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Discussion note

Economic impacts and pricing of climate risk

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Summary

- Climate risk affects the economy through physical and transition risks. Financial markets play a role in both allocating capital towards the climate transition and enabling risk sharing by pricing climate risks.
- Further investment is needed to reach emissions reductions that would keep warming below 2 degrees. This results in transition risk, particularly impacting sectors of the economy using and producing fossil fuels. Delays to emissions reductions can increase climate risk in the long term.
- Climate change increases both the acute physical risk from extreme weather and the chronic physical risk from long-run adverse changes to countries' climate and environment.
- Scenario analysis can be used to explore the impact of physical climate risk on asset prices. We put together physical climate risk scenarios that closely follow the approach of the NGFS, while attempting to address the known data quality issues in the now retracted Kotz, Levermann, and Wenz (2024) study, used by the NGFS in its Phase V scenarios. With these adjustments, we find smaller but still negative potential impacts on the equity market. There is high uncertainty related to model specifications.
- The academic literature measuring the impact of climate risk on asset prices has expanded significantly, covering different asset classes. Generally, there is evidence of climate risk increasing expected returns, consistent with theory.

1. Introduction

Climate change can impact economic growth and redistribute value between companies, sectors and markets. Risks and opportunities of climate change arise from mitigation, adaptation, and climate damages that occur despite these measures. These make climate risk a relevant concern for long-term investors.

In recent years there have been developments in data disclosure and academic research on the economics of climate risk. This has been supported by initiatives such as the Network for Greening the Financial System (NGFS), founded by central banks and financial supervisors.

In our previous work, we outlined how climate change can impact equity prices through both discount rate and cash flow channels, as well as due to financial and non-financial considerations (NBIM, 2021). In this note, we discuss different types of climate risks in detail, with a particular focus on impacts on cash flows, and how financial markets price these risks.

2. Impact of climate risk on economic growth

Climate risk is typically divided into transition and physical risk. Transition risk is driven by economic changes, technology and policies needed to transition to a lower-carbon economy. Transitioning away from fossil fuels is motivated by the need to reduce greenhouse gas emissions to limit global warming, which would otherwise increase physical risk in the long run, as well as by clean alternatives becoming economically competitive. Physical risk arises from climate and weather-related events or longer-term changes to climate patterns and the environment. In this section, we discuss types of physical and transition risk and how these may impact economic growth.

Transition risk

In many cases, reducing greenhouse gas emissions has costs in the short term. At a societal level, these costs must be weighed against the benefits of avoiding physical climate risk in the future.[1]

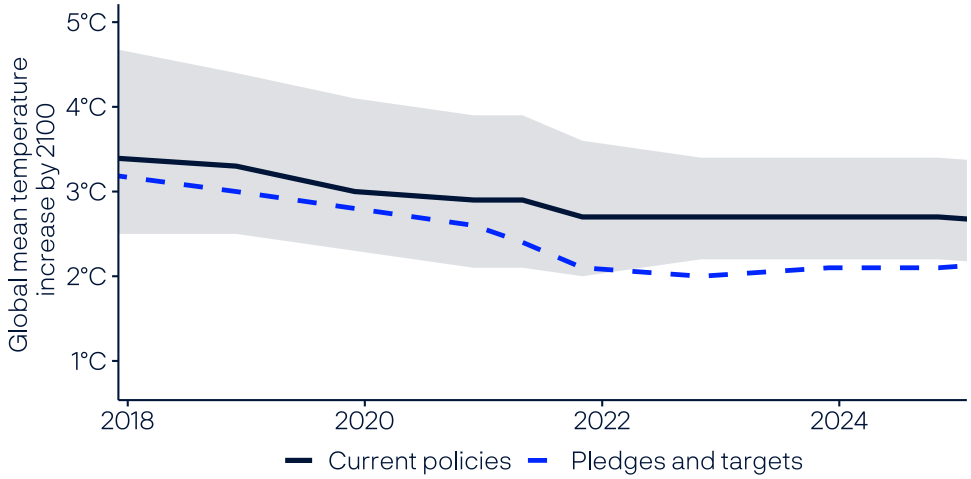
The world has so far warmed 1.3 degrees Celsius relative to pre-industrial levels. Each year since 2018, Climate Action Tracker has released its projection of future warming by 2100.[2] Figure 1 shows that its long-term warming estimates decreased between 2018 and 2022, but have since flattened. While assumptions and methodology have also changed over time, the Climate Action Tracker attributes some of the reduction shown in Figure 1 to progress in climate policy and technology.

Limiting global warming to below 2 degrees would substantially reduce the risks

[1] In the academic literature, this trade-off is often captured by calculating the social cost of carbon, which in its simplest form implies a global carbon tax. Recent estimates for the cost range from around 50 to over 500 US dollars per tonne of carbon dioxide (Tol, 2023).

[2] The Climate Action Tracker is an independent scientific project founded in 2009. It is currently maintained by the non-profit research organisations Climate Analytics and NewClimate Institute.

FIGURE 1 Projected global mean temperature increase by 2100



NOTE: Grey shaded area indicates the low and high temperature realisation modelled for the current policies scenario. Source: Climate Action Tracker, collected using Wayback Machine.

and impacts of climate change. Staying below this level would require cuts in global emissions over the next decade. According to the IPCC, reducing global emissions to net zero by 2050 is consistent with limiting warming to 2 degrees.[3] Higher warming will remain a possibility, and become more likely if the emissions reductions are delayed, or if climate feedbacks like permafrost thawing prove stronger or occur at lower levels of warming than expected.

In the 2015 Paris Agreement, 195 countries committed to keeping warming *well below* 2 degrees.[4] Governments have since pledged nationally-determined contributions to determine how to achieve this through national policy and legislation.[5] The cost of net zero would be at least as high as other large public spending programmes, such as the response to the Covid-19 pandemic and 2025 NATO rearmament.[6] This effort would result in transition risk for some companies and sectors, and opportunities for others. Its total economic impacts are challenging to measure and policy dependent.

Investment in clean energy represents a significant component of the transition, although not all constitutes a cost to the economy, as technological improvements have made some clean energy investments economically competitive independent of climate policies. Figure 2 shows how overall investment in clean

[3] Net zero means that no additional greenhouse gases are added to the atmosphere when we account for emissions removals or offsets. Technology to remove already emitted greenhouse gases from the atmosphere does not currently exist at scale, but forms a part of IPCC's assumptions.

[4] Holding warming to well below 2 degrees is best understood as taking action to reduce emissions in line with pathways that have a 90 percent or higher chance of limiting warming to 2 degrees, and that have a 33-66 percent chance to limit warming to 1.5 degrees.

[5] Country net zero plans are typically a combination of different policies, including subsidies for renewable technology, levies on emissions and regulated phasing out of carbon-intensive technologies.

[6] NGFS scenarios suggest that achieving net zero by 2050 would result in additional public investment cumulatively exceeding 25 percent of GDP for major economies including US, Japan and China. In Europe the total additional public investment required would exceed 15 percent of GDP (Network for Greening the Financial System, 2024b). Makin and Layton (2021) estimate that the cumulative public cost of the first two years of the Covid-19 pandemic was over 8 percent of GDP for developed economies and close to 4 percent for emerging economies. The commitment from NATO allies to increase their defence and related infrastructure spending to 5 percent of GDP by 2035 would result in an additional cumulative cost of 16.5 percent of GDP, assuming a linear increase from the current 2 percent baseline (NATO, 2025).

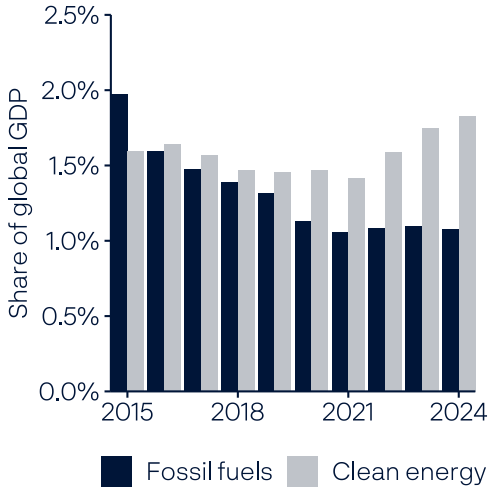
energy has evolved over time. As of 2025, two percent of world GDP was invested in clean energy each year. To reach net zero by 2050, further investment is needed. The International Energy Agency (IEA) estimates that annual investment in renewable energy would need to increase by two and a half times during the current decade.

Capital markets can support the climate transition by efficiently allocating capital toward decarbonisation investment and away from fossil fuel industries.[7] Figure 2 shows that the share of fossil fuel companies in equity markets has fallen in the last decade. Investment in innovation and research and development is needed both for physical risk mitigation and clean energy solutions. The technological progress from investing in climate innovation is however uncertain and constrained by resources. For example, critical minerals used in batteries and clean energy infrastructure are concentrated in only a few countries, making their supply vulnerable to trade disruptions.

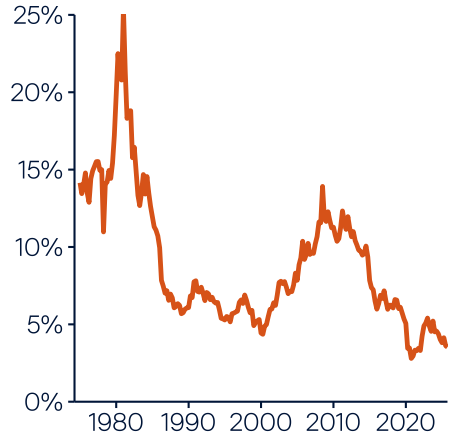
Moreover, the energy transition faces significant distribution and infrastructure challenges that create economic frictions beyond funding constraints. Energy's limited portability means that renewable capacity does not directly translate into reliable supply across different regions and over time (Kacperczyk and Licher, 2025). Uncertainty about future electricity demand has also increased due to technological developments in data and computing.[8] These considerations increase transition risk related to the deployment of clean energy.

FIGURE 2 Investment in clean energy and fossil fuels

(A) Global investment in clean energy and fossil fuels



(B) Share of oil and gas in listed equity market capitalisation



NOTE: Figure A) shows the total investment amounts reported in the International Energy Agency World Energy Investment report as share of global GDP from the World Bank. Figure B) shows the free-float-adjusted share of oil and gas stocks in the MSCI World All Cap Index. Source: World Bank, International Energy Agency, MSCI.

[7] In primary markets, capital is directly invested in renewable infrastructure or technologies, often with additional economic incentives from government subsidies. In secondary markets, pricing of climate risk and preferences can indirectly impact capital allocation through the cost of capital assumptions companies use in their investment decisions (Gormsen, Huber, and Oh, 2024).

[8] With the widespread adoption of energy-intensive generative artificial intelligence, electricity consumption by data centres is now expected to triple by 2030, increasing electricity demand (International Energy Agency, 2025).

Beyond technological challenges, there is uncertainty about the pace and scope of the energy transition itself. Climate regulations are influenced both by the legal system and political developments. Political outcomes can result in climate ambition being scaled up or down. Within the legal sphere, climate lawsuits have in some cases led countries and companies to adopt more ambitious policies and be held more accountable for their climate impacts.[9]

Postponing climate policy can increase transition risk and physical risk. On the one hand, delayed climate action means that to keep warming below a specific target, transition will have to take place faster. This can be more disruptive and come at a higher cost.[10] Climate policies may strengthen unexpectedly, causing planned economic activity such as certain types of fossil fuel production to not be viable any longer. On the other hand, if climate targets are not met, physical climate risk increases.

While uncertainty remains about whether past climate pledges will be fulfilled and whether new pledges will be made, physical risk is already materialising at current warming levels. Moreover, due to the delayed responses of the climate system, the warming taking place over the coming decades is largely determined by past emissions. This means it is important to understand the types and magnitudes of physical risk regardless of policy outcomes.

Physical risk

Physical risk can be acute or chronic, and have direct or indirect impacts. Acute risks arise from discrete hazards such as hurricanes, floods and wildfires. Chronic risks come from longer-term changes to climate patterns and the environment. Direct losses are the damages to people, property, infrastructure and natural resources. Indirect losses are the economic disruptions extending geographically and temporally beyond the initial event (US National Research Council, 1999).

To illustrate how acute physical risk can have direct and indirect effects on the economy, we use the example of Hurricane Katrina. It struck New Orleans in 2005 and remains one of the costliest climate-related natural disasters. It caused economic losses equivalent to one third of Louisiana's gross regional product in 2005, or over 200 billion in 2024 USD (US National Oceanic and Atmospheric Administration, 2025).[11] The wind, flooding and tornadoes directly caused 1,500 deaths and damaged buildings, bridges and other infrastructure (Mahalingam et al. 2018). However, the indirect losses proved at least equally severe. The disaster displaced 1.5 million people, resulted in the loss of 600,000 jobs, and disrupted transportation routes and supply chains throughout the region (Hallegatte, 2008; Hallegatte and Przyluski, 2010; Hallegatte, 2015; Mahalingam et al. 2018; Lenzen et al. 2019).

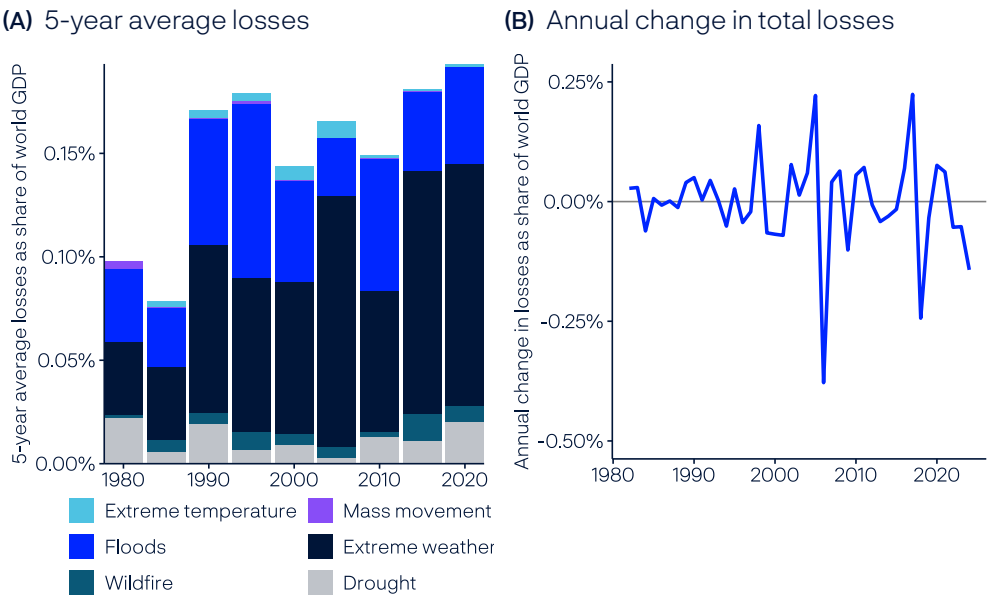
[9] For instance, in the Urgenda Foundation v. State of the Netherlands case, an environmental group successfully sued the state of the Netherlands to compel more ambitious emissions reductions to take place between 2015 and 2020.

[10] For instance, Network for Greening the Financial System (2024b) scenarios include a delayed transition with abrupt policy shifts which results in larger and more persistent economic impacts than a gradual, orderly transition.

[11] All loss figures are adjusted for inflation and stated in 2024 US dollars unless otherwise stated.

An example of the direct impacts of chronic physical climate risk is the fall in productivity in higher temperatures. Persistent increases in temperature can lower both labour and capital productivity. High heat is associated with health risks and worse concentration for workers (Somanathan et al. 2021). Companies also incur higher costs running and maintaining their equipment in such conditions (Ponticelli, Xu, and Zeume, 2023). An example of indirect impact of chronic risk is the trade disruption from water bodies that are becoming less navigable due to droughts. Quantifying the impacts of chronic physical risk has been a focus of the academic literature. In contrast, the insurance industry has focused on measuring and modelling the direct effects of acute physical risk, which we discuss first.

FIGURE 3 Climate-related disaster losses as share of world GDP from 1981 to 2023, inflation-adjusted.



NOTE: Figure A) shows the 5-year average losses from natural disasters reported by Emergency Events Database (EM-DAT) as share of global GDP from the World Bank. Figure B) shows the annual difference in total losses as share of global GDP. Source: World Bank, EM-DAT.

Bottom-up approaches to physical risk

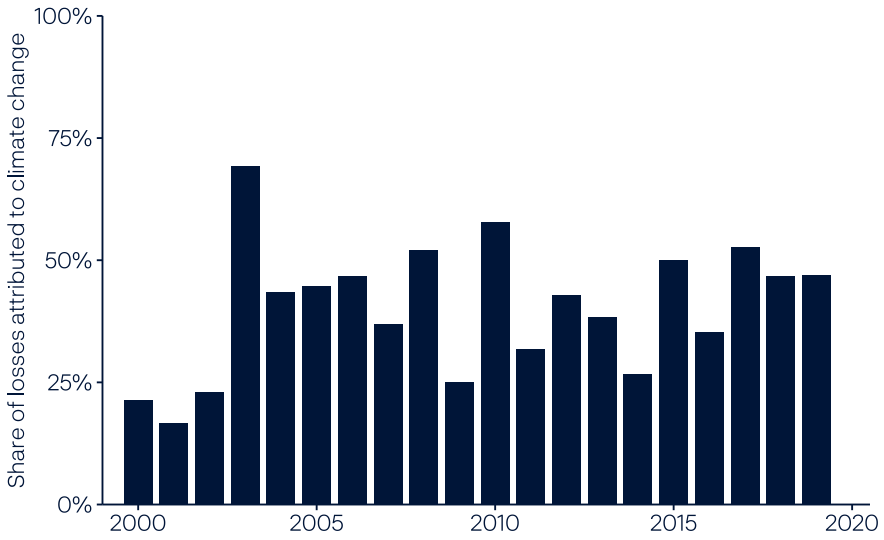
The insurance industry estimates losses from natural disasters. It mainly provides estimates for direct economic impacts of acute physical climate risk. This is based on reported insurance claims and, particularly for early estimates, catastrophe risk modelling. Catastrophe risk models simulate damages from natural disasters.[12] Institutes such as the Emergency Events Database aggregate and harmonise

[12] Catastrophe risk models quantify direct financial damages by combining hazard intensity metrics (such as flood depth or wind speed) with data on the location and vulnerability of buildings and infrastructure across a wide range of natural disasters. Indirect damages are usually only estimated if they are covered by the policy and estimated using economic models for lost revenue and increased operational costs. These models generate thousands of synthetic events through stochastic simulation, allowing insurers to assess potential losses from disasters that are physically plausible but have not yet occurred, and to understand risk distributions across time and space. When catastrophe models calibrate to historical observations, they implicitly assume relatively stationary climate conditions. As climate change alters the frequency and intensity of many perils, this assumption may weaken their predictive power. The industry has increasingly adopted climate-conditioned models, which integrate forward-looking climate information, such as changes in temperatures, into hazard modelling. The relevance of climate-conditioned models varies by application. Many insurance products renew annually and near-term climate adjustments may be modest.

natural disaster losses from multiple sources, including governments and insurers, therefore encompassing both insured and uninsured losses. Figure 3 panel A highlights that the majority of natural disaster losses in the last 50 years are due to flooding and extreme weather events (EM-DAT, CRED / UCLouvain and Our World in Data, 2025). Figure 3 also shows that in recent years, losses as a share of the world GDP have been increasing. Figure 3 panel B shows that recent losses from natural disasters vary more year-on-year. The years with high losses are driven by natural disasters exceeding historical precedents.

Economic damages tied to natural disasters are driven by two main factors which can be difficult to untangle: the impacts of climate change on the frequency, intensity, and geographic location of disasters, and the value of economic wealth exposed to disasters. Human-induced climate change has increased the risk of natural disasters (Field et al. 2012).[13] Climate change attribution studies have helped us understand how likely a specific weather event was in current conditions, against how likely the same event would have been in a world without human-induced greenhouse gas emissions (García-Portela and Maraun, 2023). Figure 4 shows 20-70 percent of annual extreme weather event damages are attributable to climate change.[14] For example, prolonged hot and dry conditions can increase wildfire risk, whereas sea level rise resulting from climate change can elevate future economic losses from storm surges (Barnes et al. 2025; Pourrabbani et al. 2020).

FIGURE 4 Share of losses from extreme weather events attributable to human-induced climate change



NOTE: Source: Newman and Noy (2023), own calculations.

As for the role of economic exposure, some of the increase in economic damages associated with natural disasters has also been attributed to the growing concentration of buildings and infrastructure in vulnerable areas. The relative

[13] For example, the latest annual assessment report from the IPCC notes that while it remains uncertain whether the frequency of tropical cyclones has increased, they have become more intense, cause heavier precipitation, and make landfall further north as a result of human-induced climate change.

[14] Years with a high share of damages attributed to climate change represent the 2003 European heat-wave, 2008 Tropical Cyclone Nargis in Myanmar and 2010 Russian heatwave and Somali drought.

contributions of climatic and non-climatic drivers to observed increases in disaster losses remain actively debated. For example, Muller et al. (2025) attribute rising hurricane damages primarily to socioeconomic factors such as coastal population growth and wealth. Grinsted, Ditlevsen, and Christensen (2019) find that an increase in wealth has contributed to larger economic damages from hurricanes over time. But when accounting for this effect, they find that climate change is also an important driver of observed increases in damages resulting from disasters.

These loss estimates from aggregated economic damages, while sophisticated, have important gaps (Gall, Borden, and Cutter, 2009). Firstly, earlier time periods have worse coverage, making it difficult to attribute the trend in reported disasters to climate change.[15] Secondly, events that have too small impacts to be reported may still have significant cumulative impacts. Finally, disasters occurring in regions with weak institutions are often under-reported (Osuteye, Johnson, and Brown, 2017; Jones, Guha-Sapir, and Tubeuf, 2022).

More importantly, these aggregate estimates do not capture the full economic impacts of physical risk. They do not include chronic risk, and even for natural disasters they focus primarily on direct damages while understating indirect impacts (Geneva Association, 2018). While the academic literature estimates that indirect effects can exceed direct damages, they vary significantly by disaster type, level of economic development, and region and thus are difficult to include in aggregate loss estimates (Rose and Wei, 2013; Hallegatte, 2015). Finally, it also matters who bears the cost. The distribution throughout the economy depends on public spending on disaster aid and recovery, and risk sharing through insurance and financial markets.[16] Smaller and less economically diversified countries face higher risks from disasters, which can increase economic inequality (UNDRR, 2025).

Top-down approaches to physical risk

Academic research has introduced top-down estimates of physical risk to address these gaps. Changes in GDP growth attributable to climate change can be a useful measure for understanding the overall impacts of climate change, as it captures both gains and losses that may offset each other at the aggregate level. Top-down empirical studies of physical risk test whether temperature and precipitation changes are associated with GDP growth. They aim to measure whether a relationship exists and how strong it is, letting the data reveal the overall effect instead of investigating the underlying mechanisms. There typically is not a detailed economic model motivating the empirical specification, which is a key drawback of these models. The resulting estimates form the backbone for projections of chronic physical climate risk scenarios and are widely used by institutions such as the NGFS.

[15] Ritchie and Rosado (2024) argue that due to the development of specialised reporting organisations and improvement in communication technologies since the 1990s, there is now more comprehensive coverage and better reporting quality compared to earlier historical periods.

[16] For Hurricane Katrina, just over 50 percent of the damages were insured (Pourrabbani et al. 2020). The insurance industry can respond to increasing risks by raising premiums and, in some cases, withdrawing from writing new policies in high-risk regions (Howden Re, 2025).

Top-down estimates can capture both permanent and temporary impacts on economic output (Schlenker and Auffhammer, 2018). The persistence of these effects depends on the impact channels, such as the productivity of different sectors and factors of production (Casey, Fried, and Gibson, 2024). For there to be a permanent impact, productivity would have to be directly related to the chronic changes in climate, such as warming, or to acute risks that occur with sufficient frequency and persistence to create cumulative chronic effects. If economies are most productive at mild temperatures, economic output will peak at a specific "optimal" temperature, with persistently lower growth when warming exceeds this optimal temperature.

We produce our own top-down estimates of physical risk following studies by Burke, Davis, and Diffenbaugh (2018), Kalkuhl and Wenz (2020) and Kotz et al. (2024).[17] We find that the impact estimates are sensitive to methodological choices and data used.[18] We provide estimates for the main approaches in the literature with consistent data and time period, including both country and subnational level of aggregation. National GDP data is from Penn World Table, and subnational data, consisting of individual administrative units within countries, is from S&P Global. This is a different source than the subnational DOSE data set from Wenz et al. (2023), which has been used in previous studies including the now retracted Kotz et al. (2024).The retraction of the study was due to inaccuracies in this data set, initially identified by Bearpark, Hogan, and Hsiang (2025).[19]

Our results following the three studies show economic impacts of temperature and precipitation changes in the short and long run.[20] These climate variables are included in a panel data model with time and geographic unit (country or subnational region) fixed effects. All three studies have statistical models of the general form:

$$\Delta \log(GDP_{i,t}) = \beta' C_{i,t} + \mu_i + \gamma_t + \theta_{1,i} t + \theta_{2,i} t^2 + \epsilon_{i,t} \quad (1)$$

where $C_{i,t}$ are climate variables, which can include lags, transformations, and interactions, μ_i and γ_t are country (or subnational) and year fixed effects, $\theta_{1,i} t + \theta_{2,i} t^2$ are country or subnational time trends, and $\epsilon_{i,t}$ is an error term.

Geographic fixed effects control for cross-sectional differences in growth that are due to factors unrelated to climate, such as institutions and geographic features. Time fixed effects control for temporal global shocks to economic growth common to all countries. The estimates of the impact of climate change on GDP growth are then based on the year-to-year weather variation within countries. For example, they will capture how the economy of a country performs when it experiences an unusually warm year compared to a typical year. While the aim is to

[17] Kotz et al. (2024), published in the journal Nature, has been retracted by the authors on 3rd of December 2025 due to inaccuracies in the underlying economic data.

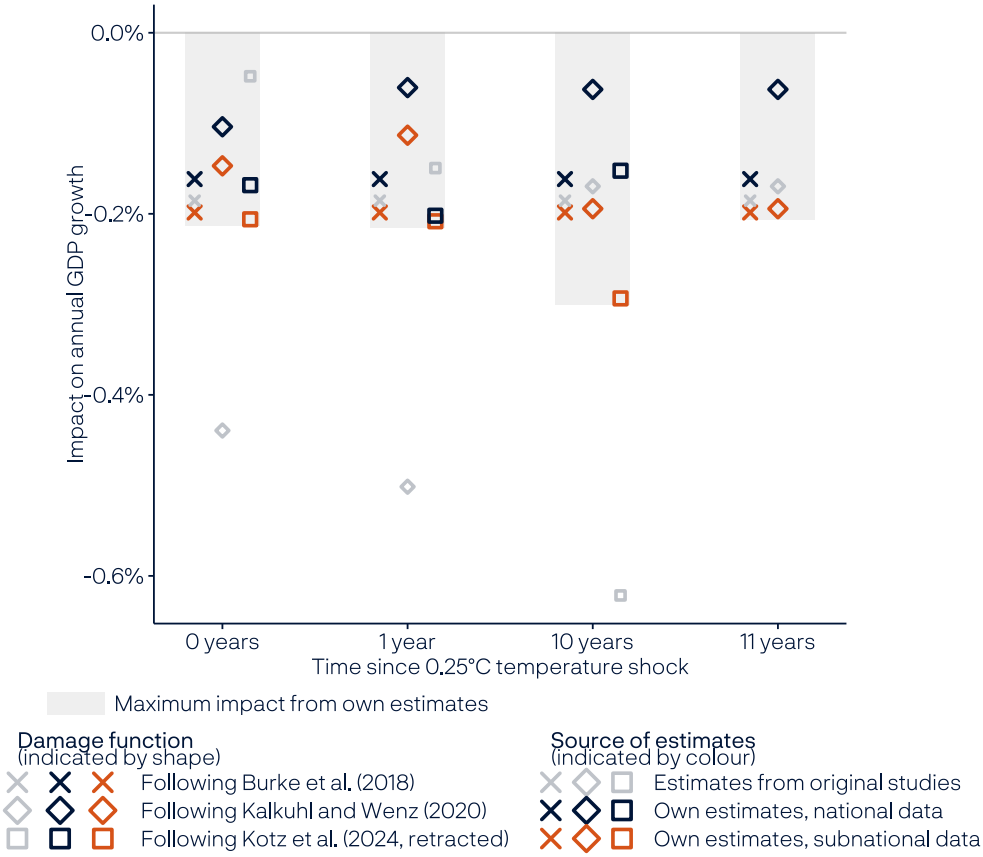
[18] The impact of methodological choices such as the specification of the damage function and the inclusion of time trends is also discussed in Newell, Prest, and Sexton (2021).

[19] Bearpark et al. (2025) identified data quality issues in the version of the DOSE data used by Kotz et al. (2024). A somewhat corrected version has subsequently been released, but as discussed in the Appendix A, we continue to find similar issues to those discussed by Bearpark et al. (2025).

[20] Kotz et al. (2024) specification also includes daily temperature variability, the number of wet days and extreme daily precipitation events, which are linked to changes in agricultural yields, flood damages and infrastructure disruptions.

model the effect of the *level* of temperature on growth, due to the fixed effects only within-country variation is used to estimate this effect. This is a limitation of this approach to project impacts of climate change over the longer term.

FIGURE 5 GDP growth impacts of a quarter degree increase in temperature



NOTE: Includes all coefficients. Estimates from original studies are as published, own estimates are using the same damage functions as the cited studies. Estimates based on country-level data are in black, and estimates based on subnational data are indicated in orange. Source: S&P Global, Penn World Table, ISIMIP3b, own calculations.

In Figure 5 we compare the impacts of a quarter degree Celsius immediate increase in average annual temperature for a hypothetical country with a baseline average temperature of 20 degrees Celsius, such as Singapore or Ecuador, at specific years following the initial temperature increase.[21] We present the results for three damage functions, using national and subnational data. In the first decade, using the methodology of Kotz et al. (2024) but different economic data, we find the largest fall in annual GDP growth of 0.3 percentage points 10 years after the initial shock. This compares to a 0.6 percentage point fall with the published estimates. The damage functions of Burke et al. (2018) and Kalkuhl and Wenz (2020) include permanent impacts. Our own estimates of these damage functions suggest that following a quarter degree increase in temperature, economic growth in a warm country would slow down by between 0.05 and 0.2 percentage points. It should be noted that the within R2, the R2 after taking out the explanatory power of the fixed effects, is modest across all specifications, ranging between 0.2 percent and 3 percent.

[21] For this exercise we made a number of assumptions. Appendix A discusses the timing of the shocks and progression of damages to GDP growth more in detail.

Climate impacts vary significantly based on a country's baseline temperature. Figure 6 shows how the marginal effects of warming depend on temperature. Countries with high baseline temperatures of over 20 degrees Celsius, such as the tropics, experience negative impacts, whereas countries starting below the optimal temperature threshold may experience higher growth under the most optimistic projections.

Figure 6 further highlights that the choice of national or subnational data affects the magnitude of estimates, especially for temperate and warmer countries. Briant, Combes, and Lafourcade (2010) show that the level of spatial granularity influences the identification of economic effects not related to climate.[22] For chronic physical risk, this issue has not yet been studied in detail.

However, there is a clear trade-off between country-level and subnational analysis. Country-level data offers broader coverage. National GDP data is available for more countries, particularly those without strong institutions that would support maintaining statistics on subnational economic activity. These countries are often the most sensitive to climate shocks and thus important to include. On the other hand, subnational data may be better at capturing climate variability within countries. If half of a country experiences drought while the other half floods, national precipitation averages may appear normal, masking critical variation. In addition, subnational data covers a wider range of climate conditions occurring within each country. This can increase statistical power by providing a larger sample size and more overall variation in temperature and precipitation. Finally, subnational data can capture more economic responses to climate shocks, as capital and workers can move far more easily within national borders than internationally.[23]

Top-down estimates of physical risk make several assumptions. GDP impacts aggregate losses with the gains from post-disaster recovery. To date we can assume most countries have had the spending capacity and resources to rebuild, but recovery may become more challenging when climate impacts become more frequent and severe in the future. Increased risk of future disasters will put pressure on public finances, particularly in low-income countries.[24]

While top-down econometric approaches offer valuable insights into the broader economic effects of climate change that bottom-up models may omit, they share some limitations.

Limitations of estimates of physical risk

A challenge with estimating climate change impacts on economic growth is that historical data does not capture the future distribution of climate outcomes. Climate change is bringing more volatile, more frequent and more severe events,

[22] Specifically, Briant et al. (2010) demonstrate that aggregating data to less granular spatial units can constrain the identification of the economic effects of trade and regional concentration.

[23] For example, Acharya, Bhardwaj, and Tomunen (2023) show that companies within the United States respond to heat shocks by shifting economic activity to unaffected regions. Such within-country adjustments will not be captured by country-level economic data.

[24] For example, see Smets, McDonald, Rezza, Hasanov, Dornan, Petrou, Doan, Parsons, Kojucharov, Last, Wilson, Shrivastava, Gamarra, Osborne, Irava, and Lele (2023) discussion on the impact of natural disasters on Vanuatu.

FIGURE 6 GDP growth impacts for different country temperature levels

NOTE: Including all coefficients. Estimates from original studies are as published, own estimates are using the same damage functions as the cited studies. Estimates based on country-level data are in black, and estimates based on subnational data are indicated in orange. Source: S&P Global, Penn World Table, ISIMIP3b, own calculations.

with sudden and accelerating changes becoming more likely as temperature rises (IPCC, 2021). This shift means that relying on historical data may underestimate risks, as it does not account for the high level of uncertainty of possible future outcomes under more severe climate change scenarios, including climate tipping points (Weitzman, 2011; Burke, Hsiang, and Miguel, 2015; Lenton, Rockström, Gaffney, Rahmstorf, Richardson, Steffen, and Schellnhuber, 2019).[25] More generally, the extent and impact of climate change is associated with deep, interacting uncertainties that current models struggle to fully capture.[26]

Changes to both economic and natural systems mean that even if historical climate patterns are repeated in the future, the economic impacts would differ from past experience. Supply chains and financial networks are making economies increasingly interconnected. This results in climate impacts

[25] A climate tipping point occurs when a small additional change in conditions triggers a disproportionately large and often irreversible shift in how a part of the climate system functions. Historical economic data cannot capture how crossing a climate tipping point would affect economic systems, though theoretical analysis suggests that these interactions would differ from the impacts of gradual climate variations present in historical data (Dietz et al. 2021).

[26] Recent work has begun developing frameworks to more formally account for them (Barnett, Brock, and Hansen, 2022).

transmitting to unexpected sectors and geographies more easily.[27] With higher physical risk, we would also expect to see more adaptation such as populations moving away from high-risk areas and investment in protective infrastructure (Deryugina and Hsiang, 2014; Dell, Jones, and Olken, 2014).

Nature degradation adds to these challenges. Environmental deterioration reduces ecosystems' capacity to deliver protective functions like flood protection and carbon sequestration, creating reinforcing cycles where nature degradation amplifies climate-related damages (Dasgupta, 2021).

Finally, both top-down and bottom-up approaches face methodological limitations in capturing the full scope of climate hazards and their interactions. Top-down models focusing on temperature and precipitation variables exclude hazards not directly related to these climate variables. Bottom-up approaches can assess different disaster types separately, but disasters often occur together or trigger each other with compounding effects that exceed the sum of their individual impacts.[28]

Top-down econometric models and bottom-up models are complementary, with each capturing different dimensions of climate risk. Bottom-up models can provide more precise loss estimates for individual hazards and help identify specific vulnerabilities and tail risk, but they do not capture their interactions or unforeseen changes to the climate and economy. Top-down analyses illustrate economy-wide effects, but there is substantial uncertainty across current estimates from top-down models, from minimal long-term effects to permanently slower growth. The existing top-down models are also not underpinned by economic modelling of the impact channels. Better understanding the economic impacts of physical climate risks will likely require a hybrid approach, where macroeconomic impacts are more grounded in the modelling of physical climate change (NGFS, 2024).

Physical climate risk and the cost of the climate transition should be reflected in the value of financial assets. In the next section we review the empirical evidence on the pricing of climate risk.

[27] An example of how losses from climate change can propagate through global supply chains is the 2010 Russian wheat crop failures, which triggered an export ban in Russia, affecting food prices in other regions (Hunt et al. 2021). Welton (2011) argues that high wheat prices were linked to social unrest in the wheat importing regions of North Africa and should be considered a possible contributing factor to the Arab Spring.

[28] For example, forests weakened by drought burn more easily and destroy buildings and infrastructure that make communities more vulnerable. When heavy rains hit this landscape the exposed population is more vulnerable to flooding and mudslides which in turn further damages buildings and infrastructure.

3. Pricing of climate risk

Despite the uncertainty and challenges, long-term investors need ways to quantify climate risk since potential losses are economically material. Climate risk can affect asset prices through multiple channels. The expectation from asset pricing theory is that investors will update their cash flow expectations based on information about climate risk, and demand a risk premium for being exposed to these risks. This means that assets that are more exposed to climate risk should have higher expected return in the long run. Conversely, assets with lower climate risk exposure have lower expected return in the long run.[29]

Scenario analysis and empirical research on the pricing of climate risk across asset classes can both help quantify these effects. In this section, we discuss both approaches, starting with physical climate risk scenarios.

Portfolio impacts of physical climate risk scenarios

The NGFS has led the development of physical risk scenarios for financial assets. Its approach to modelling chronic physical risk is based on the top-down estimates introduced in Section 2, and should be viewed in the light of the limitations discussed there. Most recent long-term physical risk scenarios in NGFS Phase V are constructed using the damage function presented in Kotz et al. (2024). This study has since been retracted, so in our scenarios we use our own top-down estimates of physical risk, while otherwise following the NGFS approach as closely as possible. We do this to be able to relate to the scenario analysis presented in our Climate and Nature Disclosures 2024.

We combine the top-down estimates with projections from different climate scenarios to calculate forward-looking GDP impacts. We then assume that a fall in GDP growth directly corresponds to a fall in expected dividend growth, and calculate the resulting impact on the value of the equity market following NBIM (2021).[30,31] An alternative to this would be to try to model expected dividend growth directly rather than based on GDP. To the extent that a climate-induced decline in GDP growth does not lead to an equivalent decline in dividend growth over the long term, our use of GDP growth as a proxy for dividend growth could lead us to overestimate the effect of climate change on the equity market.

Our results are shown in Figure 7. We include the uncertainty from using different climate models for the same climate scenario, which we discuss in more detail in the Appendix A. We estimate the median impacts for the Current policies climate

[29] These asset pricing models are discussed in NBIM (2021) both for non-financially motivated and risk-based climate investing, following Pástor, Stambaugh, and Taylor (2021), Pedersen, Fitzgibbons, and Pomorski (2021) and Giglio et al. (2021). In the non-financial model an investor has preferences for assets with green characteristics, while in the risk-based model investors can invest in a green asset that hedges physical climate risk.

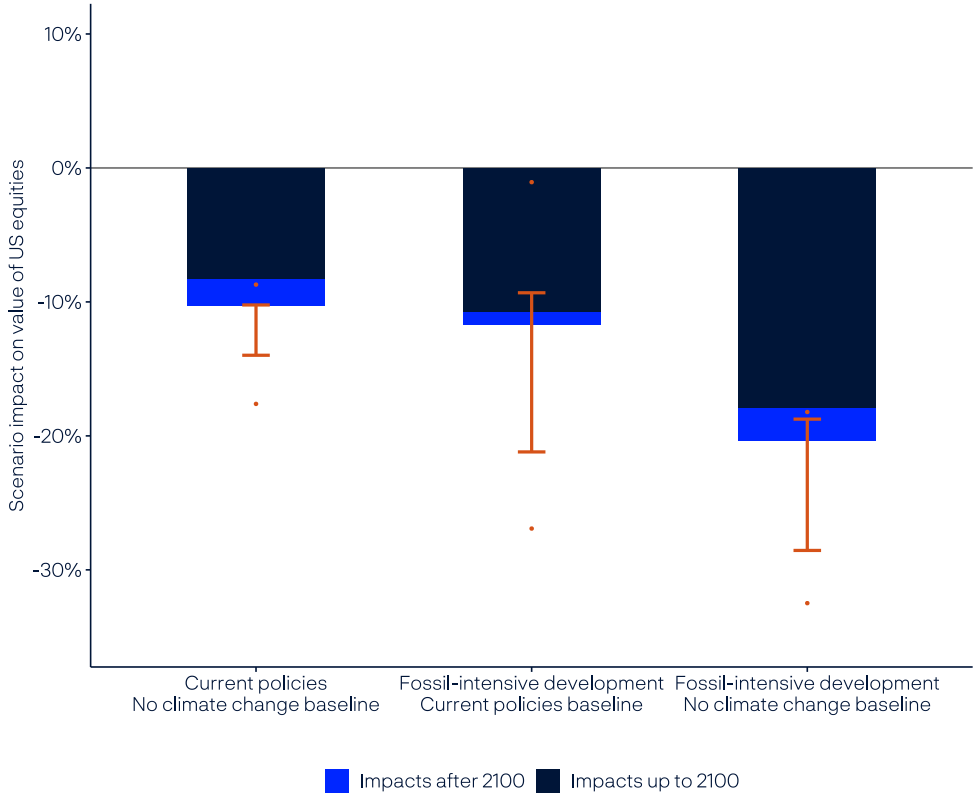
[30] In this exercise we assume that the term structure of interest rates and risk premia does not change. In practice, large negative shocks to growth expectations would likely result in an increase in the equity risk premium, and a fall in nominal interest rates, but it would require additional modelling to quantify this. Including these potentially offsetting responses would affect the estimated equity impact.

[31] We use US equities as a proxy for global equities.

scenario relative to a baseline with no climate change.[32] We find a -8 to -10 percent impact to equities depending on whether we assume warming continues beyond 2100.[33]

We also estimate equity market impacts for a scenario where investors have already priced in warming consistent with current climate policies. For this we use the fossil-intensive development climate scenario, which represents the high end of the range of future emissions pathways in the climate literature (O'Neill et al. 2016). With this baseline, we are measuring the impact of an unexpected shift from moderate future warming to a much higher warming trajectory. This captures the potential shock to the equity market if the world fails to follow through on climate policies, leading to significantly higher future temperatures than markets may have priced in. Under this surprise warming scenario, we estimate a -12 percent impact on equities.

FIGURE 7 Chronic physical risk scenarios for the equity market



NOTE: Equity data as of 31st of December 2025, damage function following Kotz et al. (2024). The bars indicate the median equity impacts from different climate models for the same scenario. The whisker plots indicate the 25th and 75th percentile of impacts from a group of climate models for the same scenario. The dots indicate the minimum and maximum. Source: NBIM, ISIMIP3b, own calculations.

The question of how much climate risk is reflected in asset prices, and whether

[32] Current policies is a scenario based on Shared Socio-Economic Pathway 2 and Representative Concentration Pathway 4.5 and results in warming of 2.7 degrees Celsius relative to pre-industrial levels by the end of the century (median estimate). This is a 'middle of the road' scenario where greenhouse gas projections follow historical trends before tapering off before 2100.

[33] With originally published estimates from Kotz et al. (2024), impact to equity value would be between -14 and -21 percent. With the national level estimates, economies with annual average temperature similar to the US experience positive impacts.

this presents mispricing, has been widely discussed.[34] Empirical studies can help measure whether investors do in fact take climate risk into account.

Empirical evidence

The academic literature defines *green* assets as having low exposure to climate risk, and *brown* assets as having high exposure to climate risk.[35] The pricing of green and brown assets has been studied across a wide range of financial assets, such as equities and real estate. In the theoretical models of the pricing of climate risk, investors expect to earn lower returns on green assets in equilibrium. However in a transition period where demand for sustainable investments is increasing, expected returns for green assets fall and their prices increase relative to brown assets.[36]

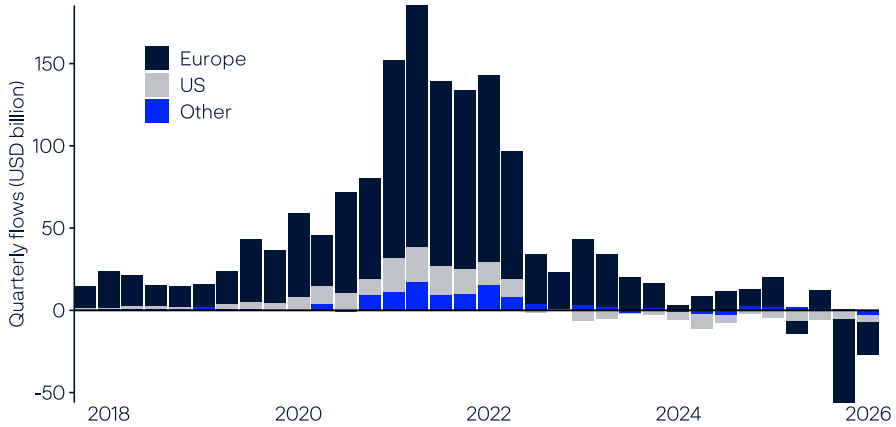
This repricing can help explain the returns of green and brown assets in the last decade. Sustainable investments increased in popularity, and over the same period, many green assets did have relatively high realised returns. There were large positive flows into sustainable funds as shown in Figure 8. Institutional investors also set up sustainable investor alliances. Their focus on disclosure has made more information on sustainability available to investors. For example, the majority of large listed companies now disclose their annual emissions. Furthermore, financial data providers have developed various metrics on both physical and transition climate risk exposures.[37]

As more data has become available, the academic literature studying the association between climate risk and asset returns has also expanded. The goal for these empirical studies is to distinguish between realised and expected returns. As described above, an increase in investor preferences or concern about climate risk can result in higher realised returns for green assets during a transition period, while having the opposite impact on expected return in the long run.

These transition periods make it challenging to identify the difference in returns that is driven by exposure to climate risk. Adding to this, major events like the Covid-19 pandemic and Russia's war against Ukraine had a large impact on energy and commodity prices. Brown assets are more exposed to these, making it even more challenging to isolate the effect of climate risk on returns over this period. Despite these challenges, the academic literature surveyed below finds evidence that climate risk is being priced in financial assets.

[34] For example, Bank of England (2021) suggests that market prices of corporate bonds may not fully reflect the risks and opportunities associated with net zero.
[35] If focusing on non-financial aspects, green assets can be defined as having positive climate impact, and brown assets as having negative climate impact.
[36] For models considering climate risk, this happens when investor awareness of climate risk increases. Within the non-financially motivated models, this would be driven by a shift in investor preferences towards green investments.
[37] For instance, see NBIM Climate and Nature Disclosures 2025.

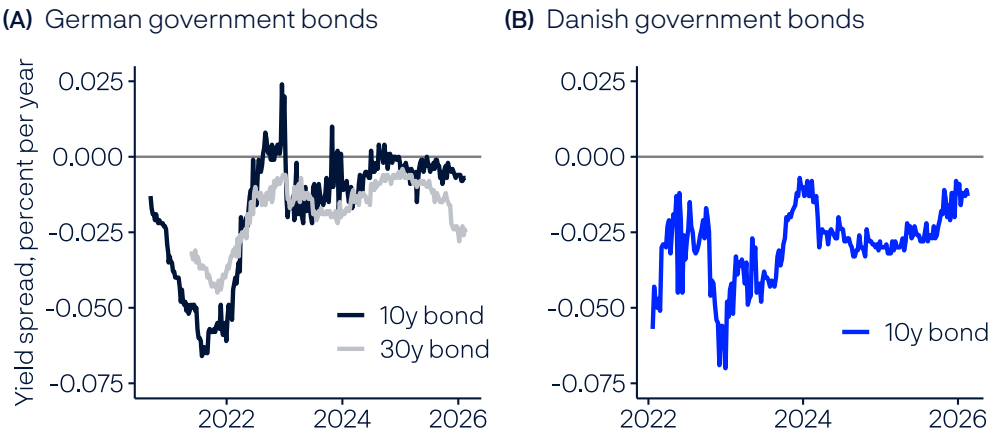
FIGURE 8 Investment flows into sustainable funds over time



NOTE: Includes investment flows into 3,432 open-end funds and exchange-traded funds that use ESG criteria as investment criteria, or pursue impact alongside financial return. Funds are grouped based on their domicile. Source: Morningstar.

In most cases, green and brown assets have different characteristics. One exception is green government twin bonds, which allow for a comparison of a green and brown asset with identical cash flows and risk properties. The German and Danish governments have issued such bonds, where both securities have the same coupon and maturity, but the proceeds from the green bond are used for sustainability projects. In Figure 9 we update the analysis of Pástor, Stambaugh, and Taylor (2022) on the spread in yield between the green and the brown bond. This difference can be interpreted as the green bond having lower expected return. Especially for the German twin bonds this spread has narrowed since 2022, but remains negative on average.

FIGURE 9 Pricing of twin government green bonds



NOTE: The figure shows the difference in bid yields of green bonds compared to their twin government bond, showing the maturity at issuance. Source: Bloomberg.

For municipal bonds, the academic literature has established a link between physical climate risk and the borrowing costs of local governments in the United States. Painter (2020) and Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2023) document that long-term municipal bonds in counties vulnerable to sea level rise are issued at a significant premium. Jeon, Barrage, and Walsh (2024)

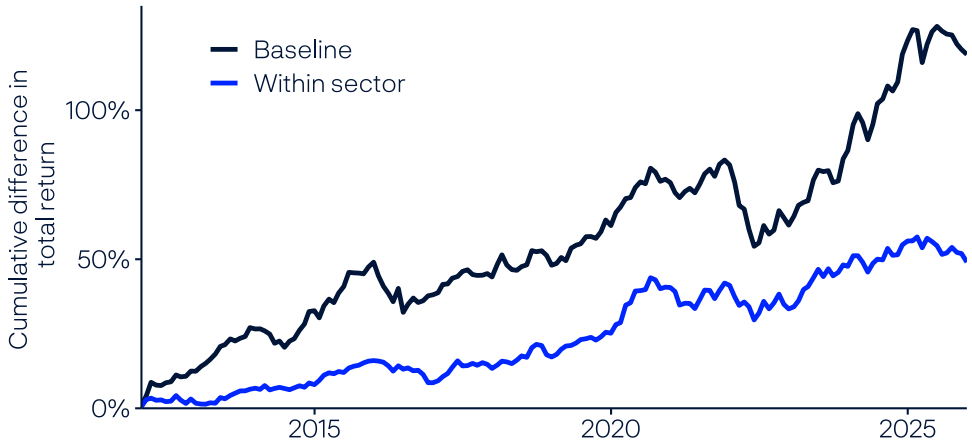
show that borrowing costs are significantly higher in municipalities with higher future wildfire risk. In secondary markets, Auh, Choi, Deryugina, and Park (2022) identify that municipal bond prices fall in response to natural disasters.

Similarly, there is evidence that real estate prices increasingly reflect physical risk. For example, Giglio et al. (2021) and Bernstein, Gustafson, and Lewis (2019) show that the risk of sea level rise is reflected in the house prices in the United States. Chiang, Feng, and Harrison (2022) find that days of extreme heat negatively impact commercial real estate returns.

Finally, there is an extensive literature on the pricing of climate risk in equities. We use equity fundamentals from FactSet and emissions data from S&P Trucost to illustrate some of the main findings.[38] For most of the results, we measure company emissions using emissions intensity, where we normalise the total greenhouse gas emissions by company revenue. This is based on the intensity for direct emissions and indirect emissions from purchased electricity and heat, known as Scopes 1 and 2. Greenhouse gas emissions are used in this setting as a proxy for companies' climate risk exposure, even if they are far from a comprehensive measure of all aspects of climate risk. For example, as reported in Table 1, clean energy stocks often have high emissions intensity.

To study the difference in realised stock returns, we sort global stocks into three groups by emissions intensity. In Figure 10, we show the resulting cumulative return spread, which is called the green-minus-brown factor in Pástor et al. (2022).[39] Over the last two decades, green stocks had higher realised returns than brown stocks.[40]

FIGURE 10 Green-minus-brown spread for global stocks



NOTE: The figure shows the cumulative green-minus-brown return spread for companies sorted by their Scope 1 and 2 emissions intensity, across all sectors or within each ICB sector. Based on total returns in US dollars, weighted by market capitalisation. Source: FactSet, FTSE, own calculations.

[38] We discuss the reliability, release timeline and different sources of emissions data in Appendix B.

[39] In our implementation, we sort stocks based on emissions intensities from S&P Trucost instead of the environmental component of ESG scores. As emissions intensities are a major component of the MSCI scores used by Pástor et al. (2022), we expectedly achieve a relatively high correlation with the original green-minus-brown spread.

[40] This result aligns with findings in the literature. For example, Zhang (2025) reports similar results for US stocks and Bauer et al. (2022) for global stocks.

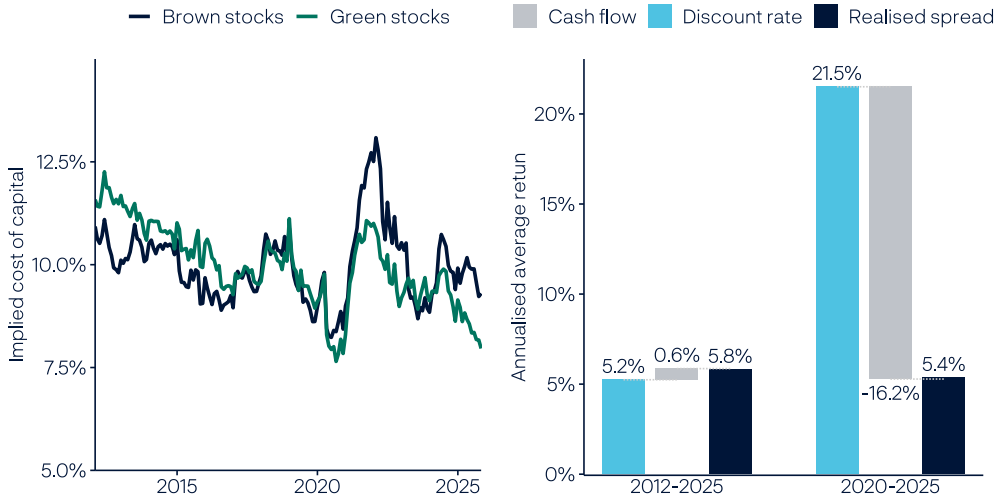
Following the methodology in Ardia, Bluteau, Boudt, and Inghelbrecht (2023), we decompose this difference in realised returns of green and brown stocks into a cash flow and a discount rate component. Our results are shown in Figure 11. This methodology uses analyst earnings estimates to measure company-specific cash flow news. Stock price moves not explained by cash flow news are then attributed to changes in cost of capital. In Figure 11A), we see that the implied cost of capital of brown companies relative to green companies has been increasing since 2012. This provides an indirect measure of changes in expected return. The decomposition shown in Figure 11B) suggests that since 2012, the green-minus-brown spread has been driven by a fall in the expected return of green stocks relative to brown stocks.

The academic literature has linked the shift in relative expected returns in this period to the growth in capital with sustainable investment objectives. Pástor et al. (2022) regress the green-minus-brown return on increasing climate attention and find that this explains a large share of the outperformance of green stocks. The impact of capital flows has also been studied through the lens of demand-based asset pricing. Using dividend reinvestment to estimate the elasticity of demand, Van der Beck (2025) estimates that flows into environmental, social, and governance investing increased the annual returns of United States environmental, social, and governance stocks by 1.9 percent in the last decade.[41] Consistent with this, Figure 11A) shows that the implied cost of capital of brown companies increased the most around the time sustainable funds received large inflows.

FIGURE 11 Drivers of the green-minus-brown spread

(A) Value-weighted implied cost of capital

(B) Return decomposition of the green-minus-brown spread



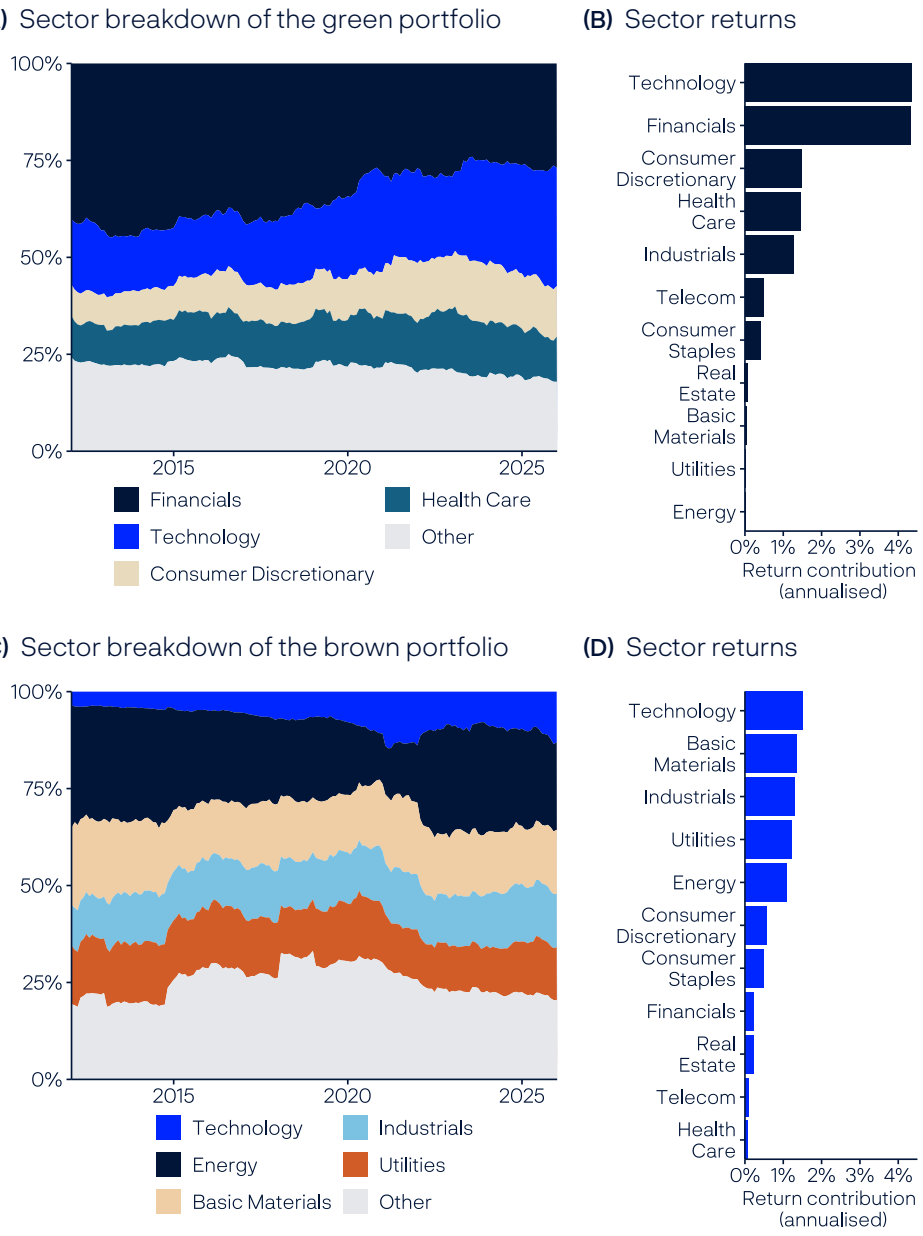
NOTE: Cash flow decomposition following Ardia et al. (2023) for companies sorted by their Scope 1 and 2 emissions intensity across all sectors. Source: FactSet, NBIM calculations.

Figure 11B) shows that since 2020, the shift in expected returns would have resulted in even higher green-minus-brown returns if there had not been an offsetting cash flow effect. In Table 1 we show that brown companies have more

[41] The author identifies 'ESG stocks' as those overweighted by mutual funds with sustainability keywords in their names. The impact on annual returns is estimated for the period from 2012 to 2023.

negative revisions to their earnings forecasts, and that the analyst consensus for their long-term earnings growth rate is also lower. However, earnings estimates for brown companies were significantly revised upwards around 2021 and 2022.[42] As also discussed in Shi and Zhang (2024), energy and commodity markets impact the cash flows of many brown companies, and during this period energy prices increased starkly especially in Europe. The average green-minus-brown spread for this period was -2.6 percent.

FIGURE 12 Sector exposures of the green-minus-brown long and short portfolios



NOTE: For companies sorted by their Scope 1 and 2 emissions intensity across all sectors.
Source: FactSet, FTSE.

[42] See Appendix B for the annual decomposition of green-minus-brown returns into cash flow and discount rate effects.

TABLE 1 Descriptive statistics for portfolios sorted on Scope 1 and Scope 2 emissions intensity

Variable	Brown	Other stocks	Green
Sample size (N)	307,903	307,669	308,103
Total emissions (Gt CO_2e)	11.02	0.24	0.06
% of clean tech index	50.0%	20.4%	29.7%
% covered by earnings estimates	69.8%	82.8%	86.1%
Value-weighted average			
Market cap in USD	$115.8B	$242.1B	$222.0B
Price to earnings	22.44	32.37	28.16
Number of analysts for estimates	18	23	23
1-year earnings revision	-1.65%	-0.74%	-0.31%
Long-term growth rate	10.15%	12.40%	12.07%

NOTE: For companies sorted by their Scope 1 and 2 emissions intensity across all sectors for 2012-2025. Green tech index is the S&P Global Clean Energy Transition Index. Total emissions are the unwinsorized Scope 1 total emissions as of 31st of December 2025. Source: FactSet, S&P.

Green-minus-brown return can also be explained by characteristics of the highest and lowest emissions intensity companies that are not related to climate risk. First, as suggested by Table 1, brown companies tend to be smaller and have lower valuations. Second, there is a difference in the sector composition as shown in Figure 12. If companies are sorted based on emissions intensity across all sectors, financial and technology companies form a majority of the green portfolio, and contribute most of the realised returns. Financial and technology are sectors with many other drivers of return beyond climate risk, which will also impact earnings expectations, implied cost of capital and the resulting green-minus-brown return. When companies are sorted within their sector, the green-minus-brown spread in Figure 10 remains positive but halves in size.

Considering the different characteristics of brown and green stocks, it can therefore be desirable to control for additional variables in empirical estimates of pricing of climate risk in equities. We therefore also use panel regressions to control for a range of firm-specific characteristics. Bolton and Kacperczyk (2021) and subsequent studies use cross-sectional regressions of asset returns with a large set of control variables and fixed effects for time, country and sector:

$$\text{RET}_{i,t} = a_0 + a_1 \text{Emissions}_{i,t-1} + a_2 \text{Controls}_{i,t-1} + \mu_t + \mu_s + \mu_c + \epsilon_{i,t} \qquad (2)$$

In this regression model $\text{RET}_{i,t}$ is the stock return of company i in period t, and $\epsilon_{i,t}$ is an error term. $\text{Emissions}_{i,t-1}$ are different emissions variables and $\text{Controls}_{i,t-1}$ are company fundamentals such as market capitalisation, book-to-market ratio, and leverage. Our results are for annual excess returns following Crosignani, Osambela, and Pritsker (2025), and are shown in Table 2. In the Appendix we also show results for only company-disclosed emissions, which show comparable

patterns.[43] We provide results both with and without industry fixed effects.[44]

Focusing on the combined emissions from Scopes 1 and 2, we find that with additional control variables, the higher performance of green stocks tends to disappear. When emissions are separated by scope, the picture is slightly more nuanced, especially for indirect emissions.[45] Positive coefficients are consistent with the prediction from asset pricing theory that in the long run, brown stocks should have higher expected returns.

TABLE 2 Regressions of Scope 1 and 2 emissions on annual excess returns of global stocks

Dependent Variable: Annual excess return	(1)	(2)	(3)	(4)
Scope 1+2 log emissions	0.330***	0.765***		
	(0.073)	(0.128)		
Scope 1+2 log emissions intensity			-0.074	0.183
			(0.087)	(0.152)
Controls	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	No	Yes	No	Yes
Observations	72,197	72,197	72,197	72,197
R-squared	0.164	0.171	0.164	0.171
Within R-squared	0.008	0.009	0.008	0.009

NOTE: For years 2004-2025, data as of 13th of February 2026. Columns (1) and (2) show regressions using log total Scope 1 and 2 emissions. Columns (3) and (4) show regressions using log emissions intensity for Scope 1 and 2. Annual excess returns are winsorized at 250 percent. Control variables are the same as in Crosignani et al. (2025). Industry fixed effects use FactSet classification. Standard errors are clustered at the firm level and reported in parentheses. Statistical significance at the 5, 1, and 0.1 percent levels is indicated by *, **, and *** respectively.

The results also show that emissions contribute modestly to explaining cross-sectional variation in stock returns. The explanatory power of emissions shown in Figure 13 is generally not high but on par with other stock market anomalies besides size and value. This supports the interpretation that transition risk measured by company emissions is priced by the financial markets.

Pricing of physical risk in equities has so far received less attention, as it is hard to measure how much different companies are exposed to physical risk. This mirrors

[43] Reported emissions are publicly available in contrast to commercial data sets such as S&P Trucost, which makes it more plausible they are considered by investors. Only using reported emissions also avoids issues related to how emissions data is imputed for companies that do not report, as discussed in Aswani, Raghunandan, and Rajgopal (2024). On the other hand, as companies in most cases report their emissions voluntarily, focusing on only disclosed emissions can result in selection bias. Our approach to identifying disclosed companies differs slightly from Aswani et al. (2024), who classify a company's emissions as 'disclosed' based solely on whether the company reports its direct emissions (Scope 1).

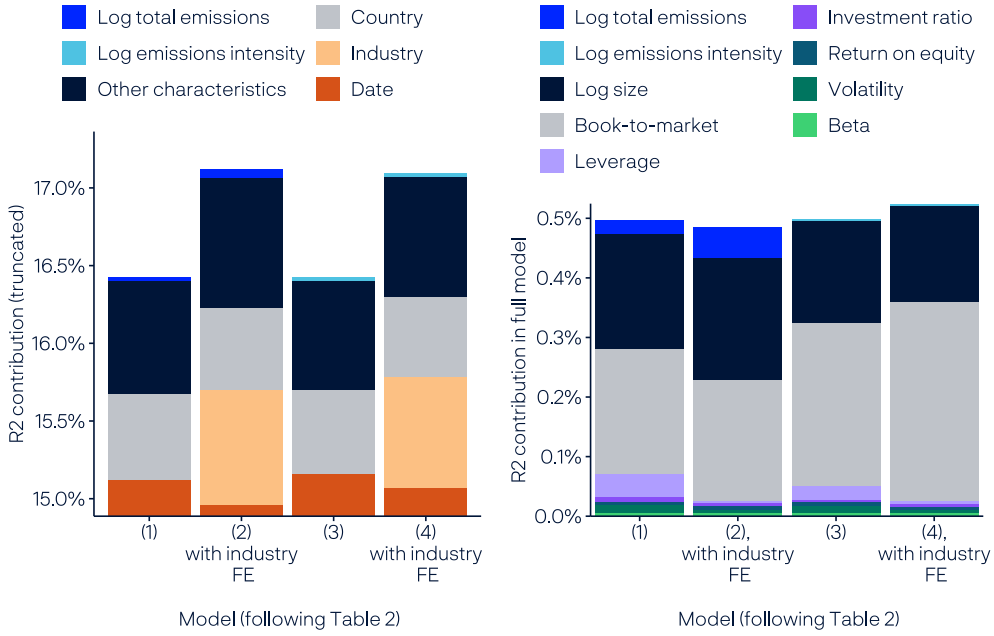
[44] Industry fixed effects can be relevant to include as not climate-focused sectors such as technology have low emissions intensity. However, removing variation across industries leaves out the return impact of investors selling out of highly exposed industries such as energy and basic materials in response to climate risk.

[45] See Appendix Table 6. We find that higher log total emissions are consistently associated with higher annual excess returns, both for direct and indirect emissions. For log emissions intensity, the results are more mixed with an insignificant negative coefficient for indirect emissions (Scope 3) when controlled for sector. These results are mostly similar in sign and magnitude to those reported in Bolton and Kacperczyk (2023) and Aswani et al. (2024).These papers also discuss the choice between total emissions and emissions intensity as proxy for transition risk.

FIGURE 13 Decomposition of explanatory power in regressions of emissions on annual excess returns

(A) Total contribution to explained variance

(B) Company characteristics' contribution to explained variance



NOTE: The figures show the marginal contribution to explained sum of squares from different factors in the regressions shown in Table 2. Contributions of each variable are floored at 0.025 percent in Figure A) and 0.005 percent in Figure B) to improve readability. In Figure A), the x-axis has been truncated. Source: FactSet, S&P Trucost, own calculations.

the complexity of estimating physical risk for the broader economy discussed in Section 2. The academic literature has so far examined physical climate risk hazards in isolation. Hong, Li, and Xu (2019) show that food companies' exposure to droughts was not efficiently priced in financial markets between 1985 and 2014. Acharya et al. (2024) find that higher exposure to heat stress is associated with higher expected returns and implied volatility. Kruttli, Tran, and Watugala (2025) find similar results for hurricanes. The Bank for International Settlements has encouraged financial institutions to explore physical risks through scenario analysis and stress testing, though the asset pricing literature has yet to examine how investors respond to the results of such exercises (Bank for International Settlements, 2024).

A company's exposure to climate risk can change over time, especially if the company changes how it is operating. A growing share of companies is making climate transition plans and setting public climate targets.[46] A company taking steps to address climate risk could be assessed by investors in different ways. On the one hand, companies that take action and actively disclose information could be those that have higher exposure to climate risk.[47] On the other hand, showing

[46] Results by Bolton and Kacperczyk (2025) show that companies that voluntarily set targets have also so far reduced their emissions, suggesting that target setting is associated with concrete environmental outcomes, even though the authors note the overall impact remains limited.

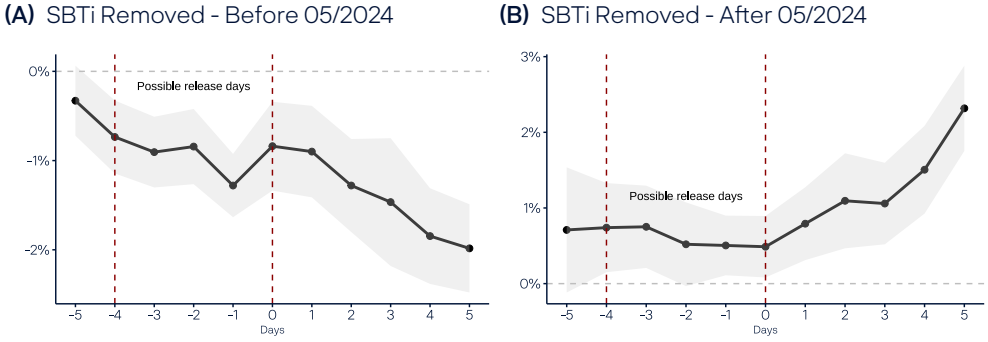
[47] For example, Sautner et al. (2023) construct a text-based measure of how frequently climate is discussed in company earnings calls, and find that companies with more exposure to climate have higher implied volatility and trade with a return premium.

effort to manage climate risk might be rewarded by the market. This could also encourage greenwashing, the overstating and misrepresenting of environmental credentials. Aldy, Bolton, Halem, and Kacperczyk (2025) find that companies that start disclosing their greenhouse gas emissions experience significant excess returns. However, they do not find similar effects for companies that announce targets for reducing emissions and reaching net zero.

In our own results, we investigate net zero announcement outcomes for the largest emitting companies, as identified by the Climate Action 100+ initiative. We use an event study to measure the effect of climate target announcements.[48] We find no significant stock price reaction overall. However, we find a 1.2 percent cumulative abnormal return for the targets that specifically reference net zero, which are the most ambitious.

On the reverse, companies that communicate less about how they manage climate risk could then be perceived as more risky. Companies that initially committed to ambitious climate targets verified by the Science Based Targets initiative (SBTi), and subsequently withdrew them, present an interesting case study of this effect, shown in Figure 14 and discussed in more detail in Appendix C. Initially, companies that failed to complete the target setting process had negative abnormal returns around the time this was made public. In the second half of the sample, companies exiting from the target initiative had positive abnormal returns. This suggests a shift in market response. We expect further research to look at how investors have responded to climate announcements over a longer period of time, and how much of this reflects their expectations of transition risks.

FIGURE 14 Cumulative abnormal returns around the company being removed from the Science Based Targets Initiative



NOTE: This figure presents the CAARs during the [-5, +5] event window. The shaded areas denote the 95% confidence intervals.

4. Conclusion

In this note we have reviewed how different forms of climate risk affect economic outcomes, and the evidence of how financial markets are pricing this risk. We show that bottom-up models and top-down econometric estimates both point to economic impacts from physical climate risk. We also discuss the economic costs

[48] For more details see Appendix C.

and uncertainty arising from the transition to net zero.

Scenario analysis and empirical research can both help quantify climate risk for long term investors. We put together physical climate risk scenarios that closely follow the approach of the NGFS, a well-known initiative founded by central banks and financial supervisors. We attempt to address the known data quality issues in the now retracted Kotz et al. (2024) study used in the NGFS physical risk scenarios. With these changes in place, we find smaller but still negative potential impacts for the equity market.

We review the empirical evidence on the pricing of climate risk for different asset classes, and find evidence that investors are pricing climate risk. In theoretical models, investors expect to earn lower returns on green assets in equilibrium, but there can be transition periods where the fall in expected returns for green assets results in an increase in their prices relative to brown assets. In the last decade, sustainable investments increased in popularity, and green assets outperformed. Our decomposition of this effect for equities finds that this outperformance can be attributed to a relative fall in the expected return of green stocks, aligned with predictions from theory.

References

Acharya, V. V., A. Bhardwaj, and T. Tomunen (2023). Do firms mitigate climate impact on employment? Evidence from US heat shocks. Working paper.

Acharya, V. V., T. Johnson, S. Sundaresan, and T. Tomunen (2024). Is physical climate risk priced? Evidence from regional variation in exposure to heat stress. Working paper.

Aldy, J., P. Bolton, Z. Halem, and M. Kacperczyk (2025). Show & Tell: An analysis of corporate climate messaging and its financial impacts. *Financial Analysts Journal 81*(1), 82–101.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht (2023). Climate change concerns and the performance of green vs. brown stocks. *Management Science 69*(12), 7607–7632.

Aswani, J., A. Raghunandan, and S. Rajgopal (2024). Are carbon emissions associated with stock returns? *Review of Finance 28*(1), 75–106.

Auh, J. K., J. Choi, T. Deryugina, and T. Park (2022). Natural disasters and municipal bonds. Working paper.

Bank for International Settlements (2024, April). The role of climate scenario analysis in strengthening the management and supervision of climate-related financial risks. Discussion Paper d572.

Bank of England (2021). Options for greening the Bank of England's corporate bond purchase scheme. Technical report, Bank of England.

Barnes, C., T. Keeping, G. Madakumbura, J. Abatzoglou, P. Williams, A. AghaKouchak, I. Pinto, V. Thompson, R. Vautard, S. Lampe, W. Thiery, R. Pietroiusti, F. Otto, M. Vahlberg, R. Singh, N. Lambrou, E. Blakely, Y. Zhu, J. Li, T. Benmarhnia, T. Longcore, M. Marlier, E. Raju, N. Baumgart, and J. Arrighi (2025, January). Scientific report: Wildfire disaster in highly exposed Los Angeles area. Technical report, World Weather Attribution.

Barnett, M., W. Brock, and L. P. Hansen (2022). Climate change uncertainty spillover in the macroeconomy. *NBER Macroeconomics Annual 36*(1), 253–320.

Bauer, M. D., D. Huber, G. D. Rudebusch, and O. Wilms (2022). Where is the carbon premium? Global performance of green and brown stocks. *Journal of Climate Finance 1*, 100006.

Bearpark, T., D. Hogan, and S. Hsiang (2025). Data anomalies and the economic commitment of climate change. *Nature 644*(8075), E7–E11.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics 134*(2), 253–272.

Bolton, P. and M. Kacperczyk (2021). Do investors care about carbon risk? *Journal of Financial Economics 142*(2), 517–549.

Bolton, P. and M. Kacperczyk (2023). Global pricing of carbon-transition risk. *The Journal of Finance 78*(6), 3677–3754.

Bolton, P. and M. Kacperczyk (2025). Firm commitments. *Management Science*.

Briant, A., P.-P. Combes, and M. Lafourcade (2010). Dots to boxes: Do the size and shape of spatial units jeopardize economic geography estimations? *Journal of Urban Economics 67*(3), 287–302.

Burke, M., W. M. Davis, and N. S. Diffenbaugh (2018). Large potential reduction in economic damages under UN mitigation targets. *Nature 557*(7706), 549–553.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Global non-linear effect of temperature on economic production. *Nature 527*(7577), 235–239.

Campbell, C. J., A. R. Cowan, and V. Salotti (2010). Multi-country event-study methods. *Journal of Banking & Finance 34*(12), 3078–3090.

Casey, G., S. Fried, and M. Gibson (2024). Understanding climate damages: Consumption versus investment. *European Economic Review 167*, 104799.

Chiang, C.-C., Z. Feng, and D. Harrison (2022). Heat stress and commercial real estate returns. Working paper.

Crosignani, M., E. Osambela, and M. Pritsker (2025). Understanding the pricing of carbon emissions: New evidence from the stock market. *Federal Reserve Bank of New York Staff Reports* (1161).

Dasgupta, P. (2021). *The economics of biodiversity: The Dasgupta Review*. London: HM Treasury.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature 52*(3), 740–798.

Deryugina, T. and S. M. Hsiang (2014). Does the environment still matter? Daily temperature and income in the United States. Technical report, National Bureau of Economic Research.

Deutloff, J., J. Heitzig, and T. M. Lenton (2025). High probability of triggering climate tipping points under current policies modestly amplified by Amazon dieback and permafrost thaw. *Earth System Dynamics 16*(3), 565–606.

Dietz, S., J. Rising, T. Stoerk, and G. Wagner (2021). Economic impacts of tipping points in the climate system. *Proceedings of the National Academy of Sciences 118*(34), e2103081118.

Dunne, J. et al. (2020). The GFDL Earth System Model version 4.1 (GFDL-ESM 4.1): Overall coupled model description and simulation characteristics. *Journal of Advances in Modeling Earth Systems 12*(11), e2019MS002015.

EM-DAT, CRED / UCLouvain and Our World in Data (2025). Economic damage by natural disaster type – EM-DAT. Dataset. EM-DAT, CRED / UCLouvain, "Natural disasters" [original data]. Major processing by Our World in Data.

Field, C. B., V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G.-K. Plattner, S. K. Allen, M. Tignor, and P. M. Midgley (Eds.) (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation*. Cambridge, UK and New York, NY, USA: Cambridge University Press.

Gall, M., K. A. Borden, and S. L. Cutter (2009). When do losses count? Six fallacies of natural hazards loss data. *Bulletin of the American Meteorological Society 90*(6), 799–810.

García-Portela, L. and D. Maraun (2023). Overstating the effects of anthropogenic climate change? A critical assessment of attribution methods in climate science. *European Journal for Philosophy of Science 13*(1), 17.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber (2021). Climate change and long-run discount rates: Evidence from real estate. *The Review of Financial Studies 34*(8), 3527–3571.

Goldsmith-Pinkham, P., M. T. Gustafson, R. C. Lewis, and M. Schwert (2023). Sea-level rise exposure and municipal bond yields. *The Review of Financial Studies 36*(11), 4588–4635.

Gormsen, N. J., K. Huber, and S. S. Oh (2024). Climate capitalists. Working paper, National Bureau of Economic Research.

Grinsted, A., P. Ditlevsen, and J. H. Christensen (2019). Normalized US hurricane damage estimates using area of total destruction, 1900–2018. *Proceedings of the National Academy of Sciences 116*(48), 23942–23946.

Hallegatte, S. (2008). An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. *Risk Analysis 28*(3), 779–799.

Hallegatte, S. (2015). The indirect cost of natural disasters and an economic definition of macroeconomic resilience. *World Bank policy research working paper* (7357).

Hallegatte, S. and V. Przyluski (2010). The economics of natural disasters: concepts and methods. *World Bank policy research working paper* (5507).

Hong, H., F. W. Li, and J. Xu (2019). Climate risks and market efficiency. *Journal of Econometrics 208*(1), 265–281. Special Issue on Financial Engineering and Risk Management.

Howden Re (2025). 2025 Los Angeles wildfires: A path forward. Technical report, Howden Re.

Hunt, E., F. Femia, C. Werrell, J. I. Christian, J. A. Otkin, J. Basara, M. Anderson, T. White, C. Hain, R. Randall, et al. (2021). Agricultural and food security impacts from the 2010 Russia flash drought. *Weather and Climate Extremes 34*, 100383.

Intergovernmental Panel on Climate Change (2021). Summary for policymakers. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, B. Zhou, et al. (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, pp. 3–32. Cambridge University Press.

International Energy Agency (2025). Energy and AI. Technical report, International Energy Agency.

Jeon, W., L. Barrage, and K. J. Walsh (2024). Pricing climate risks: Evidence from wildfires and municipal bonds. Working paper.

Jones, R. L., D. Guha-Sapir, and S. Tubeuf (2022). Human and economic impacts of natural disasters: Can we trust the global data? *Scientific data 9*(1), 572.

Kacperczyk, M. T. and D. Licher (2025). Infrastructure capacity, risk, and firm value: Evidence from U.S. electricity tightness. Working paper.

Kalkuhl, M. and L. Wenz (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management 103*, 102360.

Kotz, M., A. Levermann, and L. Wenz (2024). The economic commitment of climate change. *Nature 628*(8008), 551–557.

Krueger, P. (2015). Corporate goodness and shareholder wealth. *Journal of Financial Economics 115*(2), 304–329.

Kruttli, M. S., B. R. Tran, and S. W. Watugala (2025). Pricing Poseidon: Extreme weather uncertainty and firm return dynamics. *The Journal of Finance 80*(2), 783–832.

Lafferty, D. C. and R. L. Sriver (2023). Downscaling and bias-correction contribute considerable uncertainty to local climate projections in CMIP6. *npj Climate and Atmospheric Science 6*(1), 158.

Lange, S. (2021). ISIMIP3b bias adjustment fact sheet. Technical Report December 1, 2021, ISIMIP.

Lenton, T. M., J. Rockström, O. Gaffney, S. Rahmstorf, K. Richardson, W. Steffen, and H. J. Schellnhuber (2019). Climate tipping points—too risky to bet against. *Nature 575*(7784), 592–595.

Lenzen, M., A. Malik, S. Kenway, P. Daniels, K. L. Lam, and A. Geschke (2019). Economic damage and spillovers from a tropical cyclone. *Natural Hazards and Earth System Sciences 19*(1), 137–151.

Mahalingam, A., O. Carpenter, A. Coburn, and M. Tuveson (2018, 9). Disaster recovery case studies, US 2005 storms: Katrina, Rita, and Wilma. Case study.

Makin, A. J. and A. Layton (2021). The global fiscal response to COVID-19: Risks and repercussions. *Economic Analysis and Policy 69*, 340–349.

Muller, J., K. Mooney, S. G. Bowen, P. J. Klotzbach, T. Martin, T. J. Philp, B. Dhruvkumar, R. S. Dixon, and S. B. Girimurugan (2025). Normalized hurricane damage in the united states: 1900–2022. *Bulletin of the American Meteorological Society 106*(1), E51–E67.

National Research Council (1999). *The impacts of natural disasters: A framework for loss estimation*. National Academies Press.

NATO (2025). Defence expenditures and NATO's 5% commitment.

NBIM (2021). Asset pricing effects of ESG investing. *NBIM Discussion Note* (#1-2021).

NBIM (2021). Modelling equity market term structures. *NBIM Discussion Note* (#3-2021).

Network for Greening the Financial System (2024a, October). Climate macroeconomic modelling handbook. Technical report, Network for Greening the Financial System. Technical document.

Network for Greening the Financial System (2024b). Technical documentation, NGFS climate scenarios for central banks and supervisors - phase V. Report, Network for Greening the Financial System.

Newell, R. G., B. C. Prest, and S. E. Sexton (2021). The GDP-temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management 108*, 102445.

Newman, R. and I. Noy (2023). The global costs of extreme weather that are attributable to climate change. *Nature Communications 14*(1), 6103.

NOAA National Centers for Environmental Information (NCEI) (2025). U.S. billion-dollar weather and climate disasters. Technical report.

O'Neill, B. C., C. Tebaldi, D. P. van Vuuren, V. Eyring, P. Friedlingstein, G. Hurtt, R. Knutti, E. Kriegler, J.-F. Lamarque, J. Lowe, G. A. Meehl, R. Moss, K. Riahi, and B. M. Sanderson (2016). The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geoscientific Model Development 9*(9), 3461–3482.

Osuteye, E., C. Johnson, and D. Brown (2017). The data gap: An analysis of data availability on disaster losses in sub-Saharan African cities. *International Journal of Disaster Risk Reduction 26*, 24–33.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics 135*(2), 468–482.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2021). Sustainable investing in equilibrium. *Journal of Financial Economics 142*(2), 550–571.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2022). Dissecting green returns. *Journal of Financial Economics 146*(2), 403–424.

Pedersen, L. H., S. Fitzgibbons, and L. Pomorski (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics 142*(2), 572–597.

Ponticelli, J., Q. Xu, and S. Zeume (2023). Temperature, adaptation, and local industry concentration. Working paper.

Pourrabbani, M. S., C. Bernier, L. Bevere, M. Dolk, and E. Lindgren (2020). 15 years after Katrina: The tale of a changing risk landscape. Technical report, Swiss Reinsurance Company Ltd, Zurich, Switzerland.

Ritchie, H. and P. Rosado (2024). Is the number of natural disasters increasing? A deep dive into missing data and the limitations of disaster databases. *Our World in Data*.

Rose, A. and D. Wei (2013). Estimating the economic consequences of a port shutdown: The special role of resilience. *Economic Systems Research 25*(2), 212–232.

Sautner, Z., L. V. Lent, G. Vilkov, and R. Zhang (2023). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Schlenker, W. and M. Auffhammer (2018). The cost of a warming climate. *Nature 557*, 498–499.

Shi, Z. and S. Zhang (2024). Oil-driven greenium. Working paper, Fisher College of Business.

Smets, L., L. McDonald, A. Rezza, R. Hasanov, M. Dornan, K. Petrou, D. Doan, K. Parsons, N. Kojucharov, B. Last, J. Wilson, A. Shrivastava, J. Gamarra, M. Osborne, W. Irava, and K. Lele (2023). Dealing with disasters: Analyzing Vanuatu's economy and public finances through the lens of disaster resilience. Technical report, The World Bank, Washington, DC. Republic of Vanuatu: Country Economic Memorandum and Public Expenditure Review.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy 129*(6), 1797–1827.

The Geneva Association (2018). Leveraging innovations in catastrophe risk modelling. Technical report, The Geneva Association.

Tol, R. S. J. (2023). Social cost of carbon estimates have increased over time. *Nature Climate Change 13*(6), 532–536.

United Nations Office for Disaster Risk Reduction (2025). Global assessment report on disaster risk reduction 2025. Technical report, United Nations.

Van der Beck, P. (2025). Flow-driven ESG returns. *The Journal of Finance*. Forthcoming.

Weitzman, M. L. (2011). Fat-tailed uncertainty in the economics of catastrophic climate change. *Review of Environmental Economics and Policy 5*(2), 275–292.

Welton, G. (2011). The impact of Russia's 2010 grain export ban. Oxfam research reports, Oxfam, Oxford.

Wenz, L., R. D. Carr, N. Kögel, M. Kotz, and M. Kalkuhl (2023). DOSE–global data set of reported sub-national economic output. *Scientific Data 10*(1), 425.

Zhang, S. (2025). Carbon returns across the globe. *The Journal of Finance 80*(1), 615–645.

Appendix A: Regression datasets

Historical data We have two datasets, one for national and one for subnational climate data. Both of these use historical values of the bias-adjusted and statistically downscaled precipitation and temperature estimates of the Coupled Model Intercomparison Project Phase 6 (CMIP6).

For national GDP, we use local-currency real GDP from Penn World Table. For sub-national climate data, we use the real GDP in constant US dollars by S&P Global. We are able to match 998 regions from 50 countries with a region in the Natural Earth boundary shapefiles. The time period of our sample is 1989-2019. We filter out outliers of annual change in log real GDP exceeding 0.3 in absolute terms. Countries with more subnational regions receive a proportionally higher weight in the regression, and therefore influence the estimated coefficients more. As a result, our estimates are disproportionately affected by countries with more granular geographic units.

We also analysed the MCC-PIK Database Of Sub-National Economic output (DOSE) from Wenz et al. (2023), which is used by Kalkuhl and Wenz (2020) and Kotz et al. (2024). We investigated whether national GDP growth rates could be reconstructed from weighted subnational rates, and tested their correlation with national GDP growth estimates from Penn World Table. We found that 33 countries out of 80 included in this exercise had correlations below 0.5, and that excluding these countries had a significant impact on the estimates, bringing them more in line with our headline results.

Future climate data We construct subnational climate variable simulations based on the bias-adjusted and statistically downscaled precipitation and temperature estimates of Coupled Model Intercomparison Project Phase 6 (CMIP6) global climate models included in ISIMIP3b for two scenarios: SSP2 RCP 4.5 (equivalent to a current policy scenario) and SSP5 RCP 8.5 (equivalent to a fossil-intensive development scenario).[49] This data is available for daily intervals and at grid level for a number of global climate models from ISIMIP.

Processing of climate data In our analysis we use daily estimates of near-surface air temperature (in Kelvin) and precipitation (in $kgm^{-2}s^{-1}$) from the bias-adjusted and statistically downscaled simulations from different global climate models (Dunne et al., 2020).[50] We then calculate other variables we need for our analysis at grid level as follows. Temperature is calculated from daily mean temperature data aggregated to annual averages by averaging over monthly values. Temperature standard deviation uses monthly standard deviations calculated from daily mean temperature data, then aggregated to annual values by averaging over monthly standard deviations. Temperature seasonal difference represents the annual difference between maximum and minimum monthly means, calculated

[49] The Inter-Sectoral Impact Modelling Intercomparison Project (ISIMIP) 3b protocol defines a unified set of experiments, input data and reporting rules so that many different models can produce comparable simulations of climate-change under harmonised climate and socioeconomic conditions.

[50] Each global climate model can be run multiple times, producing several realisations (ensemble members) for the same external forcing but with different initial conditions. ISIMIP3b, however, provides one bias-adjusted, statistically downscaled realisation per model and scenario for temperature and precipitation, which we use here.

from monthly means derived from daily temperature data. Precipitation is derived from daily precipitation data converted to millimeters, aggregated to annual totals. Wet days represents the annual count of days with precipitation above 1mm threshold, using daily precipitation data converted to mm. Extreme precipitation captures the annual precipitation exceeding grid cell-specific 99th percentile thresholds derived from historical data, using daily precipitation data converted to mm. Finally, as we need these simulations at subnational level for our analysis, we use area-weighted aggregation to obtain subnational estimates using weights. These weights indicate the fraction of each grid cell's area that falls within each subnational administrative region, allowing us to map climate grid cells to subnational regions.

Representation of uncertainty in climate data We acknowledge that we are not representing all the uncertainty with these estimates. Firstly, as ISIMIP3b's primary protocol selects and bias-adjusts one standard member run per global climate model, the data we use for precipitation and temperature only represents a single simulated climate trajectory for these two variables at each location. To better represent uncertainty in future temperature and precipitation simulations, we would ideally require results from all available realisations of each climate model at each grid cell.[51] Further, we would need the bias-adjusted outputs from each of these model runs, which ISIMIP3b does not provide. We also omit uncertainty that arises from downscaling and bias-adjustment which can alter projections in CMIP6 (Lafferty and Sriver, 2023).

ISIMIP3b identifies primary and secondary models based on a number of conditions, such as structural independence of models' components, process representation and how representative of the CMIP6 group of models the selected climate models are in terms of their climate sensitivity (Lange, 2021). Since SSP2-RCP4.5 is not a core part of the ISIMIP 3b protocol, only results from a group of primary models are available. Nevertheless, to reflect the structural uncertainty from this primary group of models, we take each of the model's results and calculate damages using the damage function, the projected temperature and precipitation variables for each of these models and calculate asset pricing impacts for each. We then include the median, interquartile range, minimum and maximum in Figure 7. By doing so, we attempt to represent the uncertainty from the model's design (for example how they represent a specific physical process) and assumptions embedded in their construction.

Regressions We follow the methods outlined in all studies below using both our country and subnational level datasets, and use 1989-2020 as our analysis period for consistency. We use quadratic geographic trends in all specifications. Our results are sensitive to this methodological choice, as also discussed in Newell et al. (2021).

We follow Burke et al. (2018) by using their specification with quadratic

[51] Where models provide multiple realisations for a given scenario, these ensemble members sample internal climate variability and in some cases, alternative model configurations. Hence, they yield a distribution of temperature and precipitation at each grid cell.

temperature and precipitation terms:

$$\Delta \log(GDP_{i,t}) = \beta_1 T_{i,t} + \beta_2 T_{i,t}^2 + \beta_3 P_{i,t} + \beta_4 P_{i,t}^2 + \mu_i + \gamma_t + \theta_{1,i} t + \theta_{2,i} t^2 + \epsilon_{i,t} \quad (3)$$

where μ_i and γ_t are country (or subnational) and year fixed effects, $\theta_{1,i} t + \theta_{2,i} t^2$ are country or subnational time trends, and $\epsilon_{i,t}$ is an error term.

For Kalkuhl and Wenz (2020), we implement their specification with current and lagged climate changes, baseline levels, and interaction terms:

$$\begin{aligned} \Delta \log(GDP_{i,t}) = {} & \beta_1 \Delta T_{i,t} + \beta_2 \Delta T_{i,t-1} + \beta_3 T_i \Delta T_{i,t} + \beta_4 T_i \Delta T_{i,t-1} + \beta_5 T_{i,t} \\ & + \beta_6 \Delta P_{i,t} + \beta_7 \Delta P_{i,t-1} + \beta_8 P_i \Delta P_{i,t} + \beta_9 P_i \Delta P_{i,t-1} + \beta_{10} P_{i,t} \\ & + \mu_i + \gamma_t + \theta_{1,i} t + \theta_{2,i} t^2 + \epsilon_{i,t} \end{aligned} \quad (4)$$

where $\Delta T_{i,t} = T_{i,t} - T_{i,t-1}$ and $\Delta P_{i,t} = P_{i,t} - P_{i,t-1}$ are year-over-year changes and T_i and P_i are the sample means.

Our results following Kotz et al. (2024) regresses log GDP growth on five climate variables with up to 10-year lags:

$$\begin{aligned} \Delta \log(GDP_{i,t}) = {} & \mu_i + \gamma_t + \theta_{1,i} t + \theta_{2,i} t^2 \\ & + \sum_{L=0}^{N} \left(\alpha_{1,L} \Delta \overline{T}_{i,t-L} + \alpha_{2,L} \Delta \overline{T}_{i,t-L} \times \overline{T}_i \right) \\ & + \sum_{L=0}^{N} \left(\alpha_{3,L} \Delta \widehat{T}_{i,t-L} + \alpha_{4,L} \Delta \widehat{T}_{i,t-L} \times \widetilde{T}_i \right) \\ & + \sum_{L=0}^{M} \left(\alpha_{5,L} \Delta P_{i,t-L} + \alpha_{6,L} \Delta P_{i,t-L} \times P_i \right) \\ & + \sum_{L=0}^{M} \left(\alpha_{7,L} \Delta P\text{WetDays}_{i,t-L} + \alpha_{8,L} \Delta P\text{WetDays}_{i,t-L} \times P\text{WetDays}_i \right) \\ & + \sum_{L=0}^{M} \left(\alpha_{9,L} \Delta P\text{Extreme}_{i,t-L} + \alpha_{10,L} \Delta P\text{Extreme}_{i,t-L} \times \overline{T}_i \right) + \epsilon_{i,t} \end{aligned} \quad (5)$$

where $\Delta \overline{T}$, $\Delta \widehat{T}$, ΔP, ΔPWetDays, and ΔPExtreme represent changes in mean temperature, temperature variability, total annual precipitation, total annual number of wet days, and of days of extreme precipitation, respectively. Interaction terms with baseline climate levels ($\overline{T}_i$, $\widetilde{T}_i$, P_i, $P\text{WetDays}_i$) capture heterogeneous impacts across different climates.[52] In our results, we use $N = 10$ and $M = 4$.

GDP growth impact estimates In Figure 6 we compare the GDP growth impacts using all three models described above. In doing so, we made a number of assumptions. Firstly, we isolated the effects of temperature and disregard other climate-related variables such as precipitation, days of extreme weather, that are included in later work that builds on Burke et al. (2018). This deliberate simplification allows us to clearly illustrate how a single shock propagates through the economy

[52] All baselines are sample means of the variable, with the exception of $\widetilde{T}_i$, which is the average difference between the warmest and coldest average monthly temperature in a year.

over time. We use all coefficients, including insignificant ones. The omitting of other coefficients and the choice to include insignificant ones may moderate or exacerbate the impacts on GDP. Secondly we assumed hypothetical country temperature baselines of 5, 10, 20 and 25 degrees Celsius. Finally, we assume a single temperature shock exercised in one period, with no further warming. While the assumption that temperatures increase this quickly and stabilize at this new level is unrealistic given ongoing climate change, this simplified scenario serves to illustrate the model's dynamics and demonstrates how temperature increases affect the economy not only through direct contemporaneous channels but also through the adjustment that extends beyond the shock in the initial period.

Equity asset pricing scenarios We project future economic growth impacts under SSP2-RCP4.5 (equivalent to NGFS Current Policy) and SSP5-RCP8.5 (fossil-intensive development) based on the simulations we constructed as per above. In addition, we process the climate data to create lags and first differences, and 30-year moving average baselines for interaction terms. We then apply estimated coefficients to calculate a log GDP growth rate from 2025 to 2100.

After 2100, we assume two alternative pathways. For both scenarios, emissions peak around or a few years after 2100, but as tipping point risks persist within this trajectory, we present results under both temperature stabilisation and continued warming. If warming continues after the end of the century, this would result in further damages. We adjust the terminal growth rate based on median expected further warming from Deutloff, Heitzig, and Lenton (2025) and marginal effects from the damage function. We report scenarios both with and without this adjustment in Figure 7.

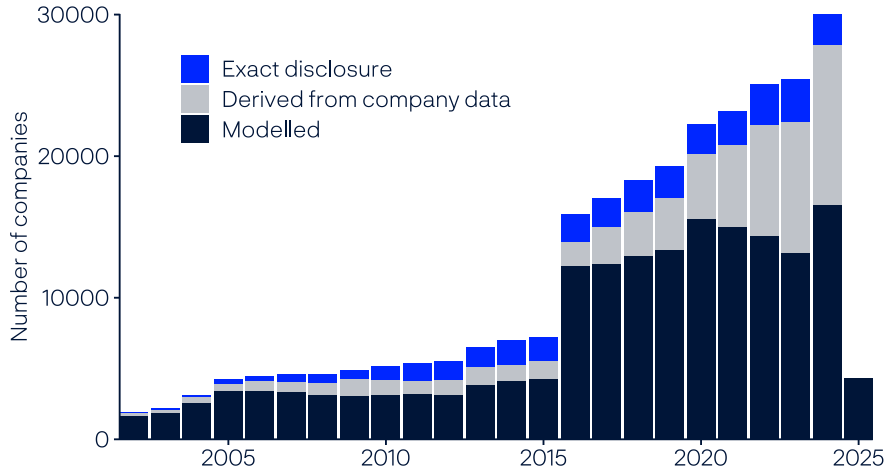
These GDP growth projections feed into our equity market present-value model (NBIM, 2021). We apply projected annual GDP impacts from our scenarios as shocks to dividend growth expectations. We hold interest rates and risk premia constant, calculating present value changes using the current term structure of discount rates. We explicitly model cash flows through maturities of 1 to 75 years. We then value the subsequent dividends as a perpetuity, with constant terminal discount and growth rates. For the scenarios with further warming after 2100, the terminal growth rate is adjusted downwards to reflect further damages.

Appendix B: Emissions data

In our analysis, we use emissions data from S&P Trucost. Our emissions data covers the three scopes of emissions: those directly caused by the reporting entity (Scope 1), emissions from the electricity the entity purchases (Scope 2), and all emissions arising from the company's value chain (Scope 3). Out of these, Scope 3 is predominantly imputed by Trucost, so we focus on Scopes 1 and 2. Emissions data is often normalised to the scale of operations of the company, most commonly by its revenue. The natural logarithm of this emissions intensity is the main measure used in our analysis. Figure 15 shows the number of companies included in our sample. In 2016, Trucost significantly expanded its coverage to more firms.

A meaningful share of this emissions data comes directly from companies. In 2024, over 24000 companies disclosed their emissions through the CDP, a non-profit formerly known as the Carbon Disclosure Project. Figure 16 describes the timing of emissions data disclosed to the CDP. The reporting period typically aligns with the company fiscal year. The final CDP scores are released one year later, although some companies publish their emissions ahead of this. In our baseline asset pricing tests, we use emissions data for the fiscal year two years preceding to account for this delay. This is quite a conservative lag to use, as annual reports would likely discuss any operational changes resulting in a large reduction in emissions.

FIGURE 15 Trucost emissions data by source and fiscal year

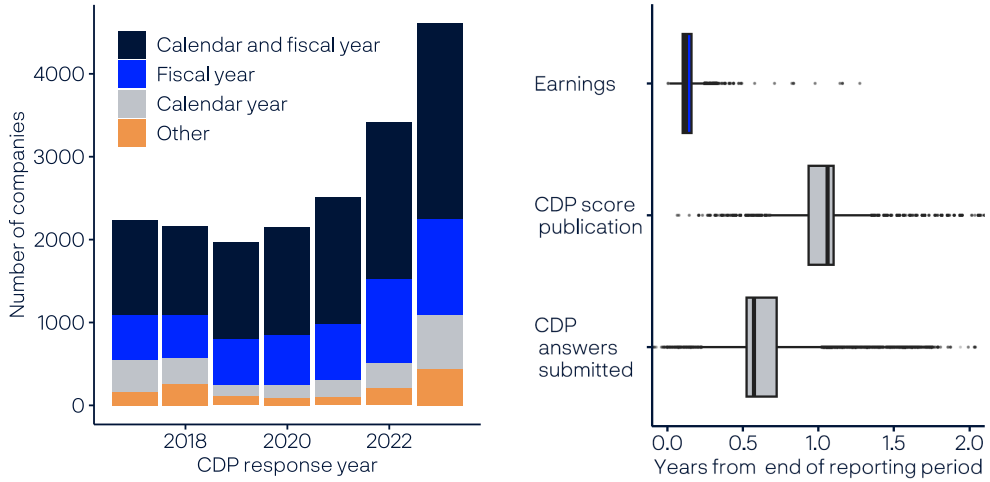


NOTE: The disclosure groups aggregate Trucost categories of Scope 1 emissions disclosure. "Exact disclosure" contains exact values from CDP, company reports, and direct communications. "Derived from company data" includes all methods where Trucost processes disclosed company data to produce improved estimates. "Modelled" comprises estimates based on revenue-intensity factors, extrapolations, and rejected disclosures. Source: Trucost, CDP.

FIGURE 16 Timing of emissions disclosures to CDP

(A) Reporting periods for companies reporting to CDP

(B) Time elapsed between disclosures and the reporting period



NOTE: For panel b) calculations are based on the CDP disclosures cycles 2017-2023, and earnings are the annual earnings report. The line indicates the median, the box the interquartile range, and points indicate outliers. Source: CDP and FactSet.

Green-minus-brown spread

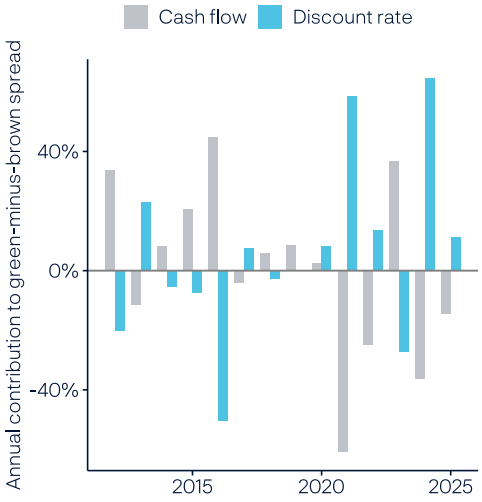
TABLE 3 Green-minus-brown spread based on different portfolio sorts and weighting

	Value-weighted			Equal-weighted		
	ER	CAPM	FF3	ER	CAPM	FF3
Intensity	0.48***	0.32*	0.31*	0.18	0.11	0.1
Within sector	0.22*	0.15	0.16*	0.02	-0.03	-0.01
Within country	0.42***	0.29*	0.29*	0.15	0.14	0.13
Within size quintile	0.48***	0.29*	0.27*	0.19.	0.11	0.11
Excluding utilities	0.22*	0.17	0.17*	0.02	-0.02	-0.01
Excluding technology and financials	0.23*	0.16.	0.16.	0.1	0.02	0.05

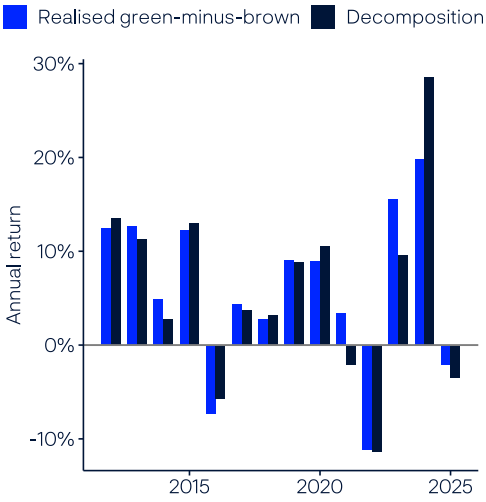
NOTE: This table presents intercepts from time-series regressions of emissions intensity long-short portfolio returns. Portfolios are constructed by ranking firms on emissions intensity and going long the lowest intensity quintile while shorting the highest intensity quintile. ER refers to excess returns, CAPM to market-adjusted returns, and FF3 to Fama-French three-factor adjusted returns. VW and EW denote value-weighted and equal-weighted portfolio construction, respectively. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.10.

FIGURE 17 Detail on the decomposition of the green-minus-brown spread

(A) Annual decomposition of the green-minus brown spread



(B) Total return spread explained by the decomposition



NOTE: Source: FactSet, NBIM calculations.

Cross-sectional regressions of emissions on stock returns

TABLE 4 Regression of log emissions intensity on annual excess returns of global stocks, only disclosed data

Variable: Excess return	(1)	(2)	(3)	(4)	(5)	(6)
Scope 1 intensity	-0.328**			0.036		
	(0.113)			(0.207)		
Scope 2 intensity		-0.059			0.226	
		(0.165)			(0.231)	
Scope 3 intensity			1.546*			-3.182
			(0.733)			(2.095)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	20,115	23,006	2,099	20,114	23,005	2,094
R-squared	0.137	0.148	0.217	0.155	0.161	0.282
Within R-squared	0.014	0.013	0.005	0.010	0.011	0.006

NOTE: Data as of 13th of February 2026. Only company-disclosed emissions. Control variables follow Crosignani et al. (2025). Standard errors clustered by firm. *, **, *** indicate significance at 5, 1, and 0.1 percent levels.

TABLE 5 Regression of log emissions on monthly global stock returns - same year emissions

Variable: Total return	(1)	(2)	(3)	(4)	(5)	(6)
Scope 1 total emissions	0.029			0.082***		
	(0.017)			(0.015)		
Scope 2 total emissions		0.085**			0.122***	
		(0.025)			(0.026)	
Scope 3 total emissions			0.120***			0.231***
			(0.031)			(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	1,530,025	1,530,025	1,530,025	1,530,025	1,530,025	1,530,025
R-squared	0.124	0.124	0.124	0.124	0.124	0.125
Within R-squared	0.003	0.003	0.003	0.003	0.003	0.003

NOTE: Data as of 13th of February 2026. Monthly returns winsorized at 100 percent. Control variables follow Bolton and Kacperczyk (2023). Standard errors clustered by firm and year. *, **, *** indicate significance at 5, 1, and 0.1 percent levels.

TABLE 6 Regressions of emissions intensity and total emissions on annual excess returns of global stocks

	Log emissions intensity						Log total emissions					
Dep. Variable: Excess return	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Scope 1	-0.097			0.041			0.179**			0.493***		
	(0.067)			(0.123)			(0.058)			(0.107)		
Scope 2		0.305**			0.345*			0.663***			0.795***	
		(0.106)			(0.151)			(0.086)			(0.123)	
Scope 3			0.347**			-0.548			0.662***			0.937***
			(0.132)			(0.307)			(0.088)			(0.167)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	72,197	72,197	72,197	72,197	72,197	72,197	72,197	72,197	72,197	72,197	72,197	72,197
R-squared	0.164	0.164	0.164	0.171	0.171	0.171	0.164	0.165	0.165	0.171	0.171	0.171
Within R-squared	0.008	0.008	0.008	0.009	0.009	0.009	0.008	0.009	0.009	0.009	0.009	0.009

NOTE: For years 2004-2025, data as of 13th of February 2026. The left panel (columns 1-6) shows regressions using log emissions intensity for Scope 1, Scope 2, and Scope 3 emissions. The right panel (columns 1-6) shows regressions using log total emissions for Scope 1, Scope 2, and Scope 3 emissions. Annual excess returns are winsorized at 250 percent. Control variables are the same as in Crosignani et al. (2025). Industry fixed effects use FactSet classification. Standard errors are clustered at the firm level and reported in parentheses. Statistical significance at the 5, 1, and 0.1 percent levels is indicated by *, **, and *** respectively.

Appendix C: Company net zero target news

In our analysis, we examine the impact of net zero announcements on stock returns, understanding whether these commitments enhance firm value by signaling reduced transition risks for investors or addressing concerns related to inadequate strategy execution.

Positive news We begin by extracting all companies listed in the Climate Action 100+ initiative that have committed to achieving net zero emissions by 2050. Climate Action 100+ is an investor-led initiative aimed at ensuring that the world's largest corporate greenhouse gas emitters take appropriate action on climate change.[53] Climate Action 100+ focuses on the top 170 emitters, assessing them against the Net Zero Company Benchmark, which evaluates the adequacy of corporate disclosure and the alignment of company actions with the Paris Agreement goals. We then manually search the net zero announcement dates through official company websites, companies' reports and media releases. We identify firms' information regarding their announcements, specifically focusing on mentions of carbon neutrality and net zero targets. Next, we collect adjusted daily stock returns data from FactSet. Following the methodology by Campbell, Cowan, and Salotti (2010), we also gather each MSCI country index returns as proxies for the equity market returns. This sample selection procedure results in a final sample of 123 announcements spanning the years 2017 to 2024.[54]

Negative news SBTi publishes the Company Target dashboard on their website, which discloses information about companies setting targets through their framework. The targets are classified as either 'set' or 'committed'. Organizations with targets 'set' have had their targets independently validated by the SBTi, while those with 'committed' status have made a public commitment to set a science-based target aligned with the SBTi's criteria within 24 months. Starting in August 2023, SBTi began removing companies that failed to submit their targets within the commitment period from the Target Dashboard and marked these as "Commitment Removed". This event could signal to the market the company's efforts regarding their transition plan. NBIM has tracked SBTi data weekly since 2022 and up to February 2025, providing a dataset on when the companies' statuses changed on the SBTi dashboard. We replicate the same process as used for positive news, resulting in a sample of 154 removed companies.

Methodology To examine the market reaction to net zero commitment news, we apply an event study methodology. The assumption behind this approach is the efficient market hypothesis, which states that capital markets immediately reflect the available new information in the firm's stock price. An event study typically focuses on analyzing abnormal returns (AR) around the announcement date by adjusting the expected normal returns, assuming no event, from realized stock returns. Thus, abnormal stock returns are assumed to reflect the unanticipated impact on the shareholder wealth from the event. In our analysis, these abnormal returns are indicative of shareholders' perceptions of net zero commitments.

[53] Climate Action 100+. https://www.climateaction100.org/

[54] Based on other data sources, we are not aware of further net zero commitments from the companies in Climate Action 100+ since the sample was collected.

Additionally, a short-term event study could reduce reverse causality bias that may occur when examining the impact of environmental, social, and governance on firm performance.

The market model is estimated as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}, \tag{6}$$

where R_{it} is the return of firm i on day t, R_{mt} is the daily return of the market index, and ϵ is the residual.

The market model is used for benchmark return, and country market indices are proxies for market indices. We use the country exchange of the main listing to match with the country market indices. The coefficients are estimated using Ordinary least squares (OLS) regression with daily return data in the estimation window. Given the estimates from the market model, we then measure the sample abnormal return of firm i on day t as follows:

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}). \tag{7}$$

To avoid bias introduced by the event itself, the event period should occur after the estimation window. Short event windows may pose challenges if event information is leaked or anticipated, while longer event windows may result in biased estimates due to the influence of confounding events. We designate the announcement date as the event date (day 0) and analyze a standard short-horizon 11-day event window of [-5, +5] to capture both pre-announcement information leakage and slower dissemination of information post event. This event window is particularly appropriate for SBTi removal events, where measurement imprecision arises from the actual removal dates. Additionally, for the full sample data, we extend several time intervals both before the event window ([-20, -11] and [-10, -6]) and after the event window ([6, 10] and [11, 20]) to examine any potential run-up effect on stock prices over an extended period. We then apply the cross-sectional test for the significance test of cumulative average abnormal returns (CAAR).

Results

Positive news Table 7 reports the CAARs of firms around the public announcement of net zero commitment. The CAAR over the event window [-5,5] is 0.7 percent and insignificant, suggesting no market responses across the sample. Additionally, in Panel A, we differentiate between announcements specifically mentioning ”net zero” and those mentioning ”carbon neutrality”, as not all net zero targets set by companies are equal. Our findings indicate that stock market reactions are significantly larger for ”net zero” announcements compared to ”carbon neutrality” announcements, which exhibit small and statistically insignificant reactions.

TABLE 7 Stock market reaction to the net zero announcement

CAAR (%)	[-20,-11]	[-10,-6]	[-5,5]	[6,10]	[11,20]
Total (N=123)	0.37	0.86*	0.69	-0.53	1.05*
	(0.6)	(0.5)	(0.6)	(0.4)	(0.6)
Panel A					
Net zero announcement (N=84)	0.25	0.85	1.25*	-0.07	0.27
	(0.7)	(0.6)	(0.7)	(0.5)	(0.7)
Carbon neutrality (N=39)	0.62	0.86	-0.52	-1.51**	2.72**
	(1.3)	(0.8)	(1.0)	(0.7)	(1.3)

NOTE: This table reports CAARs of Climate Action 100+ assessment firms around announcement of their net zero target. Panel A distinguishes between announcements specifically mentioning "net zero" and those mentioning "carbon neutrality". Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Negative news

TABLE 8 Stock market reaction to the SBTi removed announcements

CAAR (%)	[-20,-11]	[-10,-6]	[-5,5]	[6,10]	[11,20]
Total (N=154)	-0.40	-0.44	-0.26	-0.03	0.38
	(0.5)	(0.3)	(0.7)	(0.4)	(0.6)
Panel A					
Before 05/2024 (N=92)	-1.04	-0.39	-2.00**	0.24	1.17
	(0.7)	(0.4)	(0.9)	(0.4)	(0.7)
After 05/2024 (N=62)	0.53	-0.50	2.33**	-0.42	-0.77
	(0.7)	(0.4)	(1.0)	(0.6)	(1.0)

NOTE: This table reports CAARs of firms around days that SBTi change their status to "Removed". Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8 displays the results for the SBTi removal announcements. While the aggregate CAAR of -0.3 percent lacks statistical significance, disaggregating the sample by announcement timing uncovers meaningful patterns that may need further investigation.

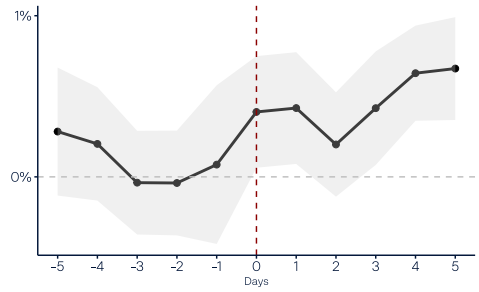
Our analysis identifies a structural break in market responses around May 2024. Pre-May 2024 removals generate statistically significant negative CAARs of -2 percent ($p < 0.05$). Commitment removals could be a signal of a company's inadequate strategy execution and a lack of commitment to sustainability. When companies fail to submit sufficiently ambitious targets through SBTi, they might expose themselves to greater scrutiny from stakeholders, including investors, regulators, and the public. This finding is consistent with Krueger (2015), which shows that shareholders react negatively when negative information about a firm's policy becomes publicly available.

However, post-May 2024 removals yield positive and statistically significant abnormal returns of 2.3 percent, suggesting a fundamental shift in market

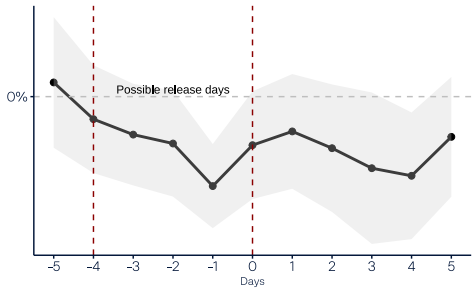
interpretation of these events. The transition from negative to positive market reactions around May 2024 may reflect changing expectations about future climate policy stringency.

FIGURE 18 CAARs around climate news announcements

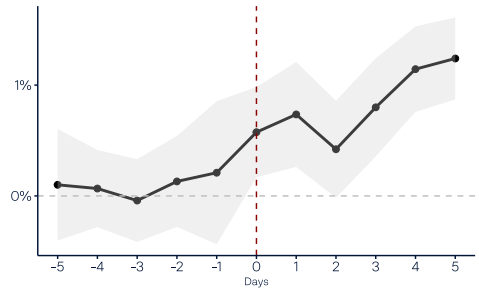
(A) Aggregate Net Zero Commitment



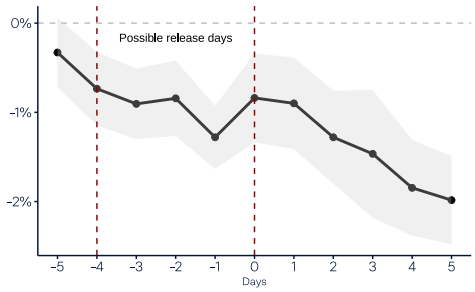
(B) SBTi Removed Announcements



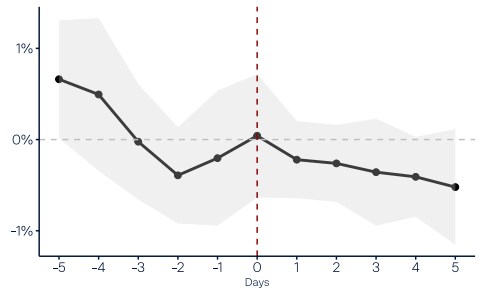
(C) Net Zero Target Announcements



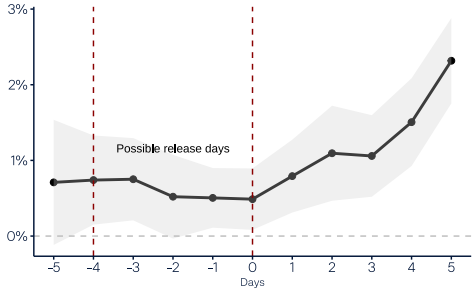
(D) SBTi Removed - Before 05/2024



(E) Carbon Neutrality Pledge Announcements



(F) SBTi Removed - After 05/2024



NOTE: This figure presents the CAARs during the [-5, +5] event window around various climate commitment announcements. The shaded areas denote the 95% confidence intervals.