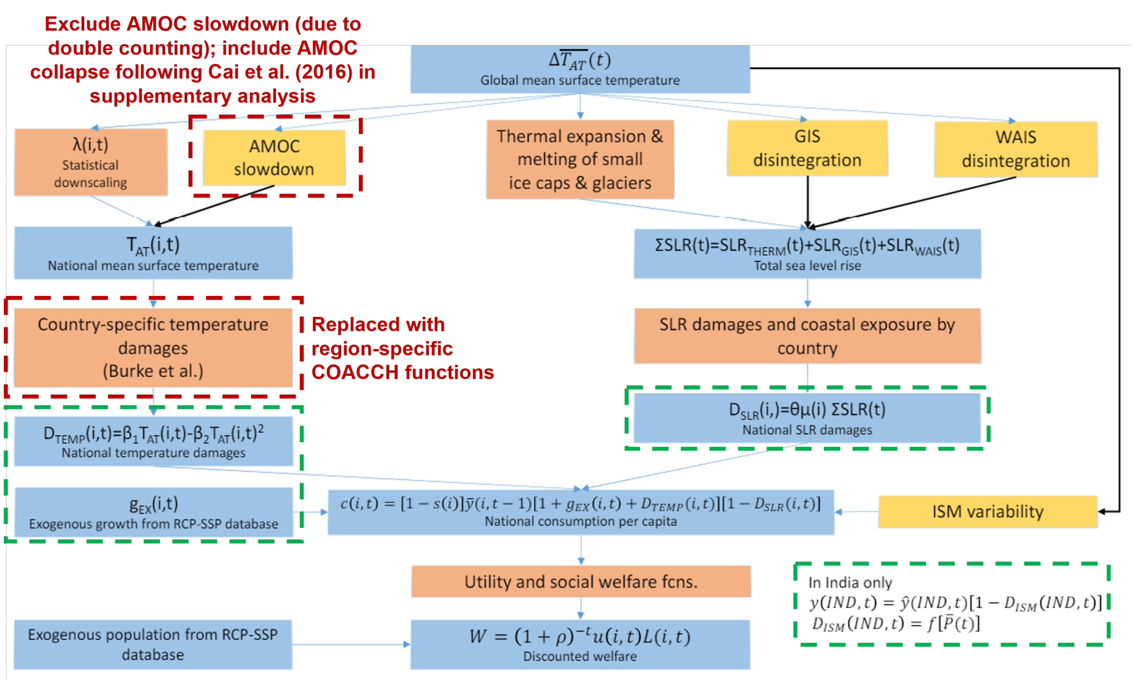

Figure S5. Overview of META's climate module with blue boxes indicating model variables, yellow boxes indicating tipping point modules, and orange boxes indicating other modules in META. Dashed red boxes and bold text denote our modifications to the original model. Green dashed boxes denote the output variables we take from META to calculate GDP in the absence and in the presence of climate change impacts (i.e., GDP^{SSP} and GDP^{CC} in Equation 1 in **Experimental procedures**). Source: Adapted from ref.[3], Figure 5 in their Supplementary Information.

Supplementary Note 3: Country-level GDP impacts of an AMOC collapse following Cai et al. (2016)

While Supplementary Note 1 above explains our reason to exclude META's module for a *slowdown* of the AMOC due to risks of double counting, our manuscript features an additional analysis based on the potentially catastrophic economic impacts of an AMOC *collapse*, which is modelled differently. As pointed out in Supplementary Note 1, there is no such risk of double counting for an AMOC collapse. Here, we explain in more detail how we calibrate the economic impacts of such a collapse in the META model following ref.[11].

The central specification of ref.[11] assumes that damages of an AMOC collapse increase linearly over a transition time of 50 years to 15% of global GDP, with no further impact of the AMOC collapse on the carbon cycle. Notably, the model by ref.[11] is global. To translate these assumptions into country-level damages, we account for the fact that an AMOC shutdown would have very heterogeneous effects on regional climates by assuming that GDP impacts are proportional to the expected temperature shifts:

$$\phi_i = \frac{abs\left(\Delta T_{AMOC,i}\right)}{\sum_i abs\left(\Delta T_{AMOC,i}\right) \times w_{i,2010}^{GDP}} \tag{S6}$$

where ϕ_i is the ratio of a country i's maximum GDP impact following an AMOC shutdown to the global GDP impact of 15%:

$$\gamma_i^{AMOC,max} = \phi_i \times \gamma_{global}^{AMOC,max} \tag{S7}$$

For instance, if $\phi_i = \frac{4}{3}$, then the GDP loss of country i increases linearly to a maximum GDP loss of $\frac{4}{3} \times 15\% = 20\%$ throughout the 50-year transition time after the AMOC shutdown begins. $\Delta T_{AMOC,i}$ in Equation (S6) denotes the maximum shift in the national temperature of country i, which we calibrate based on the country-level temperature shifts displayed in Fig. S2 above. $w_{i,2010}^{GDP}$ is the share of country i in META's global GDP in the 2010 base year. This calibration of impacts ensures that global GDP impacts are consistent with the calibration by ref.[11], given the initial allocation of GDP across countries because

$$\sum_i w_{i,2010}^{GDP} \times \gamma_i^{AMOC,max} = \gamma_{global}^{AMOC,max} \tag{S8}$$

Therefore, GDP-weighted global impacts equal the value assumed by ref.[11]. At the same time, our calibration of country-level impacts in Equation (S7) captures that countries with more substantial temperature shifts ($abs\left(\Delta T_{AMOC,i}\right) \uparrow$) are likely more affected ($\phi_i \uparrow$) than others[22]. The maximum country-level GDP impacts of an AMOC collapse based on Equation (S7) (which are reached 50 years after the irreversible collapse begins) are displayed in Fig. S6 below.

Importantly, while ref.[11] point to other studies of an AMOC collapse that suggest even higher damages, their calibration differs substantially from more optimistic studies that translated the substantial cooling effects of an AMOC slowdown (not a collapse) into GDP gains, particularly for North American and Western European countries[3,7]. However, as the Global Tipping Points Report 2023 summarizes[21], an AMOC collapse would also entail significant sea level rise in the North Atlantic, colder winters and more cold extremes in adjacent countries, reductions in precipitation with drastic implications for arable farmland in Europe, and shifts in monsoon patterns in Latin America and West Africa. Accordingly, our calibration takes a much more pessimistic take on an AMOC collapse as "the archetype of a climate catastrophe"[11], which is more informative for exploring potential impacts of low-likelihood, high-impact tipping events, despite its stylized nature—particularly given that the META model's representation of other climate tipping points is conservative and likely produces a lower bound of impacts rather than a central estimate[3].

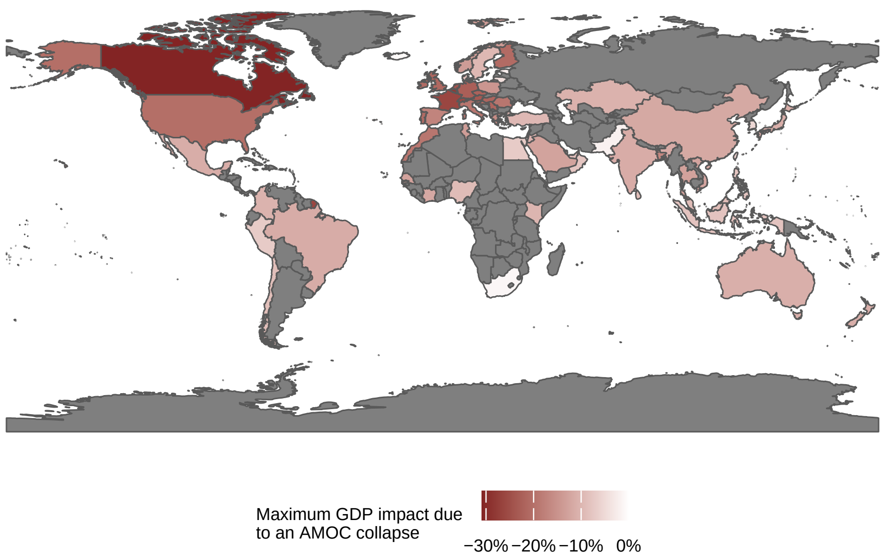

Figure S6. Country-specific maximum GDP impacts of an AMOC collapse, calculated as $\phi_i \times 15\%$, for all 68 countries that feature in any of the three stock indices considered in our analysis (other countries colored in dark grey).

Supplementary Note 4: Validating our dividend discount model against actual market capitalizations

To explore whether our dividend discount modeling approach can reproduce current market capitalizations, we calibrate baseline dividends ($D_{i,2024}$ in Equation 2 in **Experimental procedures**) by multiplying the actual market capitalization of country i by the dividend yield of the respective country's MSCI index (denominated in USD and covering large- and mid-cap stocks, consistent with the global stock indices used), as indicated by MSCI's publicly availabale factsheets for indices. Next we calculate the resulting present value of future dividends in the absence of climate change ($PV_{i,s}^{SSP}$ in Equation 2 of **Experimental procedures**) for two scenarios s, namely SSP2 and the higher-growth scenario SSP5, and compare it to the total market capitalization of all stocks in country i that are included in the MSCI All Country World Index. For index-level validations, we follow the same steps but at the aggregate index level, using index-level dividend yields.

Results are shown in Figure S7 below. For the MSCI World, the implied market capitalization by the dividend discount model is only roughly half of the actual market capitalization when using GDP growth trajectories from SSP2 and still by roughly one third lower when using SSP5. The primary reason is that our model underestimates market capitalizations in the United States, where dividend yields are relatively low (roughly 1.3% as of July 2024, compared to 1.8% for the MSCI World overall) partially due to a much higher prevalence of share buybacks as an alternative mechanism to reward shareholders instead of dividends. Therefore, estimating market capitalizations only based on dividends produces too conservative values. However, for most other major stock markets (with a lower prevalence of buybacks), the range of model results between SSP2 and SSP5 covers the actual market capitalization. As a result, the implied market capitalizations for the MSCI Emerging Markets and the MSCI Frontier Emerging Markets are fairly close to the actual values, with a minor underestimation under SSP2 and somewhat overestimated valuations under SSP5. However, aside from the US, there are other markets where actual market capitalizations are underestimated (e.g., India) or overestimated (e.g., Australia). A potential reason for such country-specific underestimation (overestimation) is that investors may expect substantially higher (lower) GDP growth for these countries than the SSPs used in our dividend discount model.

Importantly, these deviations apply to both the present value in the presence and in the absence of climate change (PV^{CC} and PV^{SSP} in the equations in **Experimental procedures**). Therefore, they have no implication for relative losses due to climate change, the main outcome of interest in this paper (L^{CC} in Equation (4) of **Experimental procedures**). Yet, the validation illustrates that despite its simplicity, the dividend discount model is broadly consistent with current valuations for most countries in our sample. However, the sizable deviations for individual markets also highlight that any simplified model covering a wide range of markets will inevitably fall short of fully capturing all relevant stock market dynamics.

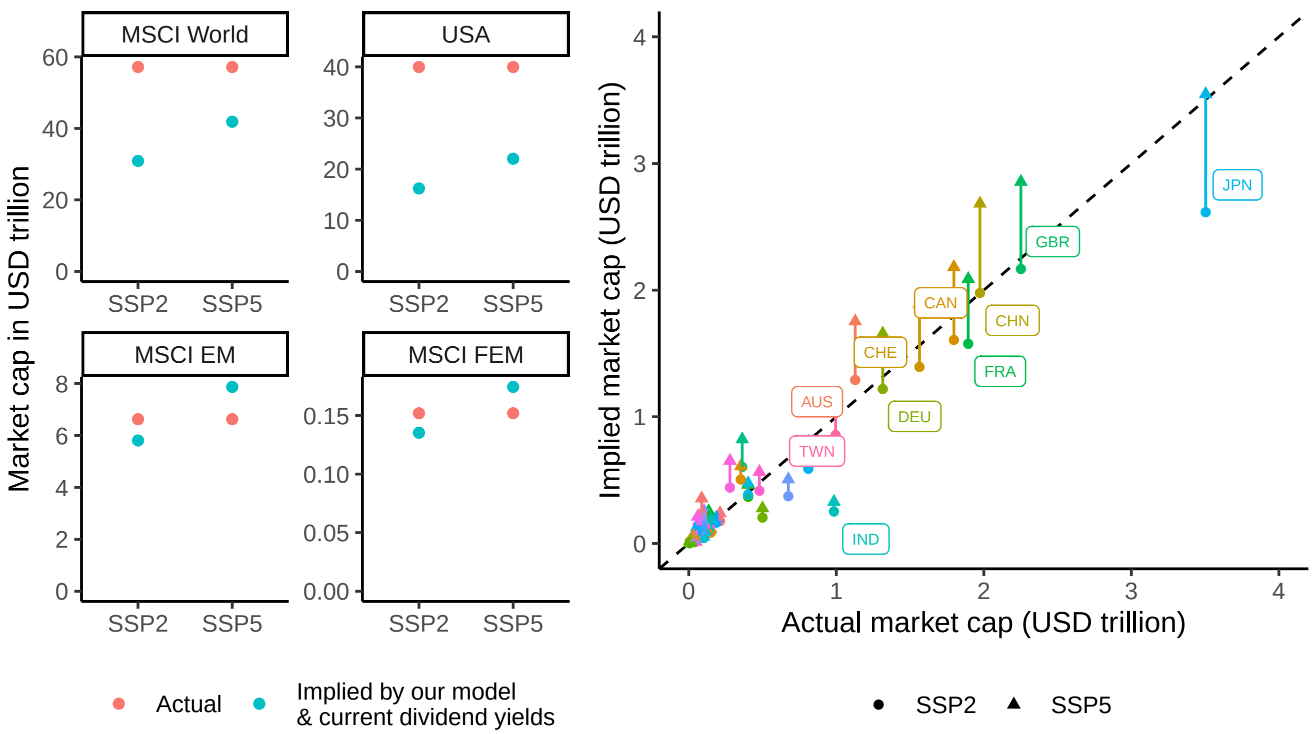

Figure S7. Actual market capitalizations and capitalizations implied by our dividend growth model (based on actual current dividends and SSP-based growth rates). Panel b displays all 68 countries featured in any of the three indices used in this paper (except the US, which are displayed separately in Panel a)

Supplementary Note 5: Examining the linear relationship between GDP and dividend growth

The methodological framework by ref.[23] to convert GDP impacts of climate change into changes in dividends assumes that a 1% shock to GDP leads to a corresponding 1% decline in dividends. To explore if this assumption aligns with empirical evidence, we use the Jorda-Schularick-Taylor Macrohistory Database[24] (version R6, accessed on 15 January 2024), which features a rich set of country-level economic and financial variables and returns covering 1870-2020 for 18 OECD countries. To explore the relationship between GDP and dividend growth, we use data from 1951 onwards, excluding years before, during, or immediately after World War II to avoid distortions due to wars, the Great Depression, and hyperinflation.

Annual GDP growth (in constant PPP for consistency with the SSP data in META) can be derived from the Macrohistory Database's data points on GDP per capita (sourced from the Maddison Project database) and population. Year-to-year growth in dividends (g^D) is not featured in the database but can be easily derived based on available data points on dividend yields, dividend returns, and capital gains. As the SSP growth rates for GDP used in the META model are in real instead of nominal terms, we adjust for inflation using the Consumer Price Index inflation of country i in year t in the Macrohistory Database (π):

$$\frac{1+g_{i,t}^D}{1+\pi_{i,t}} - 1 \tag{S9}$$

To explore the assumption of a linear (one-to-one) relationship, we regress country-level dividend growth in real terms on real GDP growth, using country and year fixed effects, country-specific linear time trends, and standard errors clustered by both country and year. As dividend growth data is not available for Canada and Ireland in the Macrohistory Database, our effective sample covers $N = 16$ countries and $T = 70$ years (1951–2020). Regarding non-stationarity, tests following ref.[25] and ref.[26] using the *plm* package in R[27] firmly reject the unit root hypothesis for both GDP and dividend growth ($p << 0.01$).

Results are displayed in Table S1 and show that after introducing fixed effects and country-specific time trends, there is a significant link between dividend and economic growth (col. 3), suggesting that a +1 percentage point increase in real GDP growth is associated with a +1.5 percentage point change in dividend growth. We find no significant evidence for non-linearity (col. 4) or a substantially different relationship if we use an alternative measure of GDP growth available in the Macrohistory Database (col. 5). The relationship seems primarily driven by country-years with negative economic growth (col. 7), for which the effect remains statistically significant with $p < 0.01$ (by testing the sum of the coefficients for "Real GDP PPP growth" and "Real GDP PPP growth $\times$ I(Negative GDP growth)"). However, the effect does not appear to be driven by years with economic crises, using a crisis dummy included in the Macrohistory Database (col. 6). Weighting each country by its current market capitalization instead of weighting all countries equally (col. 8), which assigns a very high importance to the US, reduces the point estimate, as does trimming country-years, for which dividend growth falls into the upper/lower 2.5th percentile of our sample (col. 9). Allowing for a structural break in the relationship in the 2nd half of our sample (i.e., from 1985 onward) does not indicate a significantly different relationship (col. 10), although point estimates suggest a weakening relationship over time.

This supplementary analysis comes with several important caveats. First, the Macrohistory Database does not cover emerging markets, for which the relationship may differ systematically. Second, the model deployed here is relatively simple and addresses the risk of omitted variable bias merely through fixed effects and country-specific time trends, while potential reverse causality issues remain unaddressed. Therefore, the coefficients in Table S1 do not represent *causal* effect sizes. Third, we note that the explanatory power of our models net of fixed effects and time trends (i.e., within-R^2) is low, amounting to 1% of the observed variation in dividend growth or less. For all these reasons, the regressions in Table S1 do not necessarily present stringent *proof* for the assumptions underlying the dividend discount model framework by ref.[23]. However, we note that the regression results are broadly consistent with these assumptions, as all 95% confidence intervals for the link between GDP and dividend growth cover the assumed value of one except for the specification in col. 9.

Table S1. Regressing dividend growth on GDP growth using the Jorda-Schularick-Taylor Macrohistory Database

	Real dividend growth									
	No FEs	Year FE	Main	+ Quadratic	Other GDP measure	+ Crises	+ Recessions	Market cap-weighted	Trim upp/low 2.5%	Break
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	3.07									
	(2.96)									
Real GDP PPP growth	0.837	1.59^{*}	1.50^{**}	2.06^{*}		1.39^{*}	0.984	0.632^{*}	0.517^{**}	1.70^{*}
	(0.641)	(0.554)	(0.384)	(0.778)		(0.511)	(0.637)	(0.252)	(0.168)	(0.742)
Real GDP PPP growth square				-0.045						
				(0.030)						
Barro GDP growth					1.65^{***}					
					(0.400)					
Real GDP PPP growth × I(Crisis year) = TRUE						3.69				
						(2.36)				
I(Crisis year) = TRUE						-4.37				
						(2.91)				
I(Negative GDP growth) = TRUE							-4.01			
							(5.64)			
Real GDP PPP growth × I(Negative GDP growth) = TRUE							2.54			
							(1.82)			
Real GDP PPP growth × above_break = TRUE										-0.406
										(1.51)
year FEs		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
iso FEs			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Varying Slopes										
year (iso)			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard-Errors						iso & year				
Observations	1,090	1,090	1,090	1,090	1,090	1,090	1,090	1,090	1,031	1,090
R^2	0.004	0.165	0.199	0.200	0.200	0.200	0.201	0.194	0.234	0.199
Within R^2		0.009	0.007	0.008	0.009	0.008	0.009	0.004	0.003	0.007
BIC	11,067.0	11,357.0	11,528.9	11,534.8	11,527.1	11,541.4	11,540.0	11,667.9	9,474.9	11,535.7

Clustered (iso & year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, †: 0.1*

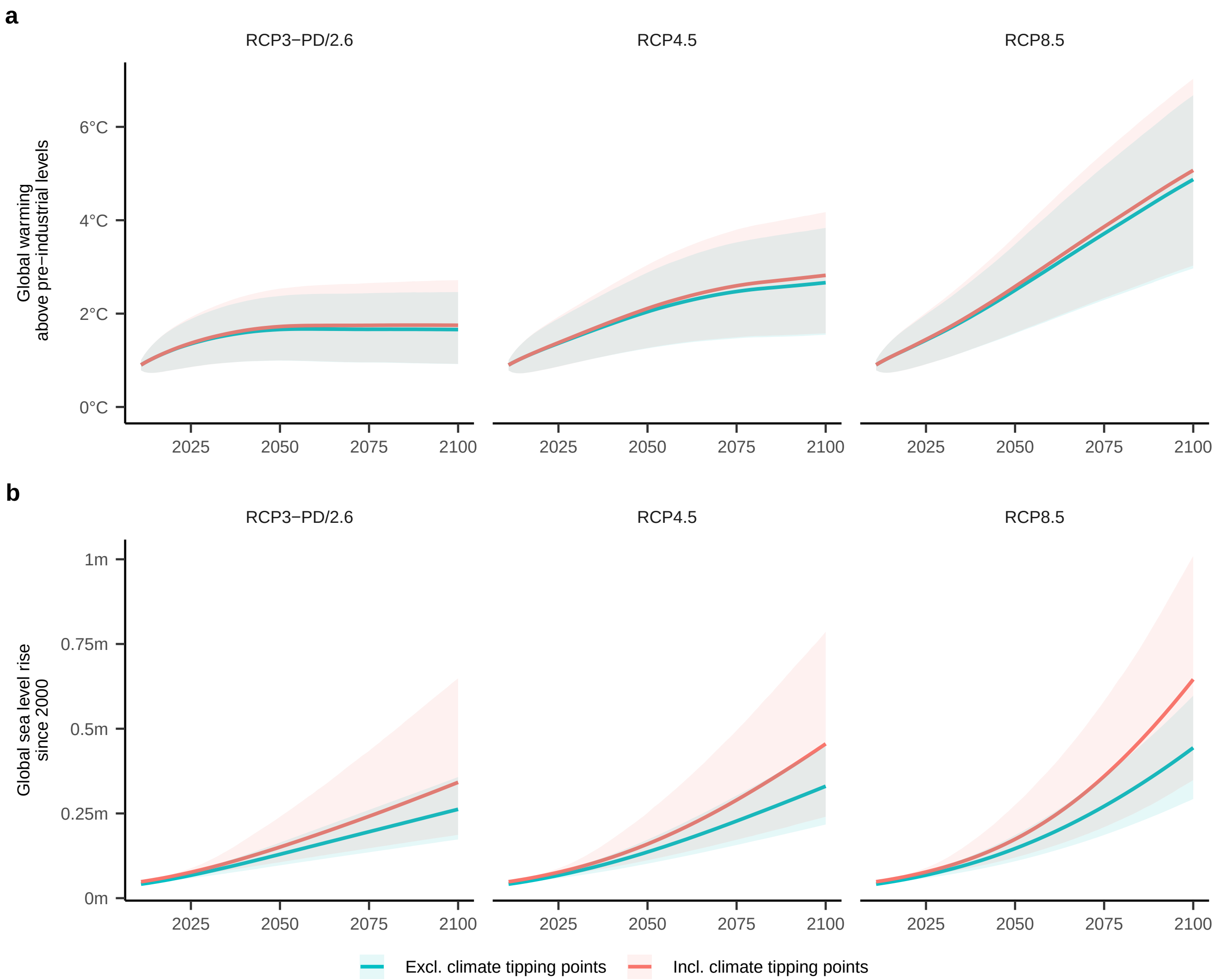

Figure S8. Global warming and sea level rise with and without climate tipping points for RCP3-PD/2.6, RCP4.5 and RCP8.5 in META. Lines denote the Monte Carlo mean, while shaded areas range from the 2.5th to the 97.5th percentile of the Monte Carlo distribution for the respective year and model specification (excluding or including climate tipping points).

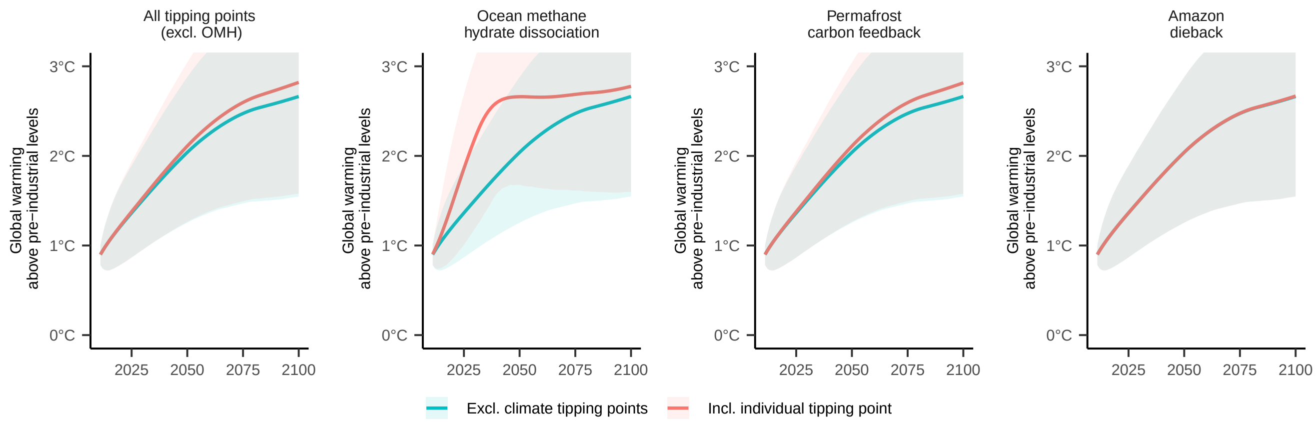

Figure S9. Global warming (Monte Carlo mean) with and without individual climate tipping points for RCP4.5. Shaded areas range from the 2.5th to the 97.5th percentile of the Monte Carlo distribution for the respective year and model specification. The y-axis is clipped at +3°C to make differences between the lines more visible. Note that ocean methane hydrates are not included in our main results (see Supplementary Note 2) and, hence, do not feature in the results for “All tipping points”.

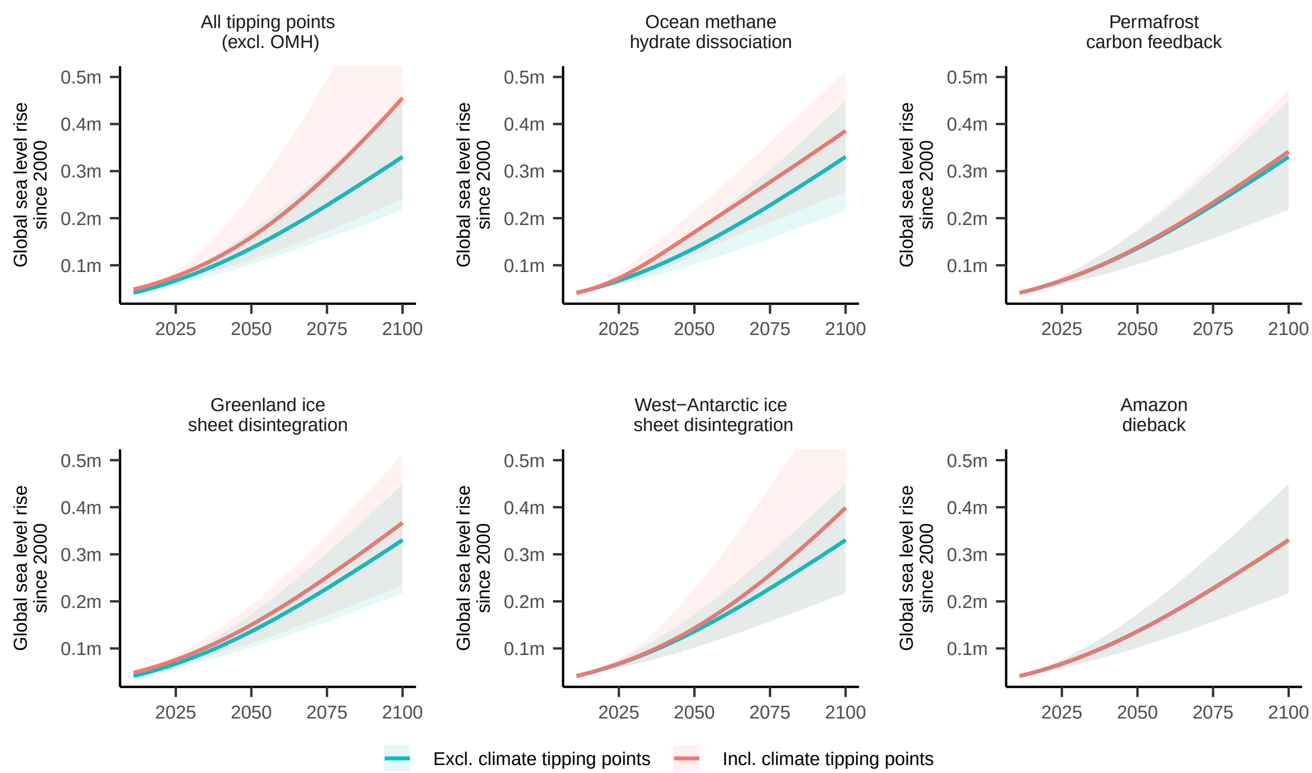

Figure S10. Global sea level rise (Monte Carlo mean) with and without individual climate tipping points for RCP4.5. Shaded areas range from the 2.5th to the 97.5th percentile of the Monte Carlo distribution for the respective year and model specification. The y-axis is clipped at +0.5m to make differences between the lines more visible. Note that ocean methane hydrates are not included in our main results (see Supplementary Note 2) and, hence, do not feature in the results for “All tipping points”.

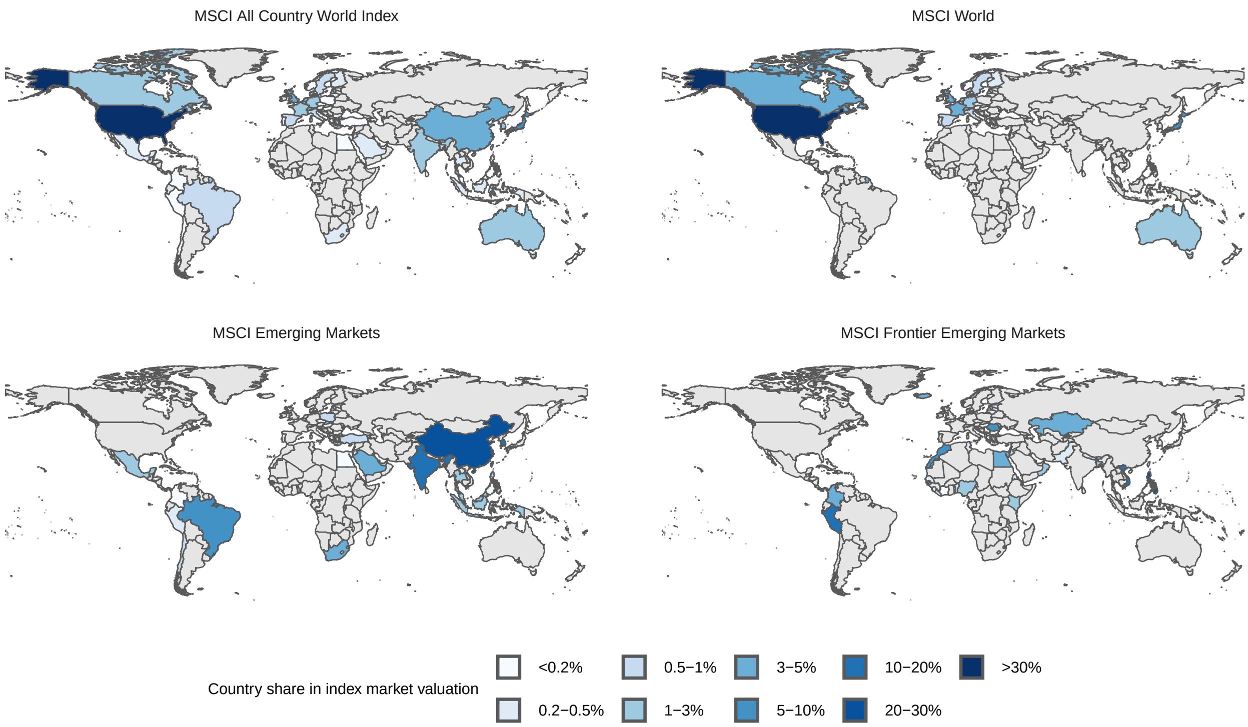

Figure S11. Country weights in the overall market valuation of different stock indices, as of 31 August 2023. The MSCI All Country World Index combines developed and emerging markets and thus gives a better overview of country shares in a global portfolio than the MSCI World.

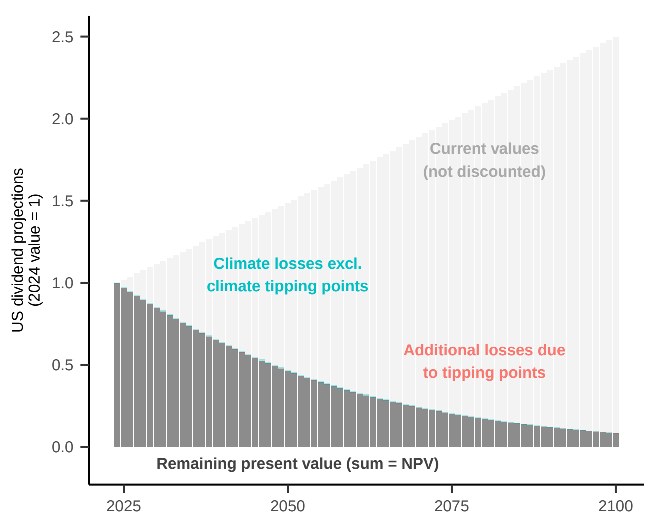

Figure S12. Fig. 1d without magnifying the climate losses excl. climate tipping points (blue bars) and the additional losses due to climate tipping points (red bars) for the sake of readability.

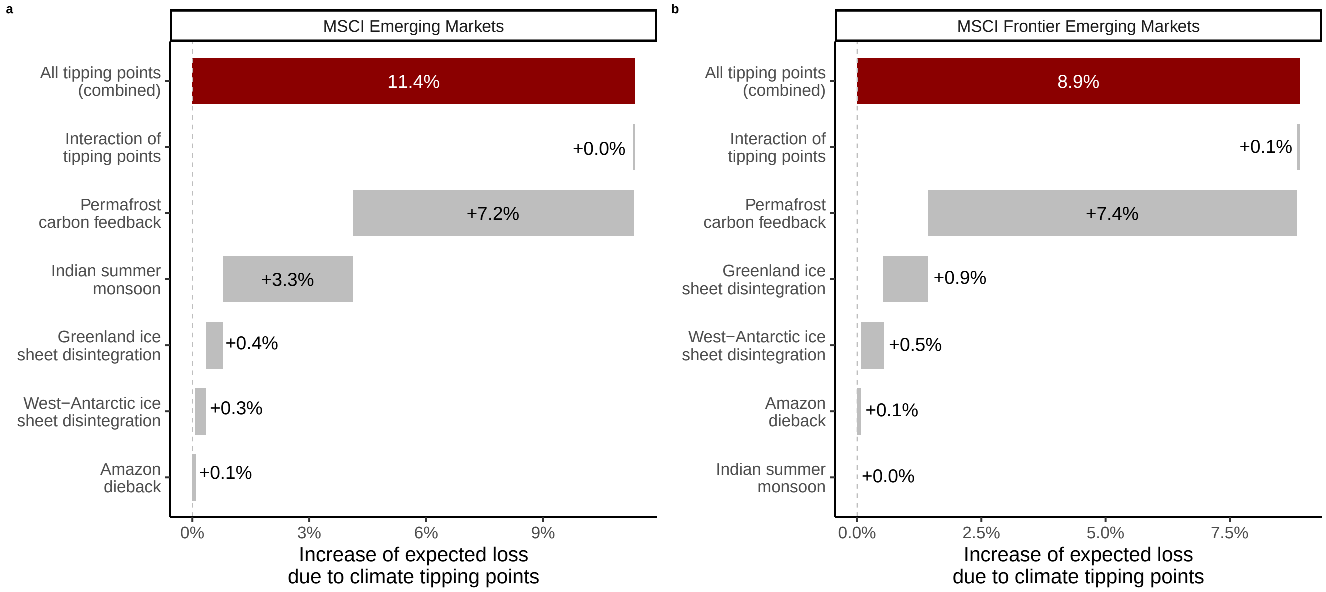

Figure S13. Contribution of individual tipping points to the overall rise in the expected loss due to climate tipping points for the MSCI Emerging Markets and the MSCI Frontier Emerging Markets under RCP4.5-SSP2. For definitions, see Fig. 4 in the main manuscript

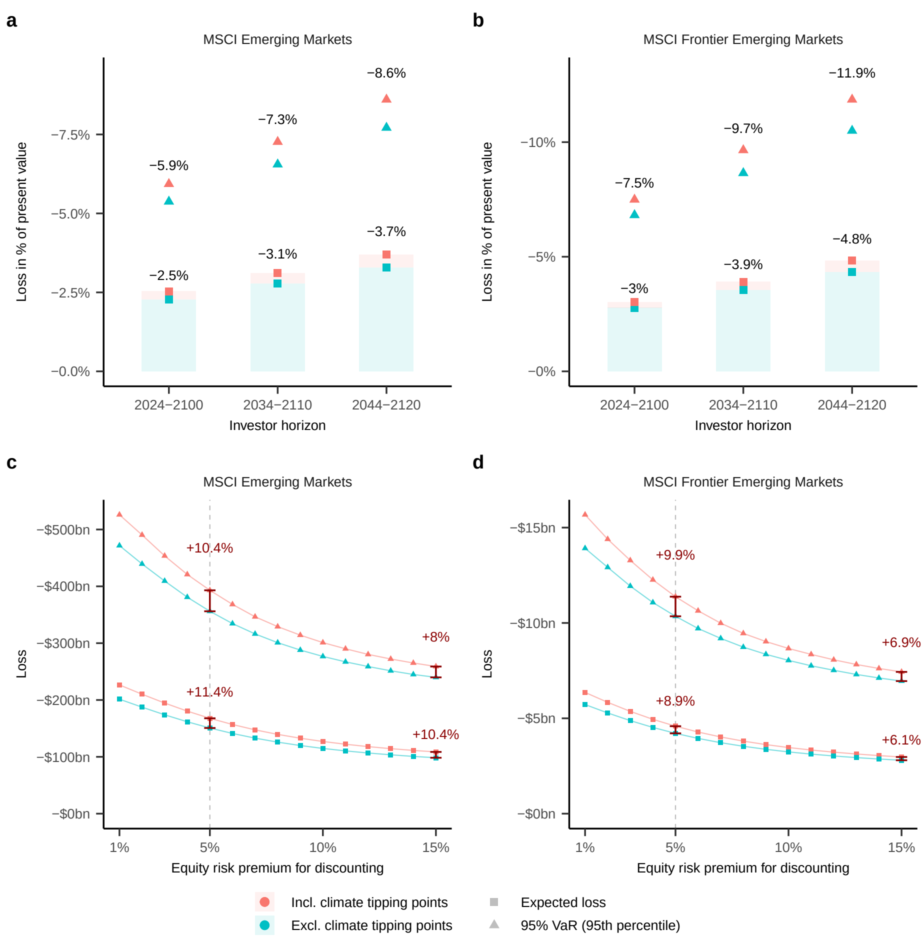

Figure S14. Expected loss and 95% VaR by investment time horizon and equity risk premium for the MSCI Emerging Markets and Frontier Emerging Markets under RCP4.5-SSP2. For definitions, see Fig. 4 in the main manuscript.

	Portfolio	RCP	SSP	TippingPoints	Mean	Median	1st perc.	5th perc.	95th perc.	99th perc.
1	MSCI World	RCP3-PD26	SSP2	all	0.92%	0.79%	0.1%	0.21%	2.1%	2.94%
2	MSCI World	RCP3-PD26	SSP2	none	0.82%	0.71%	0.09%	0.2%	1.83%	2.53%
3	MSCI World	RCP45	SSP2	all	1.52%	1.33%	0.15%	0.36%	3.39%	4.65%
4	MSCI World	RCP45	SSP2	none	1.37%	1.21%	0.14%	0.33%	3%	4.06%
5	MSCI World	RCP85	SSP2	all	2.85%	2.54%	0.22%	0.68%	6.17%	8.29%
6	MSCI World	RCP85	SSP2	none	2.61%	2.34%	0.2%	0.63%	5.56%	7.4%
7	MSCI EM	RCP3-PD26	SSP2	all	1.72%	1.5%	-0.29%	0.18%	4.15%	5.67%
8	MSCI EM	RCP3-PD26	SSP2	none	1.52%	1.32%	-0.36%	0.08%	3.71%	4.99%
9	MSCI EM	RCP45	SSP2	all	2.53%	2.24%	-0.52%	0.26%	5.93%	8%
10	MSCI EM	RCP45	SSP2	none	2.27%	2.02%	-0.57%	0.16%	5.37%	7.22%
11	MSCI EM	RCP85	SSP2	all	4.01%	3.62%	-0.91%	0.39%	9.19%	12.14%
12	MSCI EM	RCP85	SSP2	none	3.68%	3.34%	-0.96%	0.27%	8.48%	11.16%
13	MSCI FEM	RCP3-PD26	SSP2	all	2.09%	1.75%	-0.47%	0.18%	5.24%	7.38%
14	MSCI FEM	RCP3-PD26	SSP2	none	1.91%	1.62%	-0.44%	0.16%	4.75%	6.54%
15	MSCI FEM	RCP45	SSP2	all	3.02%	2.59%	-0.87%	0.2%	7.49%	10.42%
16	MSCI FEM	RCP45	SSP2	none	2.77%	2.4%	-0.82%	0.17%	6.82%	9.34%
17	MSCI FEM	RCP85	SSP2	all	4.83%	4.23%	-1.71%	0.15%	11.9%	16.24%
18	MSCI FEM	RCP85	SSP2	none	4.48%	3.96%	-1.61%	0.12%	10.95%	14.85%

Table S2. Summary statistics of the loss distribution for the key MSCI indices using SSP2 and the COACCH damage specification (main results)

	Portfolio	RCP	SSP	TippingPoints	Mean	Median	1st perc.	5th perc.	95th perc.	99th perc.
1	MSCI World	RCP45	SSP5	all	1.72%	1.51%	0.17%	0.41%	3.83%	5.26%
2	MSCI World	RCP45	SSP5	none	1.53%	1.36%	0.15%	0.37%	3.36%	4.54%
3	MSCI World	RCP85	SSP5	all	3.44%	3.08%	0.26%	0.83%	7.4%	9.96%
4	MSCI World	RCP85	SSP5	none	3.14%	2.83%	0.24%	0.76%	6.66%	8.86%
5	MSCI EM	RCP45	SSP5	all	2.69%	2.38%	-0.55%	0.27%	6.29%	8.49%
6	MSCI EM	RCP45	SSP5	none	2.42%	2.15%	-0.61%	0.17%	5.7%	7.66%
7	MSCI EM	RCP85	SSP5	all	4.38%	3.96%	-1%	0.42%	10.03%	13.29%
8	MSCI EM	RCP85	SSP5	none	4.02%	3.66%	-1.04%	0.3%	9.25%	12.18%
9	MSCI FEM	RCP45	SSP5	all	3.25%	2.79%	-0.94%	0.21%	8.06%	11.22%
10	MSCI FEM	RCP45	SSP5	none	2.98%	2.58%	-0.89%	0.18%	7.29%	9.99%
11	MSCI FEM	RCP85	SSP5	all	5.39%	4.73%	-1.9%	0.16%	13.24%	18.03%
12	MSCI FEM	RCP85	SSP5	none	4.99%	4.42%	-1.79%	0.13%	12.14%	16.47%

Table S3. Summary statistics of the loss distribution for the key MSCI indices using SSP5 and the COACCH damage specification

	Country	Expected loss (incl. TPs)	5% VAR (incl. TPs)	Expected loss (excl. TPs)	Increase of expected loss due to TPs (pp)	Relative increase
1	Mauritius	5.7%	11.6%	5.2%	0.5	+9.4%
2	India	5.6%	13%	4.7%	0.9	+19.5%
3	Senegal	5.3%	10.6%	4.9%	0.4	+9.1%
4	Cote d'Ivoire	5.2%	10.7%	4.8%	0.4	+8.8%
5	Malaysia	4.5%	10.7%	4.1%	0.4	+8.9%
6	Philippines	4.4%	10.3%	4%	0.4	+8.9%
7	Thailand	4.2%	10.3%	3.9%	0.3	+8.5%
8	Indonesia	4.1%	10%	3.8%	0.3	+8.3%
9	Viet Nam	4%	9.5%	3.7%	0.3	+8.3%
10	Netherlands	3.9%	6.5%	3.3%	0.6	+18%
11	Kenya	3.9%	8.1%	3.7%	0.3	+7.1%
12	Bangladesh	3.9%	8.5%	3.7%	0.2	+6.6%
13	Nigeria	3.7%	7.7%	3.5%	0.2	+6.7%
14	Morocco	3.5%	10%	3.1%	0.4	+12%
15	Pakistan	3%	6.7%	2.8%	0.1	+4.9%
16	Sri Lanka	2.9%	6.5%	2.8%	0.1	+4.9%
17	New Zealand	2.8%	6.5%	2.5%	0.3	+13.8%
18	South Africa	2.8%	6.5%	2.5%	0.3	+11.5%
19	Australia	2.7%	6.4%	2.4%	0.3	+13.6%
20	Republic of Korea	2.5%	5.4%	2.2%	0.2	+9.8%
21	Tunisia	2.3%	6.1%	2.1%	0.2	+9.3%
22	Chile	2.1%	7.2%	1.9%	0.2	+10.3%
23	Egypt	2.1%	6.1%	1.9%	0.2	+8.7%
24	Bahrain	2%	3.7%	1.8%	0.2	+10.2%
25	Peru	1.9%	6.6%	1.7%	0.2	+9.7%
26	Colombia	1.9%	6.4%	1.7%	0.2	+9.7%
27	Mexico	1.9%	6.4%	1.7%	0.2	+9.5%
28	Brazil	1.7%	5.8%	1.6%	0.1	+9.2%
29	China, Hong Kong SAR	1.7%	3.8%	1.6%	0.1	+6.5%
30	China, Taiwan Province of	1.7%	3.8%	1.6%	0.1	+6.5%
31	Japan	1.7%	4.5%	1.5%	0.2	+13.3%
32	Canada	1.7%	4.2%	1.5%	0.2	+10.9%
33	China	1.6%	3.7%	1.5%	0.1	+5.7%
34	Kuwait	1.6%	3.8%	1.5%	0.1	+8%
35	Denmark	1.6%	3.5%	1.4%	0.2	+14.3%
36	Qatar	1.6%	3.8%	1.5%	0.1	+7.5%
37	United Arab Emirates	1.5%	3.8%	1.4%	0.1	+7.2%
38	Saudi Arabia	1.5%	3.7%	1.4%	0.1	+7.1%
39	United States of America	1.5%	3.3%	1.4%	0.1	+10.8%
40	Estonia	1.5%	3.7%	1.3%	0.1	+10.9%
41	Lithuania	1.4%	3.7%	1.3%	0.1	+10.9%
42	Czechia	1.4%	3.7%	1.3%	0.1	+10.8%
43	Poland	1.4%	3.6%	1.3%	0.1	+10.7%
44	Oman	1.4%	3.3%	1.3%	0.1	+7.1%
45	Slovenia	1.3%	3.5%	1.2%	0.1	+10.3%
46	Israel	1.3%	3.1%	1.2%	0.1	+6.2%
47	Croatia	1.3%	3.2%	1.1%	0.1	+10.1%
48	United Kingdom	1.2%	3%	1.1%	0.1	+12.4%
49	Hungary	1.2%	3.2%	1.1%	0.1	+9.9%
50	Romania	1.2%	3.1%	1.1%	0.1	+9.9%
51	Ireland	1.2%	2.9%	1.1%	0.1	+12.4%
52	Kazakhstan	1.2%	2.9%	1.1%	0.1	+7%
53	Jordan	1.2%	3%	1.1%	0.1	+5.8%
54	Belgium	1.2%	2.9%	1.1%	0.1	+12.1%
55	Norway	1.2%	3%	1%	0.1	+12%
56	Germany	1.1%	3%	1%	0.1	+11.8%
57	Sweden	1.1%	3%	1%	0.1	+11.8%
58	Serbia	1.1%	2.9%	1%	0.1	+9.2%
59	France	1.1%	2.8%	1%	0.1	+11.4%
60	Finland	1.1%	2.8%	1%	0.1	+11.4%
61	Switzerland	1.1%	2.9%	1%	0.1	+11.2%
62	Portugal	1%	2.6%	0.9%	0.1	+11.2%
63	Austria	1%	2.7%	0.9%	0.1	+10.9%
64	Iceland	1%	2.6%	0.9%	0.1	+10.8%
65	Spain	1%	2.5%	0.9%	0.1	+10.9%
66	Turkey	0.9%	2.4%	0.9%	0	+4.6%
67	Greece	0.9%	2.3%	0.8%	0.1	+10.4%
68	Italy	0.9%	2.3%	0.8%	0.1	+10.1%

Table S4. Country-level results under SSP2-4.5 using the COACCH damage specification (used in Fig. 4) for all 68 countries that feature in any of the three stock indices considered in our analysis

	Name	Country Risk Premium
1	Sri Lanka	14.7%
2	Pakistan	12.2%
3	Tunisia	11%
4	Egypt	9.2%
5	Nigeria	9.2%
6	Kenya	7.9%
7	Turkey	7.9%
8	Bahrain	6.7%
9	Bangladesh	5.5%
10	Jordan	4.4%
11	Senegal	4.4%
12	Brazil	3.7%
13	Cote d'Ivoire	3.7%
14	Serbia	3.7%
15	Viet Nam	3.7%
16	South Africa	3.7%
17	Greece	3.1%
18	Morocco	3.1%
19	Oman	3.1%
20	India	2.7%
21	Italy	2.7%
22	Mauritius	2.7%
23	Romania	2.7%
24	Colombia	2.3%
25	Croatia	2.3%
26	Hungary	2.3%
27	Indonesia	2.3%
28	Kazakhstan	2.3%
29	Mexico	2.3%
30	Philippines	2.3%
31	Spain	2%
32	Peru	2%
33	Thailand	2%
34	Malaysia	1.5%
35	Portugal	1.5%
36	Slovenia	1.5%
37	Chile	1%
38	Iceland	1%
39	Israel	1%
40	Lithuania	1%
41	Poland	1%
42	China	0.9%
43	Estonia	0.9%
44	Japan	0.9%
45	Kuwait	0.9%
46	Saudi Arabia	0.9%
47	Belgium	0.7%
48	Czechia	0.7%
49	United Kingdom	0.7%
50	China, Hong Kong SAR	0.7%
51	Ireland	0.7%
52	China, Taiwan Province of	0.7%
53	United Arab Emirates	0.6%
54	France	0.6%
55	Republic of Korea	0.6%
56	Qatar	0.6%
57	Austria	0.5%
58	Finland	0.5%

Table S5. Country risk premium values used for the investor discount rate taken from the Damodaran database. Countries from Table S3 not listed here have a country risk premium of zero

	Country	MSCI ACWI share	GDP 2021 (in tn 2015 USD)	GDP share	Difference
1	United States of America	62.9%	20.53	26.7%	36.1%
2	Switzerland	2.5%	0.76	1%	1.5%
3	Canada	2.8%	1.68	2.2%	0.6%
4	Denmark	0.8%	0.34	0.4%	0.3%
5	China, Hong Kong SAR	0.6%	0.33	0.4%	0.1%
6	Sweden	0.8%	0.57	0.7%	0%
7	Netherlands	1.1%	0.85	1.1%	0%
8	Kuwait	0.1%	0.10	0.1%	-0.1%
9	Qatar	0.1%	0.16	0.2%	-0.1%
10	Finland	0.2%	0.26	0.3%	-0.1%
11	South Africa	0.3%	0.35	0.5%	-0.1%
12	Hungary	0%	0.15	0.2%	-0.2%
13	Australia	1.8%	1.52	2%	-0.2%
14	Greece	0%	0.20	0.3%	-0.2%
15	New Zealand	0%	0.21	0.3%	-0.2%
16	Portugal	0.1%	0.22	0.3%	-0.2%
17	Peru	0%	0.22	0.3%	-0.3%
18	Czechia	0%	0.21	0.3%	-0.3%
19	Japan	5.5%	4.44	5.8%	-0.3%
20	Chile	0.1%	0.28	0.4%	-0.3%
21	Malaysia	0.1%	0.36	0.5%	-0.3%
22	Israel	0.2%	0.38	0.5%	-0.3%
23	Thailand	0.2%	0.44	0.6%	-0.4%
24	France	3%	2.58	3.4%	-0.4%
25	Ireland	0.2%	0.45	0.6%	-0.4%
26	United Arab Emirates	0.1%	0.40	0.5%	-0.4%
27	Norway	0.2%	0.42	0.5%	-0.4%
28	United Kingdom	3.5%	3.04	4%	-0.4%
29	Belgium	0.2%	0.50	0.6%	-0.4%
30	Colombia	0%	0.33	0.4%	-0.4%
31	Philippines	0.1%	0.38	0.5%	-0.4%
32	Saudi Arabia	0.4%	0.67	0.9%	-0.4%
33	Austria	0%	0.41	0.5%	-0.5%
34	Egypt	0%	0.43	0.6%	-0.5%
35	Poland	0.1%	0.60	0.8%	-0.7%
36	Republic of Korea	1.3%	1.69	2.2%	-0.9%
37	Spain	0.6%	1.24	1.6%	-1%
38	Indonesia	0.2%	1.07	1.4%	-1.2%
39	Mexico	0.3%	1.21	1.6%	-1.3%
40	Turkey	0.1%	1.13	1.5%	-1.4%
41	Italy	0.6%	1.86	2.4%	-1.8%
42	Brazil	0.6%	1.83	2.4%	-1.8%
43	India	1.5%	2.73	3.5%	-2%
44	Germany	2.1%	3.55	4.6%	-2.6%
45	China	3.1%	15.80	20.6%	-17.5%

Table S6. Comparison of countries' weight in the MSCI All Country World Index (ACWI) and their share in the joint GDP of all MSCI ACWI countries. GDP data are taken from the Word Bank's World Development Indicators database, with the missing 2021 GDP value for Kuwait imputed with the country's 2020 value. Taiwan is omitted as it does not feature in the World Bank's GDP data. Singapore is omitted as it is not included in the META model and hence in our analysis

	Country	Weight in index
1	United States of America	70.2%
2	Japan	6.2%
3	United Kingdom	4%
4	France	3.3%
5	Canada	3.2%
6	Switzerland	2.7%
7	Germany	2.3%
8	Australia	2%
9	Netherlands	1.2%
10	Denmark	0.9%
11	Sweden	0.8%
12	Spain	0.7%
13	Italy	0.7%
14	China, Hong Kong SAR	0.6%
15	Belgium	0.3%
16	Finland	0.2%
17	Ireland	0.2%
18	Norway	0.2%
19	Israel	0.2%
20	Portugal	0.1%
21	New Zealand	0.1%
22	Austria	0%

Table S7. Country weights in the MSCI World used in our analysis (rounded to first digits). Singapore (weight: 0.4%) is omitted from our analysis as it is not included in the META model

	Country	Weight in index
1	China	29.8%
2	China, Taiwan Province of	15%
3	India	14.9%
4	Republic of Korea	12.2%
5	Brazil	5.3%
6	Saudi Arabia	4.2%
7	South Africa	3.2%
8	Mexico	2.8%
9	Thailand	2%
10	Indonesia	2%
11	Malaysia	1.4%
12	United Arab Emirates	1.3%
13	Qatar	0.9%
14	Poland	0.8%
15	Kuwait	0.8%
16	Turkey	0.7%
17	Philippines	0.6%
18	Chile	0.5%
19	Greece	0.5%
20	Peru	0.3%
21	Hungary	0.3%
22	Czechia	0.2%
23	Colombia	0.1%
24	Egypt	0.1%

Table S8. Country weights in the MSCI Emerging Markets used in our analysis (rounded to first digits)

	Country	Weight in index
1	Philippines	26.6%
2	Viet Nam	15.1%
3	Peru	12%
4	Romania	5.9%
5	Morocco	5.9%
6	Kazakhstan	4.7%
7	Iceland	4.3%
8	Colombia	4.2%
9	Egypt	3.8%
10	Slovenia	2.5%
11	Oman	2.3%
12	Nigeria	2.2%
13	Bangladesh	2.1%
14	Kenya	1.6%
15	Mauritius	1.2%
16	Bahrain	1%
17	Croatia	0.9%
18	Jordan	0.9%
19	Estonia	0.5%
20	Senegal	0.4%
21	Tunisia	0.4%
22	Sri Lanka	0.4%
23	Lithuania	0.4%
24	Pakistan	0.3%
25	Cote d'Ivoire	0.2%
26	Serbia	0.1%

Table S9. Country weights in the MSCI Frontier Emerging Markets used in our analysis (rounded to first digits)

References

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