Asset-level analysis of corporate value adjustment against climate transition risks: A comparison of stress test methodologies for the global power sector[i]

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Abstract

Combating climate change requires significant decarbonization across economic sectors, creating substantial risks for many assets—especially those with high emissions footprints. This includes the early retirement of certain assets, which can materially affect company valuations and creditworthiness. By incorporating IPCC scenarios into a microeconomic firm model with asset-level information, we examine valuation risks for power-sector companies under global net-zero action. This granular dataset allows us to directly incorporate firms' production planning into our stress-testing methodology, which is critical for modelling plant retirements by asset age, since older assets are typically more emissions-intensive and often complete their financial life well before their technical lifetime. We estimate firm-level transition costs by valuing how climate-scenario production declines and stranded-asset exposure affect firms' excess capacity using company- and asset-level features. We benchmark our bottom-up results against leading top-down approaches that ignore firm strategy and asset-age heterogeneity. Our results show that fossil fuel assets, under any temperature-target climate scenario, are expected to lose value relative to a business-as-usual baseline; however, losses vary widely across firms due to differences in asset heterogeneity, geographic region (i.e., resource abundance), and fossil fuel technology intensity. We find that the estimated transition cost is approximately 7% lower when using highly granular asset-level data to assess transition risks to companies, compared with a stress test that does not incorporate companies' ownership of assets and asset-specific features.

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Contents

1. Introduction

The economic transition towards a low–carbon economy comes with significant implications for companies and financial institutions, impacting their overall performance, and subsequent broader financial stability.[2] The transition represents a challenge for businesses operating in high-carbon sectors, which can directly affect corporate behaviour and strategies, with impacts on valuation, market, and credit risk.[3] This is particularly true for the power sector, which is a key focus for climate regulation given the amount of emissions from the sector, the size of the market, and the expected growth in global power demand. In 2024, the estimated total market size for global thermal power companies was 1.52 trillion USD. This is expected to grow to 2.13 trillion USD by 2034.[4] In addition, for publicly traded power companies across all technologies, the total market cap in 2025 was 2.378 trillion USD. Considering the emission reduction requirements of a net zero transition, particularly for the power sector, the size and expected growth of these markets represent significant financial risks, with potential impacts on broader financial stability.[5]

The uncertainty in pricing the climate transition has generally led companies and financial institutions to under-price the climate risk and the downside potential of carbon–intensive business models.[6] Studies such as Griffin et al. (2015) have found that there are limited negative stock market reactions to concerns about a carbon bubble or stranded assets for the largest fossil fuel companies, indicating pricing may be inadequate.[7] Bolton and Kacperczyk (2021) show that there are higher returns on stocks for high carbon businesses in the United States, indicating a premium on carbon–intensive companies.[8] Diaz and Escribano (2021) find that this premium is about 77 b.p. in US corporate bonds, implying lower expected returns for green companies compared to brown ones.[9] Pastor et al. (2021) show that investors have lower expected returns from green assets compared to brown ones, but that they do so as a hedge against climate risk from brown assets, demonstrating investors' continued under-pricing of climate risk from brown assets.[10] Other studies have shown that transition risk is not fully integrated by most investors, who

[2] Catriona Marshall et al. *Financial markets and climate transition: Opportunities, challenges, and policy implications*. Committee on Financial Markets Report. Paris: Organisation for Economic Co-operation and Development, 2021.

[3] Irene Monasterolo. "Climate change and the financial system". In: *Annual Review of Resource Economics* 12.1 (2020), pp. 299–320.

[4] *Global Energy Review*. Report. International Energy Agency, Mar. 2025.

[5] Stefano Battiston et al. "A climate stress-test of the financial system". In: *Nature Climate Change* 7 (2017).

[6] Philip Fliegel. ""Brown" risk or "green" opportunity? The dynamic pricing of climate transition risk on global financial markets". In: *Energy Economics* 145.108456 (2025), pp. 1–20.

[7] Paul A. Griffin et al. "Science and the stock market: Investors' recognition of un-burnable carbon". In: *Energy Economics* 52.A (Dec. 2015), pp. 1–12.

[8] Patrick Bolton and Marcin Kacperczyk. "Global pricing of carbon-transition risk". In: *Journal of Finance* 78.6 (Dec. 2023), pp. 3051–3757.

[9] Antonio Diaz and Ana Escribano. "Sustainability premium in energy bonds". In: *Energy Economics* 95.105113 (Mar. 2021).

[10] Lubos Pastor, Robert F. Stambaugh, and Lucian A. Taylor. "Sustainable investing in equilibrium". In: *Journal of Financial Economics* 142.2 (Nov. 2021), pp. 550–571.

only look at future cash flow projections, rather than fully considering climate policy goals or regulation.[11]

The potential for companies and banks to under-price the transition has led central banks and regulators to caution the possible destabilising effects of climate risk to financial stability, and policymakers have underscored the potential for the climate transition to be a source of systemic risk.[12] Such concerns have motivated financial institutions and regulatory authorities to consider the extent to which climate–related risks might undermine financial stability by implementing transition–based financial stress testing exercises.[13] However, the difficulty in implementing these stress test exercises and adequately assessing the impacts of the climate transition on power companies is due to the uncertainties regarding the future of climate policies, the variability in expected energy demand, and the composition of different power and energy generating assets for companies between renewable and non–renewable developments. Consequently, estimating the risk to companies is extremely difficult, and quantifying values is highly uncertain.

There are several quantitative methods that have been proposed to estimate the macroeconomic impacts of climate change and policies, and the implications for corporations. Van der Walt et al. (2025) has demonstrated that climate-sensitive macroeconomic variables have a significant bearing on bank equity values and balance sheets, highlighting the potential impacts of climate transition policies. Dietz et al. (2016) estimates the return on asset classes by different regions, observing the co-variance or lack of co-variance in asset classes as dependent on climate change expectations.[14] Lamperti et al. (2019) use an agent-based climate-economy model to show that climate change will increase the frequency of banking crises and the fiscal burden on GDP due to the deteriorating impacts on bank's balance sheets.[15] However, these types of climate and macroeconomy studies are often too broad to define market risk to individual institutions or companies, since they are often derived from high-level aggregate, global climate scenarios that lack the necessary granularity for companies to assign their individual market risk based on future trajectories given by the climate scenarios.

In order to more specifically evaluate company and individual asset risk, other research has looked at highly granular asset-level data to evaluate climate financial risk. Several methodologies have been developed for assessing stranded asset risk, which takes account of the estimated reduction in emissions needed to achieve climate policy goals or specific temperature targets, which are drawn from climate scenarios, and the loss in

[11] Patrick Bolton and Marcin Kacperczyk. "Do investors care about carbon risk?" In: *Journal of Financial Economics* 142.2 (Nov. 2021), pp. 517–549.

[12] Stefano Battiston, Yannis Dafermos, and Irene Monasterolo. "Climate risks and financial stability". In: *Journal of Financial Stability* 54.06 (2021), pp. 1–6.

[13] Pierpaolo Grippa, Joachen Schmittmann, and Felix Suntheim. *Climate change and financial risk*. Global Financial Stability Report. International Monetary Fund, 2019.

[14] Simon Dietz et al. "Climate value at risk of global financial assets". In: *Nature Climate Change* 6 (2016); John Y. Campbell and Luis M. Viceira. *Strategic asset allocation: Portfolio choice for long-term investors*. New York: Oxford University Press, 2002.

[15] Francesco Lamperti, Valentina Bosetti, Andrea Roventini, and Massimo Tavoni, "The public costs of climate-induced financial instability", *Nature Climate Change* 9 (2019), pp. 829 – 833.

capacity that is imposed on power generation for countries.[16] Other studies have estimated the potential range of future capacity that is at risk of early retirement by scaling down changes in production from climate scenarios to lost revenue and investment for firms.[17] Pfeiffer et al. (2016) draws on asset–level data to aggregate and project future carbon emissions of the existing thermal power infrastructure to identify individual asset risk.[18] Fisch-Romito et al. (2021) compare future projected emissions against carbon pricing and carbon budget scenarios. [19] Navarro et al. (2025) uses asset-level ownership data to estimate stranded asset risk based on the impact of carbon price projections on operating costs for fossil fuel plants.[20] Edwards et al. (2022) further illustrates how asset stranding on a large enough scale could become damaging to the broader financial system and macroeconomy. [21]

By constructing an original asset-level dataset of the global power sector, this paper presents a methodology for translating global climate scenario future trajectories into market risk assessments for individual firms, and specific asset-level risk. This is particularly relevant for the power sector, since one of the primary financial risks facing power companies in the climate transition is the stranded asset risk, or the risk of power units or plants being shut down or mothballed before the end of their expected financial lifetime, thus having to be written off on the company and bank's balance sheet. The value at risk for this is high. In order to address these issues, this paper proposes two novel features to more comprehensively evaluate transition risks. First, this paper draws on a novel asset–level database of the power sector to build a broader picture of transition risk impacting company performance in relation to other companies operating in a country or region subject to a set of climate policies and regulations with a fixed carbon budget. Second, drawing from the asset–level database, this paper develops a stress testing methodology of company market risk that draws down from climate scenarios to fit macroeconomic trajectories and variables to specific assets and companies to more accurately evaluate transition risk. By including more asset and company–specific features to developing a climate financial stress test, this paper finds that the value-at-risk (VaR), defined as the change in company's net present value, may be lower given global transition trajectories than otherwise suggested by studies using broader sectoral approaches with less granular data in climate stress testing.

[16] J. Curtin et al. "Quantifying stranding risk for fossil fuel assets and implications for renewable energy investment: A review of the literature". In: *Renewable and Sustainable Energy Reviews* 116.109402 (2019).

[17] Robert Fofrich et al. "Early retirement of power plants in climate mitigation scenarios". In: *Environmental Research Letters* 15 (2020).

[18] Pfeiffer et al., "The 2C capital stock for electricity generation: Committed cumulative carbon emissions from the electricity generation sector and the transition to a green economy", *Applied Energy* 179, no. 10 (2016) pp. 1395 – 1408.

[19] Vivien Fisch-Romito et al. "Systematic map of the literature on carbon lock-in induced by long-lived capital". In: *Environmental Research Letters* 16.5 (2021).

[20] Robert Fofrich Navarro, Lauren Liebermann, Frances C. Morre, Christine Shearer, and Steven J. Davis, "Ownership of power plants stranded by climate mitigation", *Nature Sustainability* 9 (2026), pp. 328 – 336.

[21] Morgan R Edwards et al. "Quantifying the regional stranded asset risks from new coal plants under 1.5C". in: *Environmental Research Letters* 17 (2022).

In the following, section 2 presents the methodology which translates climate scenario trajectories to individual power assets and companies in several stages. Section 2.4 introduces the compilation of the asset–level database, and the specific asset features that are used to make the stress test more accurate in pricing transition risk. Section 2.5 describes the primary outputs of the stress test that are used to assess company valuation adjustment. Section 3 describes the selection of the climate scenario trajectories that are used for the stress test. Section 4 illustrates the results and main findings of the stress test, and compares the corporate valuation adjustment based on differences in level of granularity in the stress test. Finally, section 6 concludes.

2. Methodology

This section outlines several methodological components for the climate stress testing framework. First, we discuss the choice of climate scenarios, and the approach to downscaling future energy pathways and trajectories from climate scenarios to power companies. Second, we introduce the theoretical modelling for how a climate transition policy shock is applied to a fossil fuel power company based on the composition of individual assets. Third, we outline the approach for how power companies transition to meet alignment with climate policy targets. Fourth, the climate stress test model is based on the use of a novel asset-level dataset for individual power plants, the data and coverage for which is discussed. Fifth, we present the methodology for downscaling climate scenario trajectories to real economy impacts on individual companies based on asset-specific data, and how market risk is estimated for power companies. Finally, we introduce original methodology that leverages asset-level features to better estimate the market transition risk to power companies.

2.1 Climate Scenarios

First, climate scenario trajectories are selected based on their representation of the economy, and modelling of key economic variables. There are a wide set of climate scenarios that have been proposed and published, which forecast various key variables to evaluating climate risk. This includes trajectories of temperature, emissions, GDP, and inflation across different regional geographies. Among these scenarios, there are a set of Integrated Assessment Models (IAMs) that are more specifically designed for modelling and evaluating the economic and financial impacts of the transition to a more sustainable and low–carbon economy. The climate projections from the sixth assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) have been drawn from several different methods and IAMs, as well as drawing from several different representative concentration pathways (RCPs). Consequently, the various climate scenarios available represent a high degree of variation and uncertainty in future trajectories.

Climate scenarios exist within a deterministic environment that is taken from the AR6 database, and assume values are completely met according to the global temperature target. The set of climate–adjusted economic parameters includes decarbonisation pathways, unit cost projections, and carbon tax pathways, reflecting different climate policy scenarios, demand shifts, and technological change in energy and industrial systems. The scenario parameters are exogenous and depict various socio-economic and climatological assumptions that are generated across a variety of climate–economic models with underlying differences in modelling choices and granularity. The approach used in this paper is scenario-agnostic and is intended to be applied with a variety of scenarios including the Network for Greening the Financial System (NGFS, 2020), and the International Energy Agency (IEA, 2020). The level of granularity adopted in the model largely depend on the granularity of the scenario data upon which the stress scenario is calibrated.

For each climate scenario, forward–looking trajectories are taken from a reference baseline scenario, and one type of a target climate scenario pathway. Each IAM will produce several different trajectories based on assumptions of how the future climate transition will unfold. From the set of AR6 scenarios, we consider pairs of baseline and shock scenarios modelled under a single IAM. First, the baseline is taken from an IAM as the closest approximation to or explicitly stated as "current policies" as a type of business-as-usual policy narrative. This assumes no further policy changes or carbon taxes are applied in the future, and allows for continued production. The shock scenario is applied to a baseline "current policies" with a specific temperature target or policy ambition in the future. In this case, we focus on below 2˚C temperature target, aligned with Paris Agreement priorities.

The two scenarios are compared based on a set of key trajectories included in each scenario, including the amount of energy production for each technology, fuel costs, energy prices, carbon taxes, capital expenditure, etc. Hence, the estimation of the valuation adjustment for companies within the framework is entirely consistent within the climate scenario, without pulling from different IAMs or sources. The shock scenario is applied in comparison to a baseline "current policies" with a specific temperature target or policy ambition in the future. In this case, we focus on a below 2˚C temperature target, aligned with the Paris Agreement priorities. These scenario variables are downscaled from the global and regional levels, to match with individual firm and asset–level to estimate the impact of each trajectory on each firm or asset.

More specifically, the set of transition scenarios S is defined as S = $\{s_1,\ldots,s_N\}$, where s_i denotes the applied scenario N of the total number of scenarios, in this case a baseline "current policies", and a shock "below 2˚C" scenario. Each scenario s consists of the specification of three matrices of climate–adjusted variables over time: 1) production $\mathbf{P}^s \in \mathrm{R}^{|Y|\times|q|\times|T|}$; 2) technology unit costs $\mathbf{c}^s \in \mathrm{R}^{|Y|\times|q|\times|G|\times|T|}$; and 3) carbon taxes $psi^s \in \mathrm{R}^{|G|\times|T|}$. The elements in these respective matrices are $P_{y,q,g}{}^{s,t}$, $c^{s,t}{}_{y,q,g}$, and $\psi_{y,q,g}{}^{s,t}$. Here Y is the set of sectors, q is the set of technologies, G is the set of regions, and T is time. Each of these trajectories are taken from the set of climate scenarios, which are used to stress test different possible futures of the climate transition to assess company performance in terms of corporate value at risk.

Climate scenarios provide trajectories for key variables that illustrate how reductions in fossil fuel power generation will be assigned and forecasted to accomplish a particular policy ambition or temperature target. In order to translate scenarios to company and subsequently asset–level data to assess company performance, we assign the share of power technology production under the climate scenario proportionately to each company based on the total amount of a company's production capacity. For every company i, it is composed of a set of physical production assets $a \in A$ across business units and technologies h. Production capacity of the firm is the sum of all of the asset's owned by the company across each sector y, each technology h, which is $P_i^{s,t} = \mathrm{P}_{g \in G} \mathrm{P}_{y \in Y} \mathrm{P}_{h \in H} \mathrm{P}_{a \in A} P_{iyha}^{s,t}$. From the company's total production capacity across assets, the future trajectory of the company's production is taken from the climate scenario as a proportionate share, where η_{iyha}^{t} is the market share of asset a in firm i in sector y, technology h, time t, based on the scenario s:

$$\eta_{aiyh}^{s} = \frac{P_{yh}^{a}}{\Sigma_i P_a} H \tag{1}$$

This method applies a consistent technological scenario rate of change to each asset's production, presuming each asset maintains its relative market share constant over the analysis period. Hence, assets of the same technology type experience identical relative production adjustments. The market share of production as shown in equation 1 derives the firm's responsibility in implementing the requisite change in the absolute production levels required in the scenario to achieve a certain decarbonisation climate target.

For example, according to a Paris–aligned below 2°C scenario 2050 scenario, electricity generation from coal will slowly be phased out given government commitments and the relatively higher production costs relative to renewable power generation. A company that has both electricity generation from coal and from solar will adjust its respective production levels downward in the case of coal, and upward in the case of solar, depending on the location of the plants and the applicability of regional targets that are consistent with climate objectives. Hence, the requisite production level change $\Delta P_{iyha}^{s,t}$ for a power asset is assigned based on the asset–specific share of production given by the scenario s from equation 1.

$$P_{h,a,s,t}^{i,y} = \eta_{aiyh} \times P_{h,a,s,t} \tag{2}$$

where the change in production in technology h under scenario s is simply the difference from one year in the scenario to the next, $\Delta P_{yh}^{s,t} = P_{yh}^{s,t} - P_{yh}^{s,t-1}$. Company i's overall market share across technologies and sectors is ultimately a composition of its market share from its set of assets in a given year. As a climate scenario reduces the amount of production of electricity generated from fossil fuel technologies, equation 2 indicates that a firm's fossil fuel assets will be at a greater transition risk in the future if high–emitting technologies are subject to a phase–out according to the requisite scenario production levels. Additionally, from equation 1, a firm's market share is time–varying, and could constrain a firm's production plans based on the broader scenario trend, and the amount of assets the firm is operating at the time.

2.2 Climate scenario trajectories to companies

Equations 1 and 2 are used to downscale climate scenario trajectories to individual firms based on company and asset–level information. In addition to using scenario trajectories for estimates of future company production, companies also report their own future production plans for approximately the next five years. Figure 1 illustrates how the market share of production from the scenarios and the rate of change is applied to an individual, high–carbon misaligned firm.

For instance, a high carbon misaligned firm, production at $t = 0$ starts along the "forecast" trend that projects increased production for the next five years. Equation 2 estimates a consistent technological scenario rate of change for each company–technology production, presuming each asset maintains its relative market share constant over the entire period. Hence, assets of the same technology type experience identical production dynamics. At the end of the firm's five year planned production, the scenario trend is applied under the baseline trajectory, with the share of production from equation 1 being the level of production, and the negative slope taken from equation 2.

Second, the "target" trajectory is production under the shock scenario, which has the same starting production share based on the asset or firm's total capacity, but different rate of decline. This is based on the climate scenario's stringency, given by the temperature target or policy ambition, which is a faster rate of decline compared to the baseline scenario. Given the two trajectories provided by the baseline and the target climate scenario from figure 1, the shock mechanism is applied to the firm or asset on the basis of the year of the introduction of a carbon tax at some point in the future, determined by the stress test, and production levels gradually reducing from the baseline trend to the target scenario trend. This is illustrated in figure 2, which shows the modelling for how the shock trajectory is added to link the production pathway from the baseline to the target, assuming a period of transition under the "transition" trajectory in figure 2. The "transition" trajectory is added to illustrate how a firm moves from the baseline trend to the target trend with a gradual period of adjustment to the "target" trend, observed in figure 1.

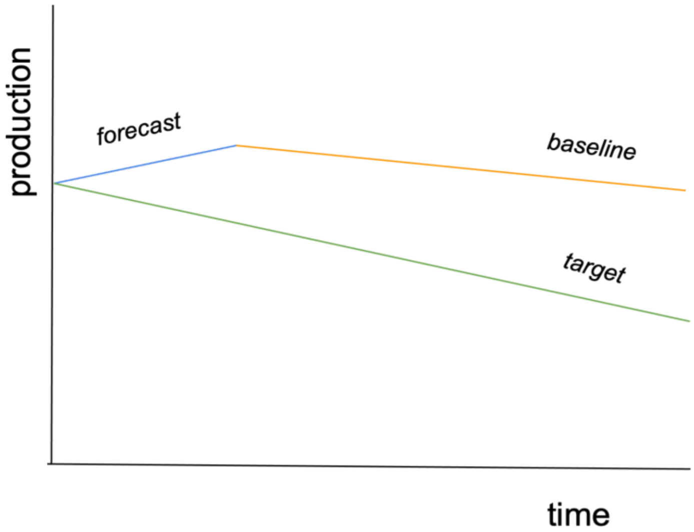

Figure 1: Future trajectory of climate scenario production trajectories under baseline and target scenario for an individual firm.

2.3 Shock scenario and compensation

In order to ensure that all production under any scenario is fully allocated and accounted for under the scenario's overall carbon budget, without exceeding the overall budget, we develop a method of compensation to account for the difference in overproduction for a firm under the baseline production level before the shock, and the lower level of production that it should have been producing under the target scenario. This leaves a difference in production that the firm produced under the baseline in excess of the target production, and hence in excess of the target scenario's carbon budget. The stress test does not allow for any misallocation of production under either the baseline or the target scenario once the shock is introduced and the firm needs to align to the target level, it also has to compensate for overproduction in the period before the shock to fully align with the new target scenario production trajectory. Therefore, the firm needs to compensate for excess production before the shock by reducing production to a level below that of the target scenario after the shock. This is illustrated by the continual decline of the "transition" trend below the target trend in figure 2.

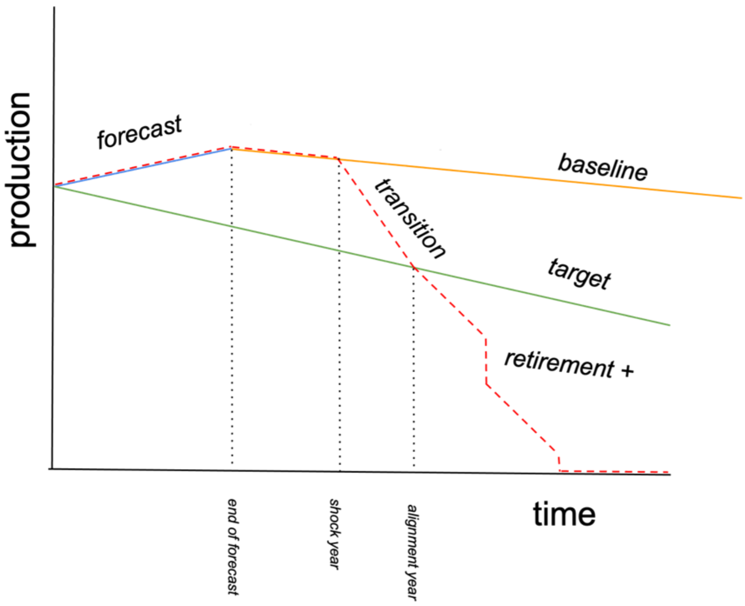

Figure 2: Application of climate policy shock to a firm in a given shock year, moving from the baseline to the target scenario.

From figure 2, compensation takes the cumulative amount of excess production from the target production trajectory, P_f, prior to the year the shock scenario is applied, ($t < S$), and subtracting it from the remaining amount of production given to the firm according to the technology market share from equation 2. The compensation mechanism essentially adds the missing or excess production from the period before the shock to the remaining production that the firm is allocated after the shock scenario as the area:

$$P_{iyha}^{S,t} = \int_S^g \left(\eta_{iyha}^y P_{ha}^y\right) + \int_T^g \left(\eta_{iyha}^s P_{ha}^s\right) \tag{2}$$

where the difference in the area under the curve from figure 2 is the shock scenario pathway S from the firm's initial target production pathway g. The excess production undertaken by the firm prior to the introduction of the shock scenario is considered excess production that the firm needs to account for in later years by reduced production from the point of the shock $t > S$. This is added to the remaining production of the firm under the scenario s that starts from the firm's initial production under the target g, ending at the scenario s.

For high carbon technologies and misaligned companies, the difference in production before the shock ($t < S$) forces additional reductions in production from the year a shock scenario occurs, with the slope of the shock scenario forcing a steeper rate of reduction for the company. This imposes greater losses and higher risk to firms that delay transitioning until a policy shock occurs in the future, making it more costly for a firm to transition. Since firm production is observed at the asset–level, the application of the shock scenario plus the compensation for over production prior to the shock can still be managed more easily by a firm's behaviour in distributing lost production across the firm's set of assets.

2.4 Data

A primary concern for climate financial stress testing is the risk to the financial viability of individual power plants, or their stranded asset risk. In order to account for and fully analyse the risk to individual power plants within a company, rather than just the overall company risk, we develop our stress test model to assess risk to individual power plant assets, using asset-specific data. Asset data includes specific information for each plant, such as location, operating capacity, age, and emissions factors. This data has been broadly taken from open-source data from the Global Energy Monitor, which covers global plants across a broad range of technologies. This also includes information on power plants that are planned, under construction, approved, or scheduled for retirement, allowing for forward–looking risk assessments that incorporate both current and anticipated production. Features such as emissions factors are either directly reported from individual assets from GEM, by the company, or taken from Climate Trace as a country–average emissions factor.

Power plant ownership identity is not standardised, nor always disclosed. However, we reconstruct the ownership chain based on disclosed ownership shares based on unit–level capacity. From the GEM data, assets are reported at the unit–level, which identifies different generating components from the same plant. Where no ownership percentage is disclosed at the unit–level, capacity is assumed to be equally divided amongst reported owners, and only direct ownership is tracked, rather than subsidiaries and separate business units within a larger organisation.

Applying this method globally, we construct a dataset of 85,285 power assets across six different technology types, including coal, gas, oil, hydro, nuclear, wind and solar. Of this total, 8,256 assets are coal, oil, or gas power plants.[22] Figure 3 illustrates the distribution of assets globally, with a high number of assets tracked in the largest economies and highest emitting countries. Further discussion of the geographic coverage of power generator assets in the dataset are discussed in appendix section 8.1.

[22] The majority of assets in the database are renewable facilities, such as solar or wind farms that have much smaller generation capacity. Of the total 85,285 assets, 43,803 are either photovoltaic or concentrated solar farms. 20,321 are on/offshore wind farms. For fossil fuel plants, there are 3,365 are coal, 1,860 are oil, and 4,632 are gas plants. 4,008 are hydro power, 345 nuclear, 1,750 biomass, and 273 geothermal. Hence, since the focus of our analysis is on the downside transition risk to fossil fuel companies, we focus on the 8,256 fossil fuel assets in the database.

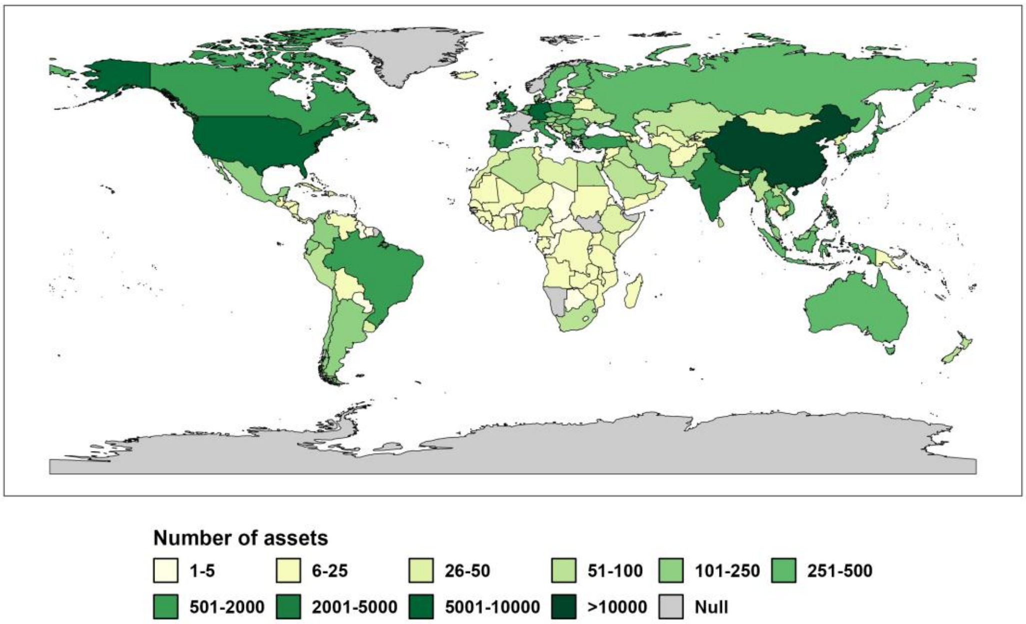

Figure 3: Global distribution of the number of power plant assets per country.

Asset–level data information not only covers operating facilities across technologies, but also incorporates firm-level information on facilities at various stages of planning, approval, or under construction, as well as changes in firm's plans based on facilities that are mothballed, cancelled, or that do not contribute to current or future operations. Figure 4 illustrates the number of facilities in the dataset based on their current reported status, which is used to determine the future trajectory of a firm's production plans and targets. This supports a more detailed risk assessment of energy trajectories for individual firms by not only considering current production, but also future production plans into forward–looking energy trajectories for firms.[23]

[23] Five–year company–level production plans are largely taken from Global Energy Monitor and ClimateTrace, where most asset–level data has been derived, but it is also taken from corporate sustainability disclosures and reports, where available.

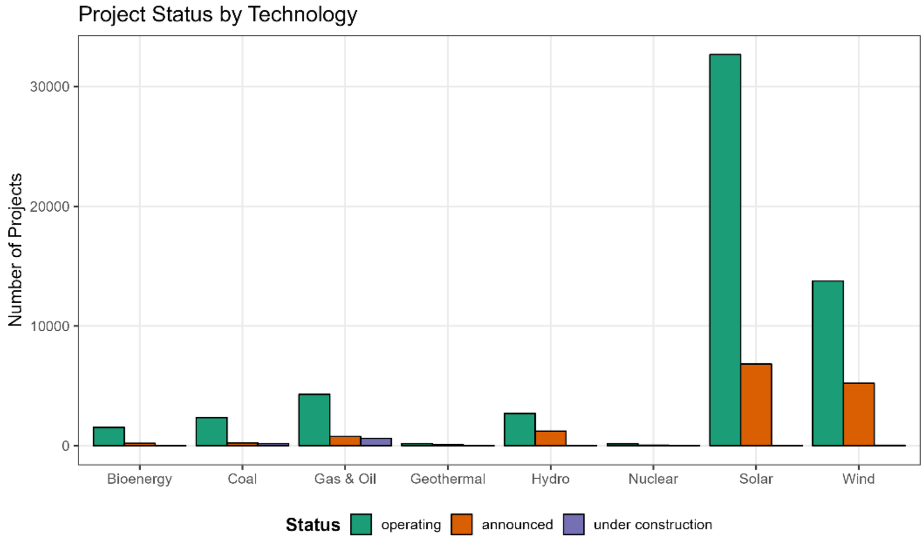

Figure 4: Number of assets by technology type and development status.

Asset features such as asset age are either reported directly from companies, from other databases that report asset–specific information, or they are inferred from the company or based on the technology. Asset age is either directly reported by the GEM data, or calculated from 2025 as the difference between 2025 and the plant start year. If multiple start years are reported from different sources, then a capacity–weighted average is used. Figure 5 illustrates coverage in the asset database of the share of assets where the age is directly known and reported, and which percentage is inferred. Similar to previous figures demonstrating the database coverage of different technologies by total capacity, the database also has a high share of coverage where asset–specific information such as age is directly reported and covered.

As several studies have focused on stranded asset risk as a significant uncertainty to economic and financial damages, this is incorporated into the assessment of market value at risk on the basis of modelling the individual asset risk more specifically, while taking into account asset–specific features.[24] Much of this is predicated on the representativeness of the power sector for countries, from which figures illustrating coverage demonstrate that the dataset has high coverage, and especially for large and high–emitting companies, representing a robust dataset for analysis.

[24] Battiston et al., "A climate stress-test of the financial system", op. cit.

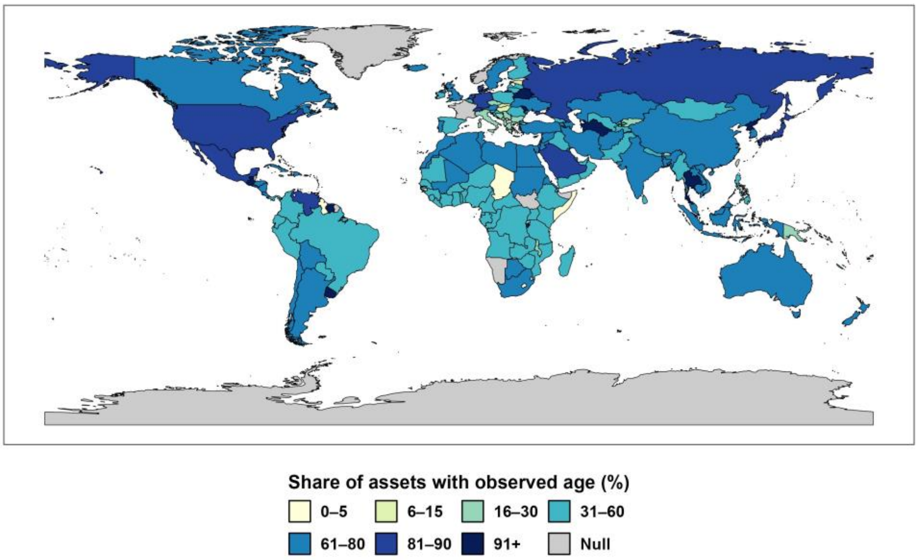

Figure 5: Percentage of country assets with age directly reported.

Finally, Figure 6 illustrates the distribution of power plants by the year they went online, and their added capacity, and technology type across all observed assets, with 93 percent of assets in the database having been built since 2000. The figure highlights the rapid increase in added capacity for renewables, particularly since 2010. However, an important distinction between fossil fuel power plants and renewables is that fossil fuel plants are more durable and characterised by much longer lifespans, with coal-fired plants able to operate for more than 65 years compared to typically half the lifespan or less for wind or solar installations.[25] Hence, an asset database of global power plants includes far more renewables with shorter lifespans and lower capacities compared to fossil fuel plants. Approximately 12 percent of the database consists of fossil fuel power plants, and 79.88 percent of the dataset consists of renewable power plants.

[25] Alexander Pfeiffer et al. "The 2C capital stock for electricity generation: Committed cumulative carbon emissions from the electricity generation sector and the transition to a green economy". In: *Applied Energy* 179 (2016), pp. 1395–1408.

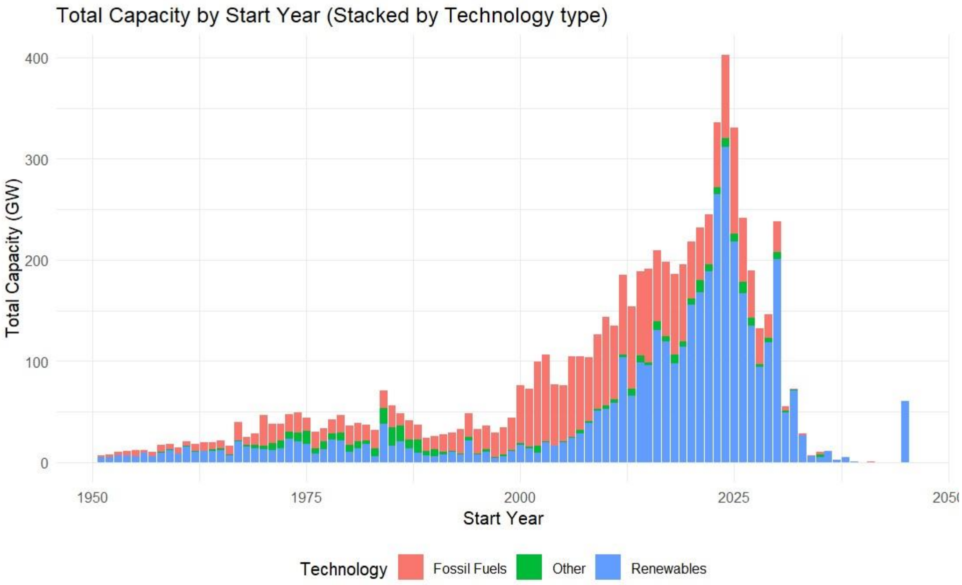

Figure 6: Distribution of total assets by start year.

Widespread heterogeneity in data coverage and reporting leads to significant uncertainty and ambiguity for firms and investors when developing target trajectories for transition planning that can lead to increased uncertainty and higher risk. This is because firms and investors have different and inconsistent metrics and data for assessing transition risk, that is more likely to lead to a firm's production and emissions overshoot, and can subsequently be more penalising for firms under shock scenarios. Having a highly detailed and granular dataset of global assets makes transition planning easier to measure and align with different climate transition scenarios, since corporate planning can be matched against other companies and production.

2.5 Corporate valuation adjustment model

From downscaling climate scenario trajectories by sector and technology to individual companies based on the composition of assets owned and operated, as outlined in previous sections, the modelling of financial risk to companies is based on corporate valuation adjustment. We use a microeconomic framework to model the asset value and profitability of climate critical firms in the real economy based on their physical asset infrastructure, from the asset–level database. Economic trajectories from climate scenarios are matched to individual power assets, and the real economy is represented by a set of heterogeneous firms i across each fossil fuel power generating technology, $\gamma \in \Gamma$.

Profits to the firm from each asset are based on the asset's actual energy production, based on the listed capacity, and the capacity factor, assigned as the share of the total asset capacity that is actually produced. While other studies estimating financial value at risk from climate transition scenarios use a standard discounted cash flow model to estimate present values scaled down from climate scenarios based on production and damages, we adjust the discounted cash flow model to a model of earnings before interest, taxes, depreciation, and amortisation (EBITDA).[26] Although there are multiple methods for assessing the value of a company, discounted cash flows is the most direct and straightforward method. However, given uncertainty or the lack of full transparency in company cash flows, and uncertainty in the appropriate discount rate, other methods of estimation in the absence of full or inferred data are better, with studies indicating that, for cross company comparisons in the absence of robust and accurate data, EBITDA proves more precise valuations.[27]

Similar to discounted cash flow models, a company's revenue is based on the amount of production of an individual asset, which is the asset's capacity multiplied by capacity factor:

$$Qt,s,a \equiv PCt,s,a \cdot CFt,s,a, \tag{3}$$

where $Q_{t,s,a}$ is the actual production of asset a, time t, as a share of the total production defined by the scenario s in MWh, as taken previously from equation 1. $PC_{t,s,a}$ and $CF_{t,s,a}$ are the asset's total capacity, and the capacity or load factor of the asset. The actual production from equation 3 is subsequently applied to the asset's expected profits based on the electricity market price, which is provided by the climate scenario at the market price $p_{t,s}$ in year t from scenario $s,$ for each country/region g.[28] Taking the production volume $Q_{t,s,a}$ and the price $p_{t,s}$ gives the revenue from the asset, which is summed across assets:

$$R_i^{s,t} = \sum_{h \in H} Q_{t,s,a} \; P_{t,s} \tag{4}$$

Equation 4 illustrates the basic intuition behind the calculation of a firm's profits from the set of assets derived from the asset–level database, and the changes in production assigned according to a future climate scenario trajectory, premised on the anticipated temperature target and a particular climate policy. This downscaling from the climate scenario assigned to company's revenues reflects similar methodologies that breakdown trajectories to companies in different climate policy relevant sectors.[29] However, rather than modelling only a company's change in revenue as the climate policy shock to the company and investor, we also include the firm's costs as part of EBITDA, which is observed at the individual asset–level to determine profits. Costs of the transition to the firm take on a number of different factors. First, there is the fuel cost per output:

[26] Dietz et al., "Climate value at risk of global financial assets", op. cit.

[27] Erik Lie and Heidi J. Lie. "Multiples used to estimate corporate value". In: *Financial Analyst Journal* 58.2 (2002), pp. 44–54.

[28] AIM/CGE 2.2 uses 17 country/regions, which are used in the stress test. However, results are represented and illustrated at a higher geographic aggregation at the R5 level. These country/regions are: Japan, China, India, Other Asia, USA, Canada, EU, Other Europe, Russia, Middle East, Africa, Latin America, Oceania, Korea, Taiwan, Southeast Asia, Rest of World.

[29] Stefano Battiston and Irene Monasterolo. "On the dependence of investor's probability of default on climate transition scenarios". In: *SSRN Working Paper* (2020).

$$c_{t,s,a} \equiv \frac{P^F_{t,s}}{\eta_{a,k}} \tag{5}$$

Which is defined as the price of fuel, $P_{t,s}{}^F$ in year t and given from scenario s per unit of production $\eta_{a,k}$, where η is the efficiency of asset a for technology k. In addition, there are changes to the firm's production based on either an increase or a decrease in fixed operations and management costs. This is defined as:

$$\frac{FOM_{t,s,a}}{2} \Delta PC_{t,s,a} \tag{6}$$

where $FOM_{t,s,a}$ is the fixed operations and management costs in year t for asset a and costs given by scenario s. The change in production capacity can increase or decrease based on the firm's production plans, adding or retiring assets from the fleet, which will change the firm's annual FOM costs. Calculating company revenue in production minus costs gives the free cash flow earnings:

$$\Pi_{t,s,a} = Q_{t,s,a}\Big(p_{t,s} - c_{t,s,a} - EF_k\, T_{t,s}(1-\phi)\Big) - \frac{FOM_{t,s,a}}{2} \Delta PC_{t,s,a}. \tag{7}$$

Accounting for revenue as $Pi_{t,s,a}$, but before accounting for additionally outflows from the company's investment and financing, these expenses in investment and financing are subsequently added in the form of capital expenditure. Capex are additional costs to the firm from either increased or rolled over capacity, where $A_{t,s}$ is added capacity to the fleet, and $R_{t,s}$ is capacity that is rolled over. Companies receive a small return for the retiring and decommissioning of asset, where $X_{t,s}$ is retired capacity, and γ is the scrap ratio fraction of capital cost recovered from retired capacity, which is set at 10 percent as a generally assumed scrap value. The cost $C_{t,s,h}$ is the capex per MW in year t under scenario s for technology h in USD/MW of capacity. This is given in the following:

$$Capex_{t,s} = \left(A_{t,s} + R_{t,s} - \gamma X_{t,s}\right) \cdot C_{t,s,h} \tag{8}$$

Hence, combining earnings model 7 and the capex model 8, they are combined as the free cashflow model per asset, which is subsequently summed over all of the company's assets:

$$J_{t,s} = \textstyle\sum_a \prod_{t,s,a} - Capex_{t,s} \tag{9}$$

Finally, from equation 9 for the free cashflow model, this is used to determine the net present value of the company from a scenario using the dividend discount model, assuming constant cash flows up to a terminal value:

$$NPV_s = \textstyle\sum_{t=1}^{T} \frac{J_{t,s}}{(1+r)^t} + \frac{J_{T,s}\cdot(1+g)}{r-g} \tag{10}$$

where the discount rate r is greater than the constant growth rate of cash flows per year g, and is summed across all years t from the scenario s, up to the final year of the scenario T.

In this way, the model captures changes in profit margins due to the comparative advantages of individual firms and technologies, incorporating the changing costs of transitioning to a business model that is aligned with the climate scenario in anticipation of, and response to, the creation of a climate policy shock. This can result in an increase or decrease in profits for firms due to the changing cost structures in the energy sector, where costs and revenues for each firm and each technology change according to the scenario trajectory.

Extending this example to two assets of different technologies, each asset will generate a different level of profit based on the fuel cost projections from the scenario trajectories. The firm's total profits will depend on the share of energy it produces from each asset according to the scenario. The share of energy produced by each technology is a trajectory given by the scenario. These two technology–specific components, energy technology cost projections and energy technology share have an impact on each firm's total energy production at each point in time, and hence determine their total net present valuation.

2.6 Dynamic transition planning and optimisation

Since our stress test is premised on a view of the firm that is composed of the aggregation from individual assets, with each asset assigned a trajectory that is downscaled from climate scenarios, we leverage this granular data to build a detailed model to more accurately model firm behaviour and optimise its transition strategy and planning by reducing stranded asset risk and broader economic risk to the firm.

First, we take the asset's age, or the remaining financial or viable lifetime from the asset dataset. While other methods of climate risk analysis downscale changes in production from global models to estimate losses to firms operating in different technologies, this imposes loss estimates on firms without considering the specific characteristics.[30] Instead, by constructing the firm aggregated up from individual assets under ownership, this enables firms to retire assets more dynamically, and over the duration of the scenario trajectory. In this model, given the production trajectory illustrated in figure 2 as well as the added risk of firm production overshoot and subsequent compensation under a shock scenario, we incorporate asset retirement as a means of reducing stranded asset risk, and incorporating reductions in firm–level production through lower capacities to more accurately assess transition costs and shock mitigation strategy.

In contrast to methodologies of climate transition risk that view the firm as static from the introduction of a shock scenario, and models of stranded asset risk that consider the individual asset risk as locked–in emissions, in this model, time is discrete and indexed by

[30] Edwards et al., "Quantifying the regional stranded asset risks from new coal plants under 1.5C", op. cit.

$t \in 0,1,2,....$ From the asset dataset, projecting into the future, assets have a constant productive capacity over a finite number of n periods, after which the asset is expected to retire. We consider each asset to have constant productivity over its lifespan, but a decline in value as it ages. This assumption is premised on an extensive literature demonstrating both features, that even if highly durable capital goods have constant efficiency over a finite useful life they face higher prices and financing relative to less durable assets, making them less viable in the long–run (Arrow, 1964; Rampini, 2019; Livdan and Nezlobin, 2021).[31]

Given the time–series of real capital stock and production for a firm, we apply the age of capital for firm i recursively starting from its initial capital age, against an index of the average technical lifespan of the asset by technology type. We assume that assets do not deteriorate in production over its lifetime and faces no additional investment costs up until the end of the technical lifespan, at which point it faces retirement with no renewal. $L_{i,q,t}$ is an indicator variable that takes the value of 1 if the plant continues operations in period t, otherwise if the plant exceeds the technical lifetime, then it is treated as zero. The asset age is the cumulation of $L_{i,q,t}$ until the asset reaches its total lifespan, where production under $\pi_{i,a}^{s,m,t}$ falls to zero as follows:

$$\mathbb{E}_{i,t}\pi_{i,a}^{s,m,t} = \begin{cases} \pi_{i,a}^{s,m,t} \text{ if } t < N_q \\ \pi_{i,a}^{s,m,t} N_q \to 0 \text{ if } t = N_q \end{cases} \tag{11}$$

From the originally compiled asset–level dataset that tracks the start year a power plant went online, we use an age index of the expected lifespan of the asset based on the technology type q. We assume that assets do not deteriorate in production over its technical lifetime, and electricity generation is given by the scenario, then proportionately applied to each firm and assets.[32] Hence, a firm's losses are not treated as static according to the firm's total capacity based on the start year of the scenario, which leads to higher estimated losses since the firm is not able to retire capacity or maximise energy and cost efficiency on an individual asset basis. Instead, from equation 11, by incorporating asset-specific features, firms retire excess capacity rather than maintaining a higher level of operating costs defined by the start year of the scenario. As a firm's production declines under a climate transition scenario trajectory, the firm also reduces capacity by allowing older assets to retire, thus reducing operating costs, and minimising asset stranding.

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[31] K. J. Arrow. "The role of securities in the optimal allocation of risk-bearing". In: *Review of Economic Studies* 31 (1964), pp. 91–96; Adriano A. Rampini. "Financing durable assets". In: *American Economic Review* 109.2 (Feb. 2019), pp. 664–701; Dmitry Livdan and Alexander Nezlobin. "Investment, capital stock, and replacement cost of assets when economic depreciation is non-geometric". In: *Journal of Financial Economics* 142.3 (Dec. 2021), pp. 1444–1469.

[32] As a firm retires assets, they are able to more easily meet transition targets and reductions under shock scenarios. However, since a firm now has lower capacity from the retirement of assets, the technology market share of production assigned to the firm is also less, from equation 1. Therefore, the firm's production share under the shock scenario s for firm i in technology h recalculates the firm's technology market share of production η_{iyhas}^{t} for each year t, based on the firm's revised capacity where asset's retire, and the capacity drops to 0.

In addition to reducing asset stranding by incorporating retirement, we also utilise asset-specific features so that firms can adjust the load factor across assets. Carbon and energy efficiency are highly correlated to the age of the asset and emissions factor, two features which are incorporated into the adjusted load factor for each asset in the firm. This follows along with recent literature showing that even under constant efficiency, an asset's productive value over a finite lifespan still incurs a relative decline in asset value.[33] Hence, although there is not an explicit assigned value to economic depreciation of an asset, a relative value is assigned to assets based on age, with newer assets being valued greater than older assets. Analysis of asset age, emissions factors, and carbon efficiency in load factor adjustments is further discussed in appendix section 8.2.

Incorporating this asset-specific information, a firm optimises a transition strategy by distributing the loss in technology-level production across the set of assets, with older ones that are closer to retirement absorbing more of the shock than newer assets, but still avoiding the total risk of asset stranding, so long as the asset is producing above the production cost for the firm, taken as the average cost across assets. Essentially, firms stagger the shock of production loss across assets in a way that maximises efficiency while reducing stranding, with older ones absorbing greater losses than newer ones, but not forcing retirement nor exceeding their capacity factor. Building on equation 11, firms apply reductions in production to retire older assets and their capacity first, allowing newer assets to continue producing, while older assets shut down first.

$$E_{i,t}\pi_{i,a}^{s,m,t} = \pi_{i,a}^{s,m,t} \times \eta_{i,q}^{s,t}\Delta P_q^{s,t} \times g\big(A_{x,t} - A_{y,t}, N_q\big) \quad (12)$$

Under equation 12, the shock scenario imposes a loss of production onto the firm, where the firm's energy production is proportionately assigned to the firm $\mathbb{E}_{i,t}\pi_{i,a}^{s,m,t}$. The shock to production is applied as the firm's share of total country production $\eta_{i,q}{}^{s,t}$ and the reduction in production based on the imposition of the shock $\Delta P_q{}^{s,t}$. The added granularity incorporated into the model through the asset–level data allows us to adjust the production shock to the firm by applying the shock in a staggered process across assets based on age and efficiency, rather than uniformly. Older assets, or those that are closer to retirement, based on the technical lifespan from equation 11, are those that take on the greatest burden of the shock scenario. However, they do not absorb the entire shock, otherwise this could force the asset stranding depending on the size of the shock. Therefore, it is applied as a staggered continuous function $g(A_{x,t} - A_{y,t}, N_q)$ from equation 12, where the difference in asset age between the oldest and youngest asset of the firm determines how much of the production shock is allocated to each asset. The shock is applied to each asset as follows:

$$g(x, N_q) = 1 - \sum_{j=1}^{n} \frac{1}{2^j} \left(\frac{1}{1+exp\big(-k(x-a_jN_q)\big)}\right) \quad (13)$$

[33] Livdan and Nezlobin, "Investment, capital stock, and replacement cost of assets when economic depreciation is nongeometric", op. cit.

where g is the scaling function for how the shock is assigned to the asset based on the asset age relative to all other assets in the firm, $x = A_{x,t} - A_{y,t}$, and N_q is the reference threshold of the technical age of the asset for each technology q. k is the constant for which there is a gradual reduction in the proportion of the production shock that is assigned assets that are newer, or the difference in age between $A_{x,t}$ and asset $A_{y,t}$. a_j assigns the proportion of the shock that is assigned to the asset, with the oldest assets, or those with the greatest difference in age, absorbing the highest proportion, but not so much that it forces the asset stranding. Instead, the shock is distributed across assets, but more weight is put onto older assets than newer ones, so that the firm gradually retires older ones first, while retaining newer assets with higher efficiency. In addition, equation 11 still applies, and all assets are still ultimately retired without renewal and production goes to zero once they reach their technical lifetime.

Although equation 13 leverages asset-specific information to distribute the production loss across assets, there is the possibility that the proportion of the shock that is assigned to the oldest asset in a firm could exceed the asset capacity, which would thus force asset stranding. In order to control for this, added constraints are incorporated to equation 13 to prevent the forced stranding of an asset. Equation 14 limits the amount of shock that is applied to an asset to avoid asset stranding based on the asset's allowed capacity of production.

$$Q_{x,t} \leq C_x \times max\left(g\left(A_{x,t} - A_{y,t}, N_q\right) \times P_q^{s,t}, 0\right) - \eta_{i,q}^{s,t} \qquad (14)$$

The asset x of the firm q has its production adjusted under $g\left(x, N_q\right)$ from equation 13, which is applied to the asset's share of production in equation 14, where $g(A_{x,t} - A_{y,t}, N_q)$ is the ranking of assets in the firm by age. $P_q^{s,t}$ is the shock scenario applied to the firm, and $\eta_{i,q}^{s,t}$ is the firm's remaining technology market share of production. The maximum value for the amount of production that can be allocated to an asset is based on the asset's capacity C_x, and subsequently the asset's allowed capacity $Q_{x,t}$.

This illustrates how the distribution of a firm's lost production under a shock scenario is subsequently assigned to each asset of the firm based on the asset's age. It also prevents asset stranding by ensuring that the distribution allows for some production to be retained by all assets in the firm, up until the asset retirement, while still optimising the firm's financial viability of assets. Changes in production to assets are subsequently aggregated up to the firm level, from which cash flows from production are calculated, as previously illustrated in equation 3.

Subsequently, the value adjustment is defined as the difference in the net present value of firm i after a shock and the net present value of the firm under the baseline scenario. In this way, the model captures the expected change in a company's valuation following a sudden shift to the Paris– aligned "shock" scenario from the initial baseline scenario. The shock is assumed to represent a tail event which impacts the valuation of the power generation firms in our sample allowing us to better explore the uncertainty in the tail of the distribution of valuations.

$$\mathrm{VaR}_i^{\mathrm{NPV}} = \mathrm{A}_i^{\mathrm{stress}} - \mathrm{A}_i^{\mathrm{baseline}} \tag{15}$$

The difference in a company's NPV under the *stress* and the *baseline* scenario is subsequently the measure of a company's valuation adjustment under a particular transition scenario. This methodology is uniformly applied across all assets in the global power plant dataset, and aggregated by company ownership.

3 Climate scenario trajectories

For this study, estimation of valuation adjustment for power companies uses climate scenarios provided by the Sixth Assessment report (AR6) database, using the AIM/CGE 2.2. This is the primary IAM that is applied to the stress test model, since the methodology is focused on the application of a late and sudden policy shock scenario that occurs at some point in the future.[34] The divergence between baseline and shock should only be observed at a future trajectory, rather than having a divergence in energy production from a climate policy shock that occurred at some point in the past, which would not be fully captured by the stress test since the methodology is forward–looking.[35] Hence, for the purposes of this study, the AR6 AIM model is used for both the baseline and shock scenario in order to be internally consistent with the framework of the stress test that a shock needs to occur at some point in the future.[36]

For the baseline trajectory, this is premised on the AR6 scenario that is closest to a "current policies" framework, or a business–as–usual narrative. This assumes that the only climate, energy, and environmental policies applied are those that are currently implemented, and that there are no significant climate policies that will be added in the future. This narrative is not considered to be Paris–aligned, as these pathways exceed the 2˚C warming by end of the century, where it is instead 3˚C.[37] This is compared to the climate shock scenario, which ensures a Paris–aligned temperature target below 2˚C by the end of the century.

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[34] Stefano Battiston and Irene Monasterolo. "Enhanced scenarios for climate stress-test". In: *Inspire Sustainable Central Banking Toolbox Policy Briefing Papers* 16 (Apr. 2024), pp. 1–18.

[35] As illustrated previously in section 2.2, modelling for a company's electricity production occurs at a point in the future, which allows companies time to both maximise profits under the baseline, and have time to transition to the target pathway. If the scenario narrative applies a climate shock with a divergence that occurred in the past, then this affects how the stress test models a firm's future profits and cash flows between the baseline and shock trajectories, which can lead to significant distortions in valuation. If a climate scenario has a policy that was introduced in the past, there is a greater divergence between the baseline and shock trajectories from the current start year of the scenario in 2025, where companies have a greater build–out of capacity under the baseline, but then are forced to make more steep reductions than otherwise anticipated due to a wider divergence in the future. This forces some companies to operate at a loss due to more steep reductions than the climate scenario had been based on.

[36] We conducted our analysis across a wider set of scenarios analysed in the stress test framework, but due to the shock and divergence in pathways from the scenario having occurred at some point in the past, leading to distortions in valuation due to both the transition pathway mechanism and the compensation mechanism, these other scenarios are not the focus of analysis.

[37] *NGFS long-term scenarios for central banks and supervisors*. Workstream on Scenario Design and Analysis. November: Network for Greening the Financial System, 2024.

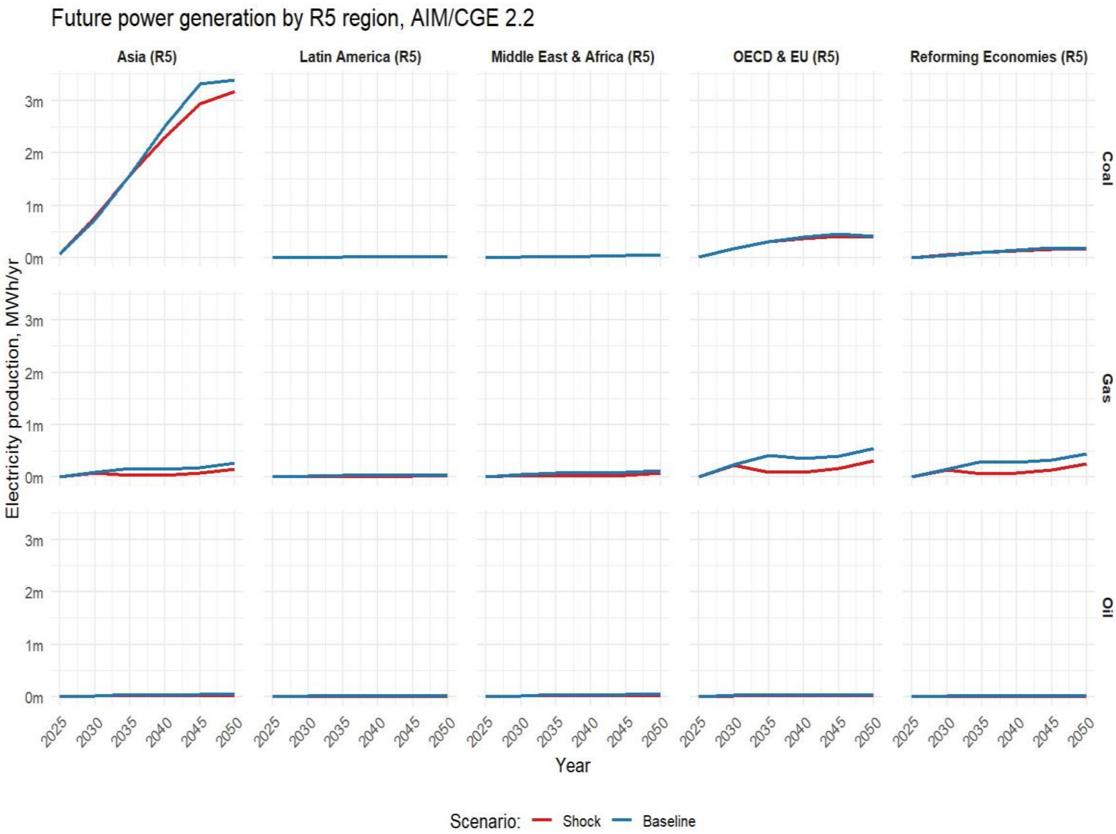

Figure 7: Production trajectory trends for AIM/CGE 2.2 of fossil fuel technologies according to R5 regions, 2025 – 2050.

From the AR6 scenarios, the baseline and shock scenarios are based on the illustrative mitigation pathway categories, using C5 as the baseline and C3 as the shock. The C5 baseline scenario is based on a close approximation to a "current policies" framework, where global average temperature increases are estimated between 2.5 to 3.0˚C, which is a low stringency, and a larger carbon budget.[38] This is compared to the climate shock scenario provided by AR6, and categorised as C3, based on the temperature target of restricting warming to below 2˚C, and having a more restrictive carbon budget limiting fossil fuel companies' ability to emit in order to achieve net zero emissions before the end of the century.[39] The difference between the two narratives is based on the allotted carbon budget estimated over the entire century, from a base start year of 2015 to 2100, and the necessary policies and stringency required in order to meet climate targets within those budgets. The baseline AIM scenario in C5 gives a larger carbon budget of 1200 gigatonnes of CO2 over the 85 year period, whereas the C3 climate scenario has a temperature target of below 2˚C by the end of the century, hence allows for less total emissions of only 900 gigatonnes of CO2 over the same period.

[38] Under the AR6 C5 scenarios, for AIM/CGE 2.2, this corresponds to the EN-NPi2020-1200f scenario.

[39] This corresponds to the AIM/CGE 2.2 scenario of EN-NPi2020-900f, which is premised on lower emissions in the future, and a medium to high level of stringency.

In order to compare the magnitude of difference in the amount of expected power generation for each fossil fuel type under AIM, figure 7 shows the total production trajectories of electricity for each fossil fuel technology type from the baseline and shock scenario, according to the R5 level of regional aggregation.[40] From the figure, each column shows the future energy production trajectory for each of five global regions to 2050, and each row shows the trajectory for each of three fossil fuel technologies, coal, oil, and gas.

Trends from the figure illustrate two important characteristics of the AIM model that are applied to the stress test. First, across all regions, the C3 shock scenario that meets the temperature target of a below 2°C warming, imposes lower energy production for all three fossil fuel technologies. Hence, based on modelling of corporate NPV based on revenue and cash flows from production, this would lead to lower profits for companies under the shock scenario compared to the baseline. As revenues are modelled to corporate NPV, this corresponds to lower overall corporate valuations.

Second, both the shock and baseline trajectories follow the same pathway until 2030, when the trends begin to diverge. This divergence is similarly observed across all fossil fuel technologies and regions, indicating that the introduction of the shock is consistently applied, making the stress test analysis consistent in drawing out comparisons.

Third, there are some important distinctions in the narrative of the AIM model that are observed from the trends in figure 7. First, in contrast to several other IAMs, coal shows a continuous increase in production over time to 2050, as opposed to other IAMs that show a decline until coal is entirely phased out. A continuous increase is observed for both the baseline and the shock scenario of AIM, even if the shock scenario shows less coal production than the baseline. The baseline "current policies" for most IAMs shows some level of increase in coal production in Asia before beginning a gradual decline between 2030 or 2040, so the AIM trends demonstrate some consistency with other IAMs, except for the magnitude of the growth to mid–century. The difference in coal production is subsequently based on the build–out of other type of fossil fuels or renewable energy capacity in other regions of the world, such as the expansion of gas production in the OECD economies, the European Union, and the reforming economies of the former Soviet Union. Other IAMs may assume a larger build–out of gas in Asia to replace coal, but in the case of AIM, by comparison, the assumption is that Asia will continue to remain reliant on coal.

This highlights the variability in assumptions on the future build–out of fossil fuel technologies based on different IAMs. Although scenario providers develop narrative pathways that are consistent with and categorised according to global temperature

[40] The R5 regional aggregation is defined by the IPCC for the AR6 scenarios as five macro–regions used to categorise and model countries together. This is the highest level of aggregation used across IAMs for the AR6 scenarios. The five regions refer to both geography, as well as level of economic development. *Asia* refers to emerging economies of Asia such as China, India, and Southeast Asia. *Latin America* refers to Central and South America including Mexico and the Caribbean. *Middle East and Africa* refers to the Middle East, North, and Sub-Saharan Africa. *OECD and EU* refers to the OECD member states, and countries of the European Union, including North America, Europe, Japan, South Korea, Australia, and New Zealand. Finally, *Reforming economies* refers to Eastern European countries and countries of the former Soviet Union, including Russia, Ukraine, Central Asia, and non–EU Eastern Europe.

outcomes on the timing and magnitude of emissions reductions, the trajectories and assumptions made for each scenario can vary extensively. In the case of AIM/CGE 2.2, the IAM estimates a higher development of coal in Asia compared to other fossil fuel technologies to mid–century. From other IAMs, scenario trajectories may assume a different development of fossil fuel technologies such as gas, but the variation in energy production for fossil fuels across IAMs will invariably demonstrate a wide range in trajectories depending on each IAM and the assumptions made in reaching temperature targets according to different climate policy ambitions, stringencies, and emissions reductions.

3.1 Company Trajectories

Production trends from figure 7 are applied to individual companies within each country, and distributed according to each asset based on the reported total capacity, and the firm's reported five–year production plans. Hence, according to each scenario, each company has a different production trajectory that is translated into profits under the baseline. These trajectories further vary by the extent of each firm's five–year production plans, overall capacity, and the extent of alignment or misalignment before the shock is applied.

For this paper, we are focused on illustrating the results of a stress test on the downside risk of the climate transition, so we look only at fossil fuel assets and companies in coal, gas, and oil technologies. This reduces the number assets in the dataset from the full set of 85,285 to 8,256 assets globally.[41] Hence, when conducting the stress test and applying scenario trajectories, we are focused on assessing the downside risk of the transition to fossil fuel companies. Therefore, company valuation adjustments under the stress test do not account for the full operations and business units of an energy company, but focus on valuation loss and asset stranding in their fossil fuel business. Further discussion of the modelling of renewable power generation and the upside benefit to companies is discussed in appendix section 8.3.

Focusing on the downside risk for fossil fuel companies, the translation of climate scenario trajectories to company performance in terms of reduced production are illustrated based on the asset and capacity phase out. This is illustrated in figure 8, which shows the comparison of two company trajectories in the stress test using the same fossil fuel technology.

Figure 8 compares the individual company-level trajectories for two gas power companies in the US based on the production trajectory taken from AIM/CGE 2.2. From the figure, the trends illustrate the application of the AIM scenario to each company's trajectory under the baseline, and the trend from the "target" pathway, or the temperature target scenario, which limits global emissions to 900 gigatonnes of CO2. The "shock"

[41] The majority of assets in the database are renewable facilities, such as solar or wind farms that have much smaller generation capacity. Of the total 85,285 assets, 43,803 are either photovoltaic or concentrated solar farms. 20,321 are on/offshore wind farms. For fossil fuel plants, there are 3,365 are coal, 1,860 are oil, and 4,632 are gas plants. 4,008 are hydro power, 345 nuclear, 1,750 biomass, and 273 geothermal. Hence, since the focus of our analysis is on the downside transition risk to fossil fuel companies, we focus on the 8,256 fossil fuel assets in the database.

trend is the application of the stress test's climate policy shock, taken at a point in the future to align with the future divergence in trajectories observed in the scenario.[42] For this stress test, the shock year is assumed to be 2033.[43] Further discussion of how company assets are aggregated, and the pathway of the company transition, including the retirement of assets and the staggered distribution of asset shock are discussed in appendix section 8.4.

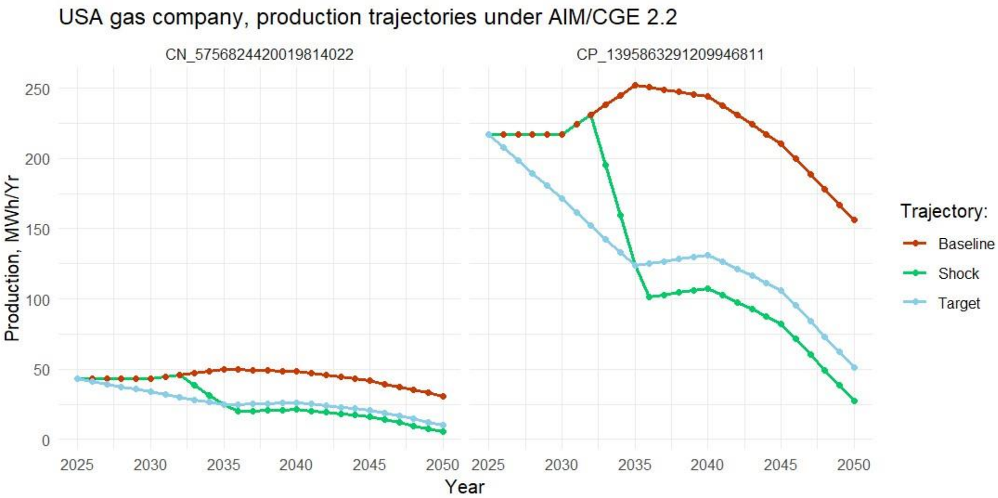

Figure 8: Production trajectories applied to two sample gas companies in the US from AIM/CGE 2.2.[44]

From the figure, we demonstrate how the stress test is modelled for individual companies. First, future production, loss, and risk trend for each company is different, representing the general heterogeneity in power companies that is overlooked in the absence of asset–specific information. Second, despite being drawn from the same scenario, the trends do not exhibit the same pattern of decline, so each company's transition risk is specific to the company, based on the company's profile of number of assets in the fleet, the company's forward–looking production plans, as well as each country's specific carbon budgets and

[42] The AIM/CGE 2.2 from the AR6 ensemble states that the pathways follow nationally determined contributions narrative until 2030, at which point there is an implementation of a stronger mitigation policy constraint. This is evident in the divergence in pathways from 2030.

[43] The stress test narrative for a misaligned high carbon power company is as follows: the company follows along the five-year production plans from 2025 to 2030. Then firm production increases to the baseline production level according the "current policies" scenario to maximise profits. The shock year for the stress test is 2033, when a climate transition policy is assumed to be introduced. Firms are given a period to transition along the "shock" pathway to meet the new, lower level of production under the climate scenario "below 2C" pathway, which the firm meets in 2035. However, due to the need to compensate for excess production and emissions in the earlier period when the firm was producing and emitting more under the future production plans and baseline pathway, this needs to be compensated in the subsequent years beyond 2035.

[44] Trajectories are compiled based on the aggregation of capacity of individual power assets held by each company, and the share of total country capacity is applied to the company as the overall share of production under the baseline and shock scenario trajectory. Company names have been anonymised in the plot.

climate transition policies, including their carbon price. While these figures illustrate how scenario trajectories are mapped onto individual companies based on the asset database, they do not alone determine a company's performance in valuation adjustment between the baseline and the shock scenario.

From these trends, as outlined previously, annual production over time is modelled to net profits, according to asset and firm costs to determine EBITDA, which are input into the stress test model. These trends, along with several other variables previously outlined are used to model a company's net profits based on their allocated production under the scenario, which subsequently is used to determine a company's net present value. Company NPV is then compared under the baseline trajectory to the transition scenario to determine the value at risk under the climate policy scenario.

4 Results

Application of the stress test model to assess valuation change under a climate transition scenario is summarised according to the AIM/CGE 2.2 model, and compared according to region and fossil fuel technology, and compared to other IAMs. First, comparative regional and technology analysis determines how the scenario production trends from figure 7 are mapped onto company assets, and then from assets to company value adjustments between baseline and shock climate scenarios. It is expected that production trends would similarly be reflected in aggregate for company valuation adjustments, but may not entirely compare across regions. This is because production trends drive company revenue, which determines valuation, but there is a different composition of companies owning assets in each region. This would affect the allocation of production and revenue between companies, and subsequently affect valuations differently. Hence, in aggregate, valuation changes should reflect production trends, but losses may accrue differently between regions.

Second, the stress test methodology is premised on leveraging asset-specific information to better evaluate climate financial risk. To do this, we compare the results of company valuation changes under an asset–based stress test model in relation to the valuation change that does not account for asset information. This simply draws down the scenario trends into the net profit equation outlined previously, but omitting further methodology that scales down shocks and distributes losses to the asset-level. Comparison of the two methodologies illustrates the amount of valuation that is either missing or lost when climate stress testing methodologies do not account for asset–specific information.

4.1 Value at-Risk Under Asset Heterogeneity

The primary output of the stress test is an assessment of the difference in comparative company valuation under the baseline compared to the shock scenario. The valuation adjustment is measured for the technology power company's net present value, based on the discounted annual earnings, profit, and cost model illustrated previously. From this, the individual measure of value adjustment is compared from the baseline scenario of "current policies" to company value under the shock scenario, which is the "Below 2˚C" pathway.

The aggregate results of the stress test on company valuation change using the AIM/CGE 2.2 model from the AR6 scenarios are illustrated in Figure 9. The figure shows the aggregate value of power companies across all three fossil fuel technologies in each of five R5 regions. For each plot, the aggregate net present value of companies is compared between the baseline scenario values in green, and the shock scenario in brown. The percentage change between the two aggregate valuations is also shown to highlight differences between the shock and baseline.

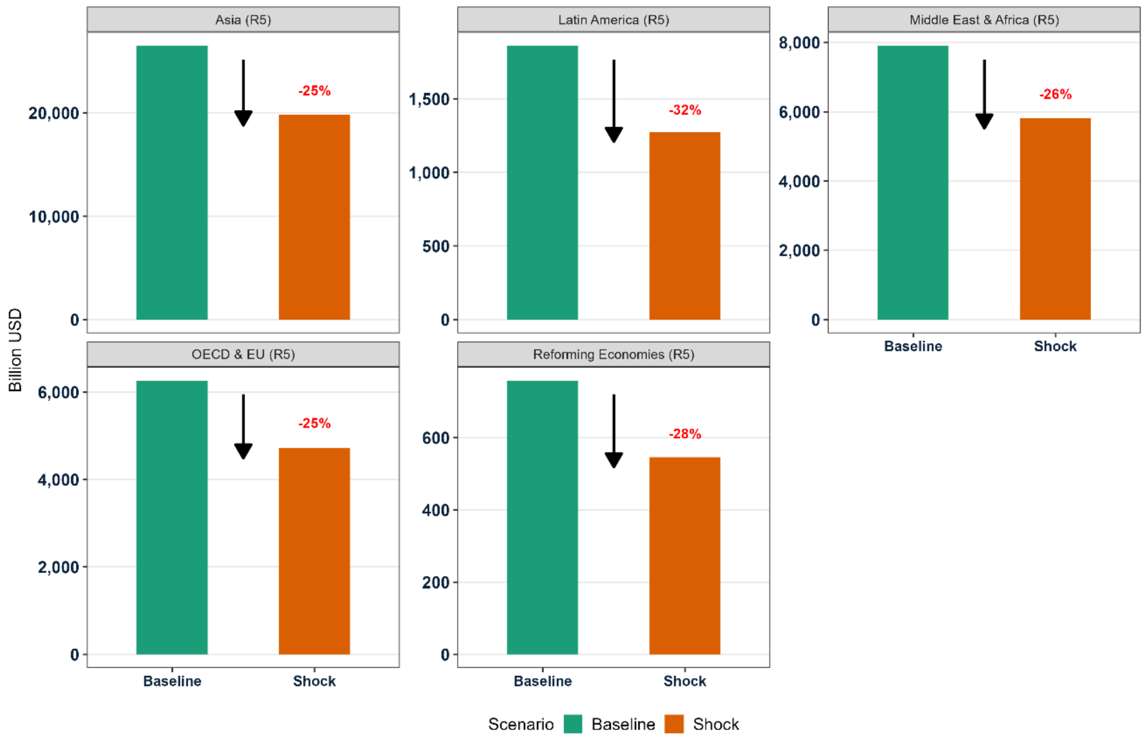

Figure 9: Difference in stress test company values and losses by R5 region.

Across all plots, results show consistency in the stress test that all fossil fuel power companies are expected to lose value under a climate scenario that limits warming to less than 2˚C by end of century, compared to a trajectory where no further climate policies are implemented. These findings are consistent with widespread expectations for the fossil fuel sector.[45] Comparative assessment across regions demonstrates that some regions indicate higher risk than others.[46]

From figure 9, total losses by region show that the greatest percentage losses are in Latin America, with similar percentage differences for the Middle East and Africa, the OECD economies, and the reform economies of the former Soviet Union. This is consistent with the overall high carbon technology production trends by region illustrated in figure 7. Over the scenario period 2025 to 2050, the difference in the carbon budget under the shock scenario compared to the baseline has the greatest percentage difference in the Middle East and Africa, and Latin America, with a 2.56 and 2.46 percent lower carbon budget for each region for the 2025 to 2050 period, respectively. While the figure highlights the percentage change in valuation under a climate scenario, the aggregate valuation differences have been scaled for each region for comparability. Despite these larger percentage declines in aggregate company values under a shock scenario, the total value lost is highest in Asia.

To compare total value losses from baseline to the shock across regions, figure 10 illustrates the lost value for each region. In contrast to the percentage changes highlighted in figure 9, Asia shows the greatest loss in value, followed by Latin America, and the Middle East in Africa. Hence, while percentage losses are higher for regions such as the OECD economies, Latin America and the reform economies of the former Soviet Union, by total value, all other regions show higher aggregate losses.

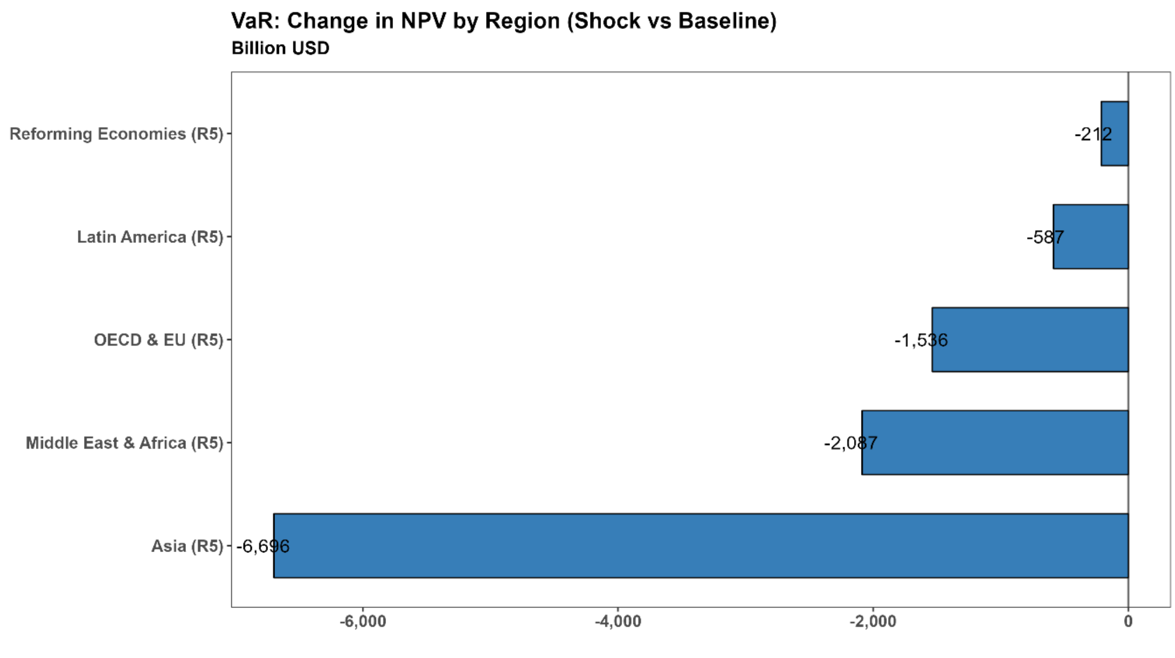

Figure 10: Cumulative company valuation change by R5 region, AIM/CGE 2.2

[45] Gregor Semieniuk et al. “Low-carbon transition risks for finance”. In: *WIREs Climate Change* 12.1 (Jan. 2019), pp. 1–24.

[46] Louison Cahen-Fourot et al. “Capital stranding cascades: The impact of decarbonisation on productive asset utilisation”. In: *Energy Economics* 103.105581 (2021).

Comparing the different trajectories from a climate scenario and applying them to corporate valuation assessment, as illustrated in the asset–based stress test, supports a highly granular evaluation of a company's potential valuation change. Consistency in the correspondence of climate scenario patterns illustrated by the AIM model and implications for company valuation in each technology/region demonstrates how the asset–based stress test methodology transparently allocates production under a scenario to each individual asset owned by a company, and operating in each R5 region, with changes in valuation based on differences in the assumptions of each scenario trajectory. Understanding the potential future trajectories of fossil fuel demand and production under different climate scenarios for each company operating in a sector and region can better support corporate sustainability planning and strategy.

4.2 Value at-risk: Asset-heterogeneity versus homogeneity

The primary focus of this paper has been to present a novel dataset and framework for evaluating the valuation adjustment for companies by using an asset database to better profile the impact of climate policy shocks on companies, model firm behaviour, and reduce risk by having more detail in the individual asset risk. In order to evaluate the stress test methodology according to the level of granularity in a company's assets and production, figure 12 compares the aggregate amount of valuation adjustment between the baseline and shock scenario, and the difference in the estimated losses based on the level of company and asset granularity in the stress test. Estimates of the aggregate valuation change between the two methodologies are compared based on the application of asset–specific data, features, and characteristics to compile a company's portfolio risk, applying this added information to minimise firm losses and reduce asset stranding while adhering to climate policy goals. This is compared to a less granular methodology, where costs and losses to firms are applied from the scenario–level to the company overall, rather than to the individual assets.

Results are illustrated in figure 12 according to the estimated losses to fossil fuel companies, as the difference between the baseline and shock scenario. Hence, they all appear negative, as all thermal power companies have lower values under the shock compared to the baseline scenario, where a shock climate scenario imposes faster fossil fuel reductions compared to a baseline scenario that assumes business–as–usual. The total valuation across companies is illustrated by R5 regional aggregation.

From the figure, valuation estimates demonstrate that for every region, using asset–level data to evaluate financial risk, the loss in valuation between baseline and shock is lower using more highly granular asset data, compared to a methodology that omits this data, asset–specific features, and minimises stranded asset risk.[47] The difference in

[47] Valuation adjustment is based on the difference in company valuation under the shock scenario compared to the baseline. Estimated company values have been compiled according to company and asset–level aggregation for both shock and baseline scenarios. This section compares company valuation estimates compiled according to asset and company–level aggregation in the shock scenario, but using a common baseline compiled at the asset–level. Hence, valuation changes under both an asset and company–level shock

valuation risk based on the granularity of data in the stress test is high, ranging from 2.6 percent in the Middle East and Africa, to near 16 percent in the reforming economies of the post–Soviet Union. Hence, the risk is lower using asset–level data compared to less granular assessment that only observes risk at the company–level.

These percentages represent significant differences in valuation adjustments across regions. For Asia, the difference in granularity in the stress test amounts to nearly 10 percent, representing a difference of 684.4 billion USD, by having company and asset specific information to reduce shock impacts and asset stranding. For the OECD and European Union, this difference is 222.9 billion USD, and for the Middle East and Africa, this is 56.3 billion USD. These represent significant differences in valuation and potential losses simply by having greater detail of individual assets to better model company behaviour. Overall, the total difference in valuation change from baseline to shock scenario based on the level of granularity represents 1 trillion USD less losses when using asset–specific data compared to a methodology that only has company–level information.

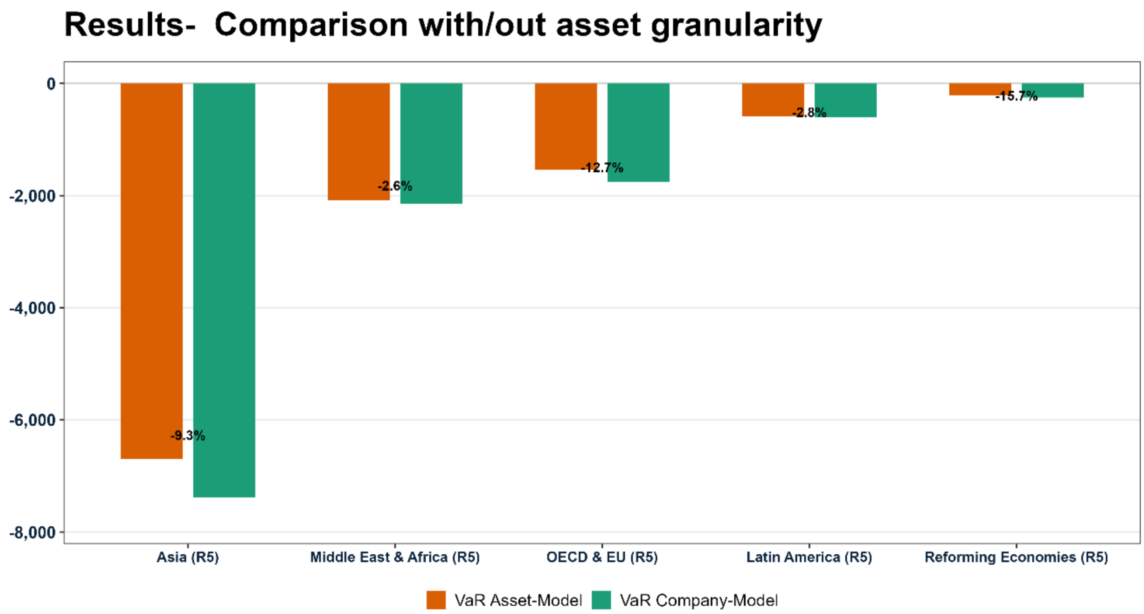

Figure 12: Comparison of power company valuation loss between the baseline and shock scenario based on level of data aggregation in the stress test, aggregated to R5 region.

The difference in company value loss between baseline and shock scenarios, illustrated in Figure 12, demonstrates two key findings for climate stress testing. First, that different methodologies applied to climate stress testing of companies in hard-to-abate sectors can represent large differences in the assessment of company valuations and adjustments under different climate scenarios. This is significantly dependent on the

scenario are compared to baseline values using asset–level data. Further comparisons analysing the robustness of these results using separately compiled baselines for asset and company–level, as well as using a common company–level baseline are discussed in appendix section 8.5.

trajectories in the climate scenario, and the methodology for how transition shocks are applied to individual companies. This has been illustrated by differences in aggregate company valuations when using a standardised methodology, and only omitting company–specific information.

Second, by incorporating firm–specific information such as the individual assets owned and operated by a company, as well as taking into consideration the firm's five–year future production plans, we present a methodology that more accurately assesses a company profile by incorporating more specific features and characteristics. In doing so, this methodology shows that the cost of transition for fossil fuel companies is lower than otherwise estimated when not accounting for firm–specific information, individual assets, or strategically minimising a firm's stranded asset risk. Overall, we find that the more specific asset–based information and the strategic planning of production shocks to a firm reduces the potential valuation adjusted losses by 1 trillion USD based on the differences in the level of granularity in the stress test, with significant variation between technologies and regions. Estimation of the valuation difference based on level of granularity in the stress test is further discussed in appendix section 8.5.

5 Estimating the cost of transition based on data granularity

Results from comparing the aggregate valuation loss from baseline to shock scenarios show that the level of granularity and company–specific information in a climate stress test makes a significant difference in the assessment of valuation risk and the cost of transition. By adding asset–specific information such as age heterogeneity to a company's production and cost trajectories under a climate transition scenario, we find that the cost of transition and the risk of asset stranding is significantly less than would otherwise be estimated or projected from a climate stress test that does not include this information.

Leveraging more specific information on individual fossil fuel assets, the methodology laid out in this paper models two key features to lower costs and risk to firms that would otherwise not be available at a more highly aggregated firm–level stress test. First, we reduce the risk of asset stranding by allowing firms to distribute the lost production from a climate shock scenario across the firm's full fleet of assets in a way that maximises firm production and profits, while minimising costs based on the remaining years and emissions intensity of each asset, rather than force companies under a production shock to retire assets immediately. This allows firms to continue running assets closer to the full financial lifetime, and enabling higher capacity for production, while still meeting climate scenario reductions on fossil fuel energy by distributing the lost production shock across assets in a way that maximises production and revenue, while minimising costs.

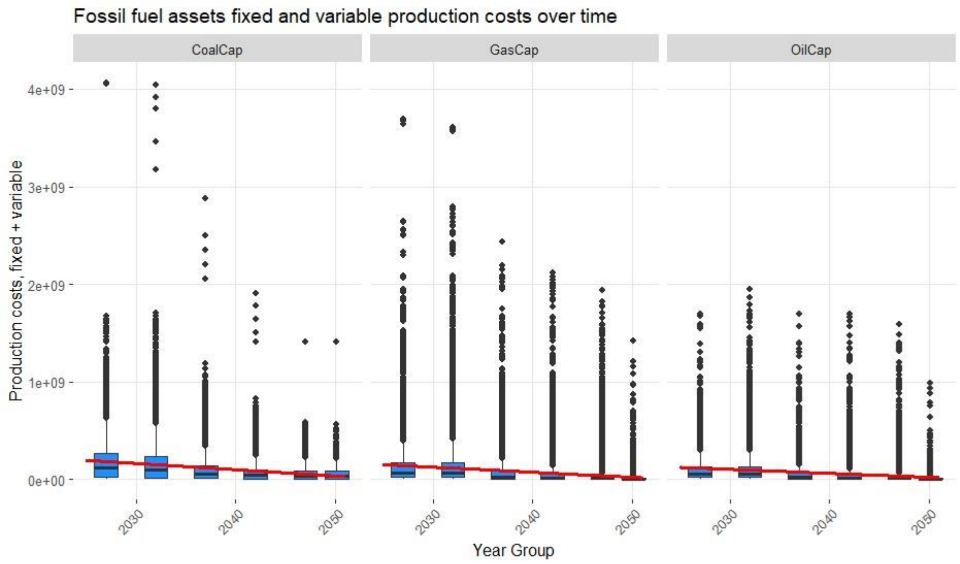

Figure 14: Individual coal, gas, and oil assets by production costs, fixed plus variable, by starting year of asset production.

Second, having information on asset age allows for a more realistic and direct approach to estimating firm–level costs, rather than projecting costs without knowing or dynamically applying changes in a firm's production capacity. If a climate stress test does not have more granular data than company–level information, then a climate financial stress test cannot observe nor account for dynamically changing production costs to a firm, but can only assume the costs from the aggregate capacity that is given or reported by the company. In this case, firm capacity and production costs are held constant over the duration of the stress test, rather than dynamically able to change or decline by the firm being able to retire assets, reduce capacity, and reduce costs. By having this asset–level information on age, capacity, emissions factors and intensity, a climate financial stress test more realistically estimate costs and risks to firms. An additional key feature from the asset data is the incorporation of a company's five-year future production plans into the NPV calculation, which play an important role in the transition pathway. The role of five-year production plans are discussed in appendix section 8.6.

These two asset–based features are the focus of the difference in the level of granularity in the asset and company–based stress test. In order to illustrate the impact that these two asset–based features have on the estimated cost of transition for companies, it is firstly observed on the basis of the production costs per asset, as illustrated in figure 14.

Production costs are the combination of fixed and variable costs that are applied in the stress test to each individual asset, and then aggregated to overall annual company costs.[48] By having asset–specific information on asset age and costs, this contributes to lower estimates on the cost of transition, as illustrated in figure 14 unit production costs decline. Hence, as a company retires older assets that have either met or are near their financial lifetime, they can retire assets without facing losses from asset stranding.

[48] Fixed and variable costs to individual assets are based on the asset capacity, and changes in capacity that are taken directly from the climate scenario trajectories on production costs.

Additionally, by incorporating asset–based modelling that distributes a loss in energy production across assets, it enables companies to maximise profits by distributing more production to newer assets that have lower production costs rather than older assets where emissions intensity and production costs are higher.

Having asset–level information provides a more accurate assessment of company risk from a shock climate transition scenario since it enables firms to efficiently reduce capacity without full asset stranding, and optimise cost reductions by loading more production to newer assets in the fleet. In the absence of this type of information, production costs cannot be estimated according to the age of individual assets the company owns, or adjusted over time based on the capacity that is retired. Instead, it can only be observed from what the company reports at the start year of the stress test, and either estimated forward or simply assumed constant.

Figure 15 shows the trends in company–level production costs, based on costs that are either compiled from the asset–level and then aggregated to the company, or costs that are simply observed at the company–level. Production costs are set as the unit variable and fixed costs that are given by the climate scenario. However, in the case of the company illustrated in figure 15, production costs are based on the firm's fleet of assets where production under a shock can be distributed to assets with lower production costs, but also can continue to run older assets without stranding them.

Additionally, by using asset–specific data, firms retire capacity once an asset has reached its expected lifetime, and thereby reduce costs from retired capacity. However, in a stress test that does not observe changes in firm capacity, production costs are only assumed to decline, or expected to remain constant, based on a given capacity for the company. This results in costs being inaccurate and overestimated by not being able to observe the firm's reductions in capacity over time.

From figure 15 the comparative trends in production costs under a baseline and shock scenario show higher costs and greater divergence under both scenarios at the company–level. This is because the company–level stress test does not observe changes to a firm's capacity from retired assets, and hence capacity and costs are assigned only at the start of the test, and carried forward without retiring. This is observed in the continued costs to the firm that are carried forward to the end of the stress test, in 2050. Whereas in reality, given the age of the firm's existing fossil fuel assets, nearly all of the firm's assets are expected to retire, based on reductions in capacity and reductions in costs observed in the asset–level cost trend. These added costs continue to accumulate for the firm, hence lead to higher assessed losses for the firm when only company–level information is available compared to an asset–based stress test.

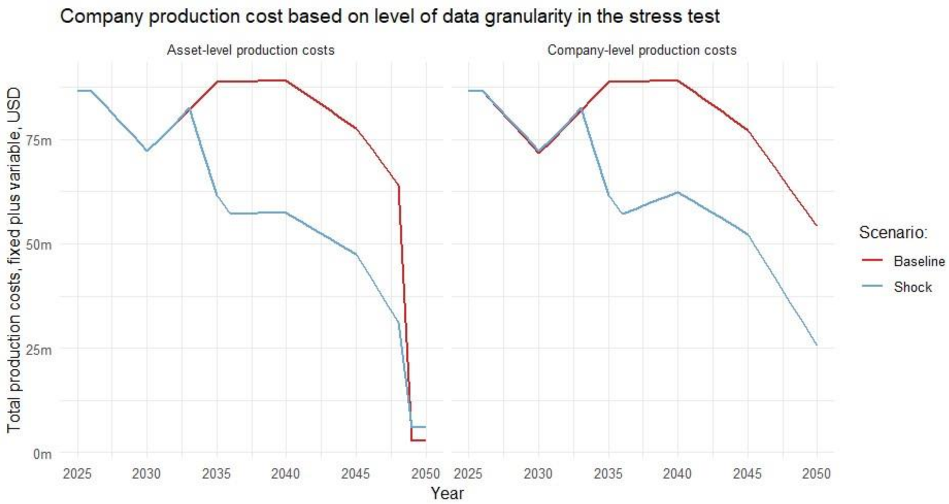

Figure 15: Comparative production cost trends for a firm in the stress test, based on asset or company–level information. Production costs are fixed plus variable costs from the climate scenario.[49]

6 Conclusion

Several methodologies exist for assessing the macroeconomic impacts of climate policies, and estimating the value of stranded assets, which are subsequently aggregated to determine the probability of corporate value at risk.[50] However, these methodologies and estimates are often too broad based to define shock scenarios for individual institutions or companies due to the lack of granularity in the company's profile and exposure based on various transition risk scenario pathways.[51] Hence, the variety of methodologies that exist for assessing transition risk, and the lack of granularity or consistency in the comparative assessment raises the uncertainty for companies in developing any effective risk mitigation or climate policy aligned strategy, due to the range of outcomes that can result at the individual company–level.

While there are several stress test methodologies that evaluate corporate transition risks according to targeted emissions reductions via revenues and costs in the real economy, the primary uncertainty in conducting climate stress testing is the assessment of individual corporate risk. This uncertainty is related not only to the specific company profile, but also due to the comparative allocation of production or emissions reductions that need to be met by each company. For any one company, uncertainty in the performance, risk, or profile of other companies that are subject to similar climate transition policies makes the assessment of any corporate strategy uncertain, as companies

[49] Production costs are estimated for an anonymised coal power company to illustrate how costs are projected forward based on level of company and asset-specific granularity in the dataset.
[50] Dietz et al., "Climate value at risk of global financial assets", op. cit.
[51] Battiston, Dafermos, and Monasterolo, "Climate risks and financial stability", op. cit.

may view their own transition risk profile more favourably than other companies operating in the sector, but without knowing the risk profile of other companies.[52]

By developing a highly granular asset–based stress test that constructs company portfolios and performance based on individual assets, the assessment of corporate risk from future climate transition scenarios is consistent and comparable between companies and countries. Findings from this paper show that the methodology consistently applies transition production and emissions trajectories from climate scenarios to individual companies based on the portfolio of assets, as illustrated in the modelling of corporate energy production shocks from climate scenarios. This is also comparable across companies as the allocation of energy production to each asset is based on corporate ownership of the country's energy mix from the climate scenario. Hence, findings illustrate differences in the total corporate valuation adjustment based on each fossil fuel technology, which shows consistency in the valuation loss under the shock scenario compared to the baseline across fossil fuel technologies.

Most importantly, by constructing a climate stress test from the asset–level, we leverage key features and characteristics to model firm behaviour that has not been previously used or applied in other climate financial stress tests. First, stranded asset risk is one of the primary transition risks for companies.[53] Within the assessment of stranded asset risk, one of the most important variables is the asset's age of financial viability. We have integrated asset age into our methodology that allows firms to retire older assets in the fleet to minimise the stranded asset risk. This contrasts with prevailing methodologies that simply account for stranded asset risk based on total capacity to the sector and country, and the assumption of future carbon emissions that are already "locked-in" rather than dynamically adjusted within or between firms.[54] By incorporating this into our stress test model, we are able to more accurately assess the firm's risk of asset stranding, and better evaluate the firm's valuation adjustment under a stress scenario.

Second, by incorporating asset–specific features, we primarily address asset stranding, but also optimise a firm's profits by distributing a transition risk shock across the fleet of assets, which is staggered according to asset age and inferred carbon intensity. This methodology further improves on a firm's transition risk assessment by allowing firms to allocate shocks according to financial viability, where assets that are closer to their financial lifetime absorb more of the transition shock of lost production compared to newer assets in the fleet, based on the inference that newer assets have a lower carbon intensity than older assets. This highly granular asset–based modelling further supports a more accurate assessment of a firm's transition risk by accounting for model features that are specific to each firm's individual profile and risk based on the composition of each asset and characteristics.

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[52] Oh-Suk Yang and Jae-Hoon Han. "Assessing the effect of corporate ESG management on corporate financial and market performance and export". In: *Sustainability* 15.3 (2023).

[53] Ben Caldecott et al. "Stranded assets: Environmental drivers, societal challenges, and supervisory responses". In: *Annual Review of Environment and Resources* 46 (2021), pp. 417–447.

[54] Deger Saygin et al. "Power sector asset stranding effects of climate policies". In: *Energy Sources, Part B: Economics, Planning, and Policy* 14.4 (May 2019), pp. 99–124.

However, while the methodology and results presented offer valuable insights into the risks faced by individual companies, they are subject to several important caveats and limitations. First, the methodology has only been applied to one IAM, so the results have not yet been robustly evaluated across multiple scenarios. This is related to the second limitation in the methodology, which requires a climate scenario divergence to occur at some point in the future. Since we have used scenarios from the AR6 dataset, scenarios have a base start year of 2015, making several variable trajectories outdated and inaccurate since scenarios have a climate policy divergence that began in a past year. This leads to much higher and inaccurate losses in the stress test since the compensation mechanism accounts for the entire area under the curve from the start period, forcing asset stranding due to an already wider divergence in the start year of the stress test. Third, the methodology has focused on more dynamic modelling of transition strategy and planning by firms through using asset data, but has not incorporated technologies that are key to mitigating against stranded asset risk, such as CCS technologies. By incorporating this technology into a firm's production strategy, this would lead to even lower losses in valuation under a climate policy shock. Further analysis and development of the methodology should incorporate these features to further improve the valuation adjustment according to a wider set of scenarios.

This paper has demonstrated the consistency and comparability of an asset–based stress test methodology with an overview of corporate valuation adjustment compared to all other companies in that technology sector and country, which enables individual firms to observe their own climate and sustainability strategy in relation to the performance of other firms that would be subject to the same climate policy shocks. In addition to developing a consistent and comparable asset– level climate stress test, we also find that by incorporating individual asset modelling features, the transition risks and valuation adjustments are lower across companies and technologies. We find that the largest reduction in lost value is in gas, with nearly 10 percent less of a valuation change between baseline and shock scenarios by using asset–specific features, which amounts to nearly 1.1 trillion USD globally. Oil also has approximately a 5 percent lower aggregate valuation loss between baseline and shock scenario by accounting for asset–features, or nearly 100 billion USD globally. Finally, coal has 1.4 percent less valuation loss between baseline and shock, or 84 billion USD globally.

While these results are based on global climate scenarios, we have particularly emphasized the importance of highly granular data to improve stress test modelling. Therefore, further improvements in the assessment of climate risk in financial stress testing would benefit from more granular climate scenarios, or those that are based on national-level models and power-sector specific decarbonisation pathways. The generalised global AIM scenarios that have been fit in this case to company and asset-specific trajectories also overlooks extensive variation in country strategies and policy priorities, which should be more accurately modelled at a national-level to further improve stress test risk assessments. Overall, findings demonstrate that an asset–based methodology for conducting climate financial stress testing improves the comparability and consistency of valuation change across companies, and also finds that the change in valuation under risk scenarios is actually lower when accounting for firm and asset–specific information and features.

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8 Appendix

8.1 Data

In order to observe coverage of our asset–level power dataset from figure 3, the sum of the total capacity across assets in a country is compared to the total reported capacity for each country and technology. Data from the total reported country capacity in each technology is taken from the Ember energy database. Figures A1 and A2 illustrates the coverage of the asset–level dataset according to different fossil fuel technologies. From the figure, the asset–level database has very high coverage of a country’s total capacity in coal and gas power generation. This varies between countries, but importantly, for some of the highest emitting country for each technology, coverage is above 95 percent of listed capacity.

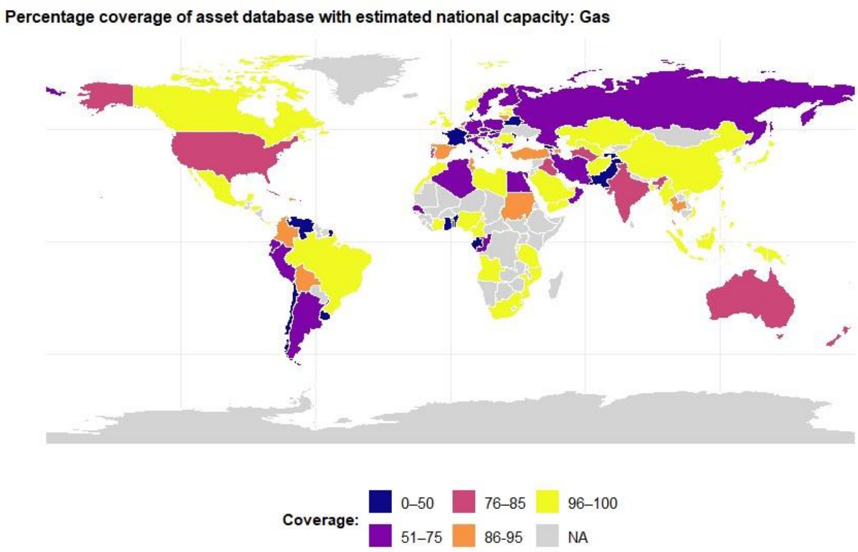


Figure A1: Gas capacity

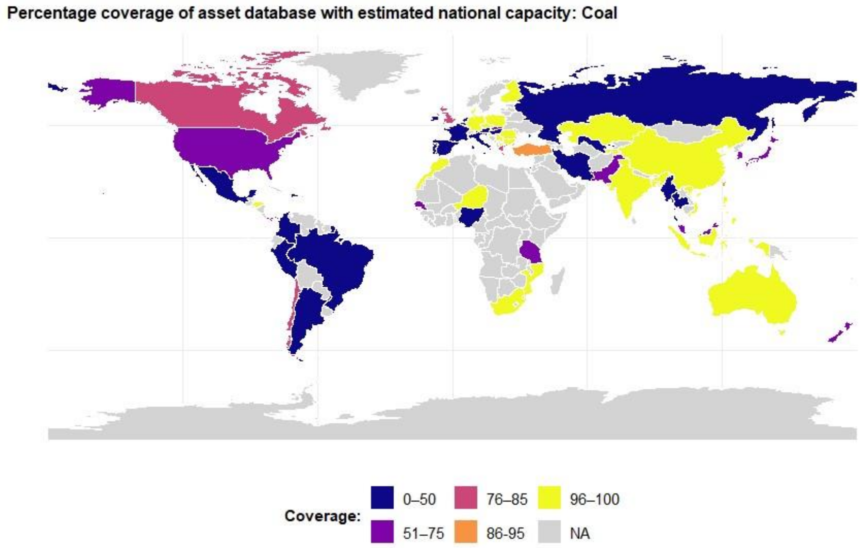


Figure A2: Coal capacity

Although figures A1 and A2 show no data for some countries, this is due to the lack of country– level reports of total capacity, rather than missing asset–level data of power plants in those countries. When comparing coverage of assets per country to main figure 3, the asset database includes reports of assets in every country. Hence, although they appear is missing data for several countries, particularly in Africa, they are actually represented better in the individual asset database, rather than in the total reported country capacity database.

8.1 Appendix: Carbon efficiency

Age is incorporated into the model of firm behaviour to minimise losses from climate policy shocks and reduce asset stranding. The premise that a firm should retire older assets first relative to newer ones in the fleet is based on financial viability, since older assets should be closer to their expected financial lifetime rather than newer ones. However, this is also premised on the assumption that older assets are less emissions efficient than newer ones, therefore to additionally reduce emissions intensity, a firm should also retire older assets.

In order to determine the extent to which age is an indicator of emissions intensity, we model emissions intensity as the emissions factor in the asset database relative to the start year in a simple OLS linear regression model. We include only fossil fuel power plants, regressed on year, and group according to technology type, with the baseline being coal, and including separate indicators for gas and oil. Results are illustrated in table A1.

	(1)	(2)	(3)	(4)
Variable	Time trend	Technology, capacity-weighted	Technology, emissions factor	Production costs
Year	–0.000071***	–0.000055***	–0.00012*	–0.078***
	(0.00005)	(0.0102)	(0.00008)	(0.0004)
Gas		–0.0024***	–0.0476***	–0.728***
		(0.00001)	(0.0034)	(0.007)
Oil		0.0034***	–0.017***	–0.757***
		(0.0003)	(0.0045)	(0.009)
Intercept	0.1496***	0.118***	1.201***	176.41***
	(0.0102)	(0.0102)	(0.0163)	(0.874)
R–squared	0.0227	0.0721	0.715	0.156
Obs.	8402	8402	8402	238,041
Dep. var.	em. factor	em. factor * capacity	em. factor * capacity	Prod. costs

Table A1: Emissions factor by age and technology type. Capacity–weighted emissions factors by size of facility and emissions factor, age, and technology type.

From the table, results confirm that asset age is significantly and negatively related to emissions factor, used as a close proxy for intensity. Although the coefficient is small, it represents a decline in the ratio of emissions per unit of power generated in each year a new power plant goes online. Further, as expected coal, which is the baseline technology, has the highest emissions intensity, with oil having a significantly lower intensity, on average 0.16 lower emissions factor relative to coal, and gas having the lowest at 0.46 lower emissions factor on average compared to coal.

These results are further illustrated in figure A3, which shows the range in carbon intensity for assets based on the start year, grouped into five–year ranges. From the figure, most ranges of carbon intensity are clustered toward the bottom of the distribution, with the range in the emissions factor ratio less than 1. There are some outliers in the distribution, particularly in later years. However, the middle 50 percent range still narrows and the mean is lower in later years, even as some outlying power plants have higher emissions factors.

Figure A3 plots all fossil fuel technologies together to show the overall negative trend in emissions factors across coal, oil, and gas technologies for newer and younger assets. To compare the trend for each technology, figure A4 plots each individual asset's start year and emissions factor, separated by technology. Overall, coal power plants have the highest emissions factors, followed by oil, and gas has the lowest. The trend line indicates that across all fossil fuel technologies the trend is negative, indicating lower emissions factors for newer plants, with a slightly different rate of decline for each technology.

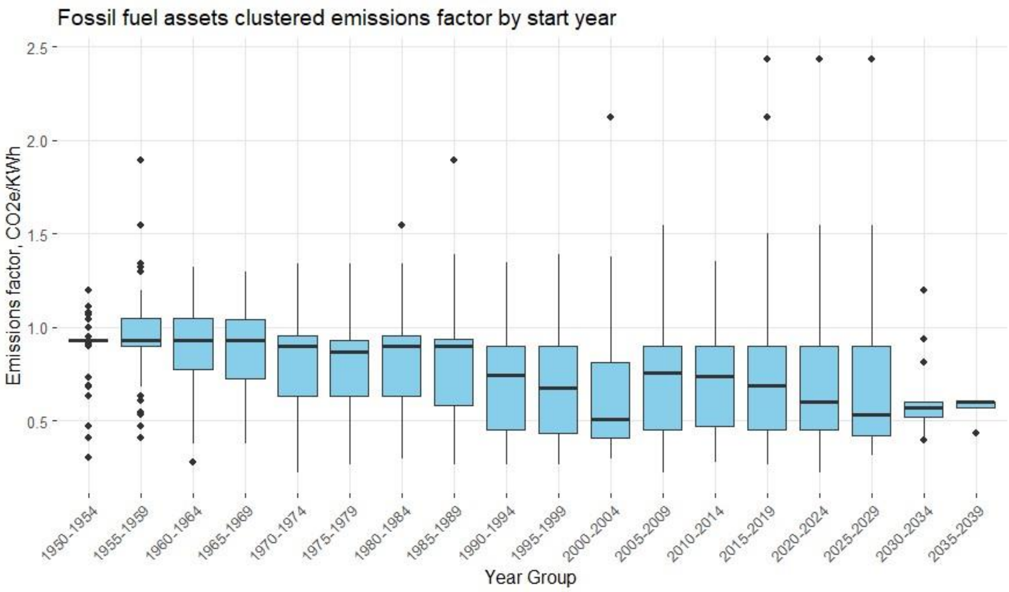


Figure A3: Fossil fuel power plants by age and emissions factor

The negative relationship in the lower emissions factors for newer fossil fuel power plants is further illustrated from figure A4, which illustrates the individual coefficients of emissions factors in each 5–year groups, separated by technology. The trend shows a clear secular decline in the relationship between the year a power plant goes online and the emissions factor, demonstrating clear increases in emissions efficiency relative to the asset's age, supporting previous evidence from table A1, and figure A3.

Evidence from table A1 and from figure A4 confirm the expectations that newer assets should have a higher carbon efficiency than older ones. Hence, in addition to the assumption that older assets should be closer to their age of financial viability relative to newer assets, age also serves as a proxy for emissions intensity based on emissions factor, demonstrated by the significant negative relationship between emissions factor and asset age.

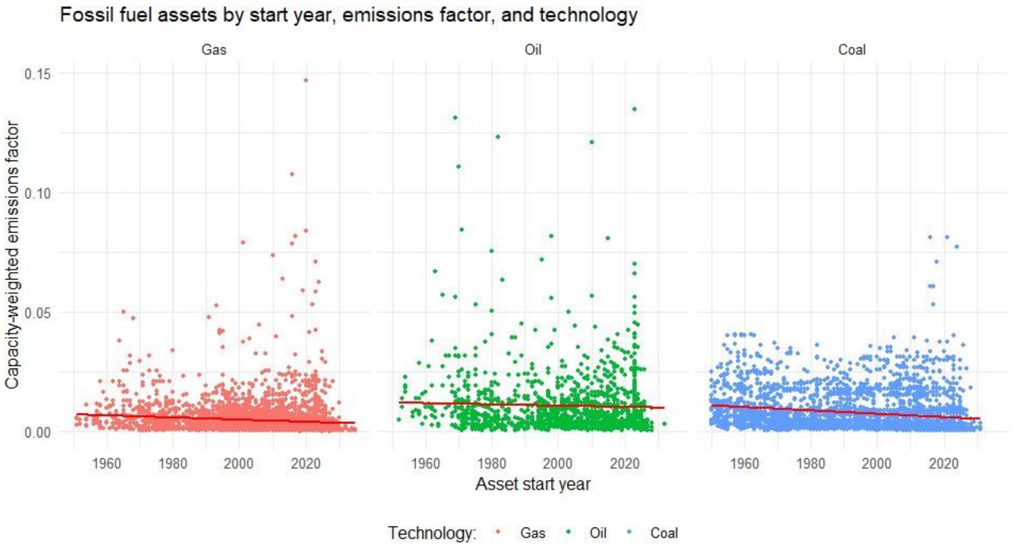


Figure A4: Fossil fuel power plants by start year, capacity–weighted emissions factor, and technology

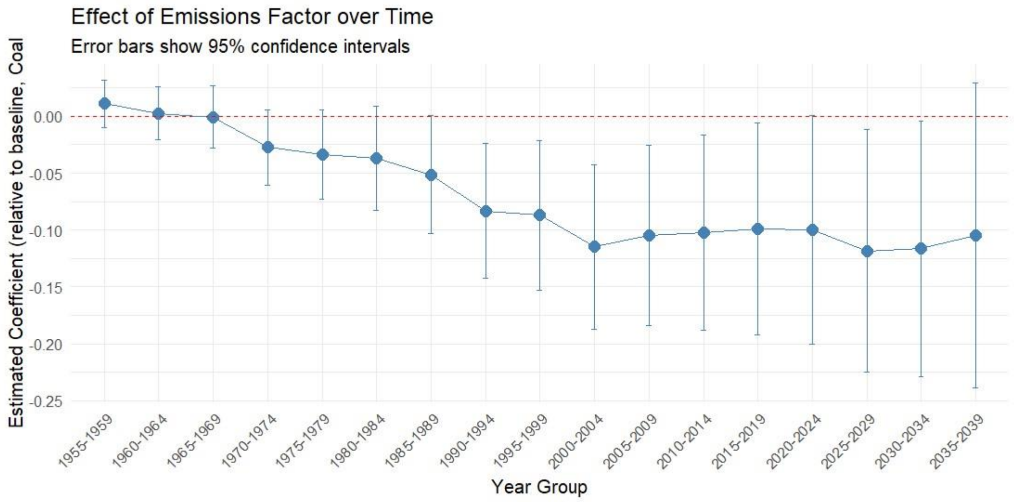


Figure A5: Start year coefficients on emissions factor and confidence interval in 5–year age groups.

Finally, our main findings illustrate that higher granularity in asset–specific features can reduce costs to firms in meeting climate transition targets by retiring assets, and by distributing a production shock across assets based on age, as a proxy for not only for lower emissions factors and emissions intensity, but also for production costs. In column 4 of table A1, the regression is run on a time series of years and the production costs per asset, taken as the combination of fixed and variable costs. Both fixed and variable costs are taken from the climate scenario, and are downscaled to individual assets. Since production costs vary over time, observations are not just taken at the start year of the asset, but are taken for the future trajectory of the asset's lifetime, which is on average 28 years for the lifetime of assets to 2050 from the current year of the scenario, 2025.

Results from column 4 of table A1 confirm similar findings as that observed for emissions factors, which is that production costs per asset decline over time. Hence, by having greater asset granularity in a climate stress test, it enables firms to better navigate shock scenarios by distributing shocks across the fleet of assets, enabling newer assets to take on more production to compensate for reductions, while also minimising costs by preventing asset stranding, but still reducing production costs through the distributive allocation of a climate transition shock scenario.

8.2 Appendix: Modelling capacity increases for renewable power companies

This paper has focused on stress testing the downside transition risk to fossil fuel companies, however we have also included modelling and analysis for all types of power generation, including renewables. The incorporation of renewables into the stress test framework is different than what has been presented in the main analysis, which has focused on using asset–level information to reduce losses, transition costs, and asset stranding. In the case of renewables, climate scenarios uniformly model an expansion of renewable power generation capacity. As a result of expanding capacity for renewables, the inverse problem applies, which is rather than assets becoming stranded, companies expand capacity and need to create additional assets that do not exist and have not been planned.

In order to apply growing renewable production from climate scenarios and attribute this to company revenue, we develop a methodology for adding company capacity to assets that do not yet exist, and goes beyond existing firm capacity. The maximum possible renewable asset capacity is simply set at the current level observed for renewables under the baseline, where the maximum observed capacity from existing renewables continues to be the maximum capacity for all future renewables. Even as scenarios increase energy production from renewables, the stress test does not allow asset capacity to grow beyond the pre–defined capacity limit set based on real observed renewable assets.

In order to account for a firm's added renewable capacity where no development plans or assets exist, we develop a model for the creation of synthetic assets that accounts for added production in the shock scenario, and a firm's existing capacity from the asset database. For each company, technology, and region, synthetic assets are introduced from the start of the divergence and shock year *S*. The synthetic asset's capacity is calculated in each year as:

$$P^{synth}_{i,h,g,t} = \max\left(0, C^{LS}_{i,h,g,t} - \sum_{a \in A_{real}} P^{baseline}_{a,t}\right) \quad \forall t \geq S \tag{A1}$$

$C_{i,h,g,t}{}^{LS}$ is the company's generation capacity under the shock late–sudden climate scenario trajectory for technology *h* in geography *g* at time t. $P^{baseline}_{a,t}$ is the baseline capacity of the set of real assets *a* at time *t*, A_{real} is the set of existing assets observed in the asset database, and $P_{i,h,g,t}^{synth}$ is the production capacity of the synthetic (new–build) asset for company i, technology h, geography g, at time t that does not exist and has not been planned.

From equation A1, $P_{a,t}^{\text{baseline}}$ is the total production provided by existing renewable assets in the database at time t under the baseline scenario. The capacity that is added to the firm under the shock scenario is $C_{i,h,g,t}^{LS}$. Hence, the difference between the two is the amount of added production capacity for the firm under the shock that is beyond the firm's existing capacity under the baseline. If the difference between the two is positive, then there is a gap in the firm's capacity between existing assets and the production trajectory under the shock scenario. This must subsequently be compensated by the creation of new asset capacity. Consequently, the synthetic asset "fills the gap" between business–as–usual production from real assets and the accelerated build–out of added units and capacity that is required for each company to meet the climate scenario target.

Upon creation, synthetic assets receive unique identifiers, and are treated as new assets in the database. Once added, they are incorporated into the standard modelling for company NPV. This includes age tracking for retirement, fixed and variable production costs set the same as existing assets, and unit revenue held constant as existing assets for each firm.

Since these assets are added to fill the unassigned production capacity gap under the shock scenario in which production capacity exceeds capacity in the baseline, synthetic assets only exist in the shock trajectories, but not in baseline trajectories. Hence, they do not fully align in the number of assets that exist between the baseline and shock scenario.

This method ensures that the build–out of renewable capacity imposed by the climate scenario does not exceed the maximum capacity of real assets observed in the asset database. If synthetic assets are not created, then increasing production under the scenario would be allocated to a firm's existing capacity. This would exceed the maximum capacity of existing assets, and it would create very high outlying profits and outlying NPVs for renewable companies, as there would be no additional costs or expenditure to firms for the increasing production of renewables once they start producing beyond their maximum capacity. This methodology ensures that the combined output of real and synthetic assets matches the company's trajectory as derived from climate scenario data in each year, and that unit costs and revenue continue to be proportionate to existing cost to earnings ratios.

8.3 Appendix: Company trajectories

Company production trajectories are taken from the aggregation of power plant assets owned by the company, with production assigned to a company based on its overall share of technology-based capacity, downscaled from the climate scenario. Figure A6 illustrates the breakdown of individual asset trajectories from a coal company, and demonstrates how it is aggregated to company-level. From the figure, each asset is assigned an age at the start of the scenario period in 2025, taken from the asset data. The trajectory of each asset is given a gradual reduction trend to allow the company to phase out each asset, rather than becoming stranded from the imposition of the transition trajectory. Newer assets take on increased production at higher levels, while other assets show steady declines without increasing, indicating the distribution of the staggered shock and the increased production of more efficient assets. Each phase of the company's transition is also highlighted.

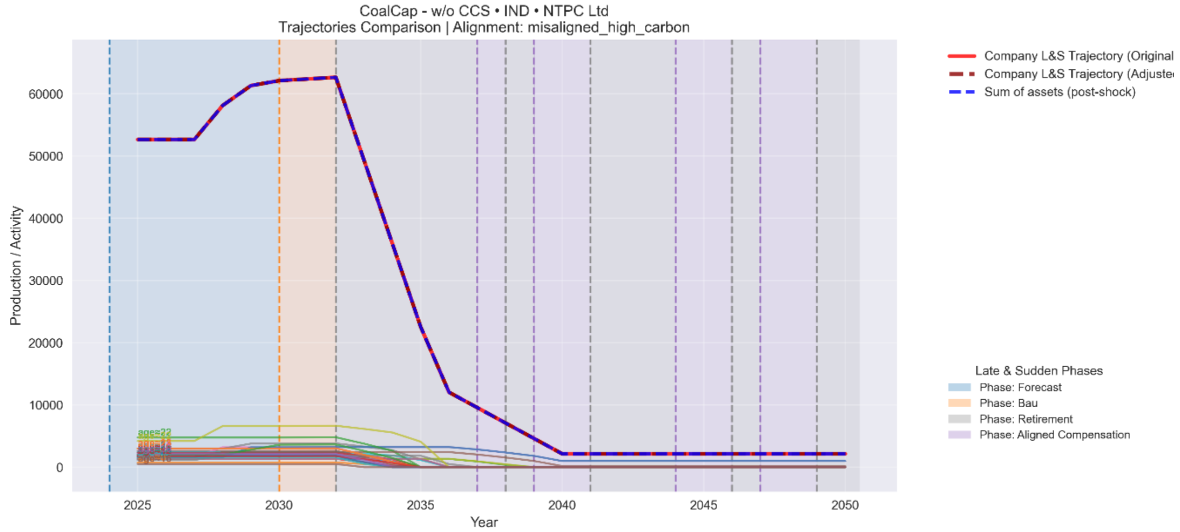


Figure A6: Modelling illustration of the transition scenario for a coal power company.

Figure A6 highlights how a company production trajectory is applied to individual assets and subsequently aggregated to the company-level. Additionally, individual asset trajectories illustrate how the asset-specific modelling for retirement and carbon efficiency shape the production trend for each asset. This figure illustrates only the transition trend for a misaligned coal company, but it is also reconstructed for each company under a baseline trend. The resulting NPVs compare the difference in company performance between the climate transition trend and the baseline trend, as illustrated in figure A7.

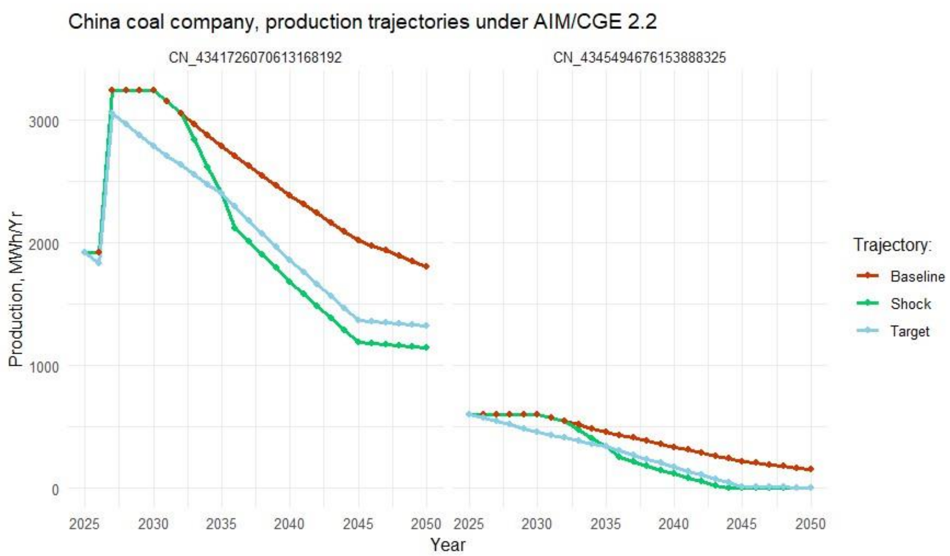


Figure A7: Production trajectories applied[55]

8.4 Appendix: Scenario baseline

Analysis in section 4.2 has compared the aggregate valuation change under a shock and baseline scenario according to different levels of granularity only in the shock scenario, using either asset or company–based data. This has been compared against a baseline valuation that has been derived using the asset–based methodology. Hence, while valuations under the shock scenario are estimated differently, the valuation adjustment is compared against a common baseline. While this method has been used to illustrate the main results of valuation adjustment, there are two other methods to consider, which are evaluated in this section as a measure of the robustness of results.

While the shock values are separately calculated at the asset or company–level, the baseline values can be compared at either level, or as a separately derived baseline for each. The main results in section 4.2 use baseline values derived using the asset–level methodology, however comparing these results to a company–level baseline still produce similar results. Using the same shock scenario values, the baseline values are replaced from an asset–derived baseline used in section 4.2 to a company–derived baseline. The results are illustrated in figures A8 and A9.

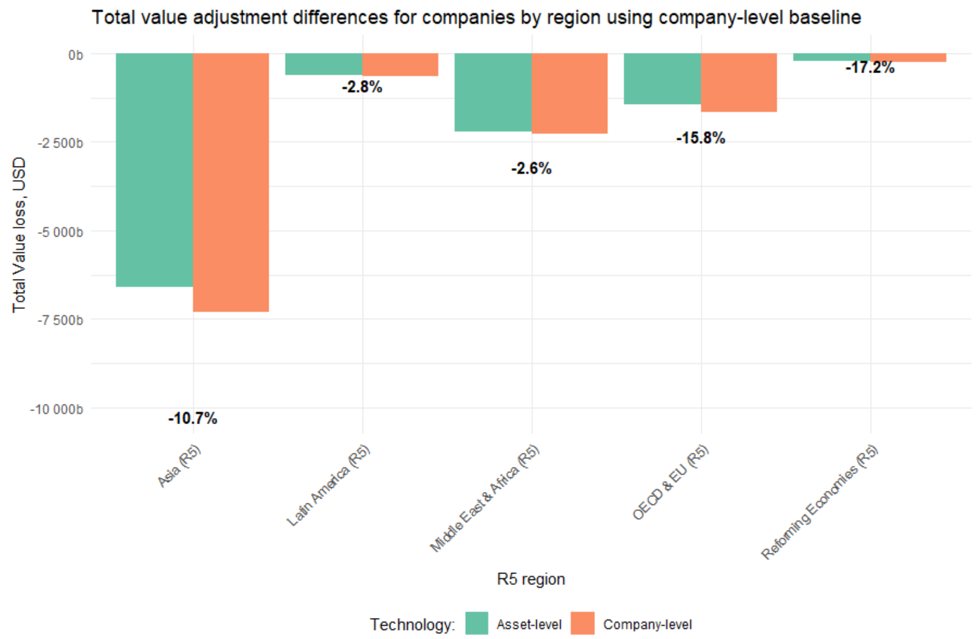


Figure A8: Comparison of power company valuation loss between the baseline and shock scenario using a company-level baseline, aggregated to R5 region.

[55] Company production trajectories for coal have been anonymised to illustrate the company modelling from baseline to shock scenario trajectories according to the "target" pathway that transitions the company from the baseline to the shock in a gradual way.

Figure A8 shows the resulting differences in regional company and asset-level losses when the baseline values are calculated at the company-level, rather than at the asset-level. The figure shows slight differences in the magnitude of valuation loss. Across all regions in figure A8, they consistently show that an asset–level methodology shows lower losses compared to a company–level methodology.

Aside from using a common baseline to determine the shock valuation adjustment, baseline and shock values can also be calculated separately for the company and asset-level. In this way, an asset–based valuation change compares baseline and shock values using the asset–based methodology. Separately, a company-based valuation change compares both baseline and shock values using only the company–level methodology. The results of this are illustrated in figures A10 and A11.

When using separate baseline values derived from either the company or asset–level methodologies, results show a smaller difference in the magnitude of valuation loss compared to previous findings. From figure A10, in the case of Asia, this magnitude difference between asset and company– level valuation is 2.5 percent, whereas when using a common baseline this difference was closer to 10 percent for Asia. However, this is not consistent across all R5 regions. For Latin America and the Middle East, different baselines show a greater magnitude of valuation loss. For the OECD, European Union, and Reforming Economies, the magnitude difference is lower using separate baselines rather than a common one.

Despite representing some smaller differences in methodologies when using separate baseline values, when comparing across all R5 regions, results are consistent to the extent that they show an asset–level methodology estimates lower losses between shock and baseline compared to a less granular company–based methodology. This result remains consistent across different methodologies for deriving a baseline and comparing it against different shock value granularities. Hence, this demonstrates broad consistency in the finding that an asset–based stress test that models more specific behaviours and strategies to minimise stranded asset risk and absorb transition policy shocks demonstrates a lower risk and lower cost of transition for power companies.

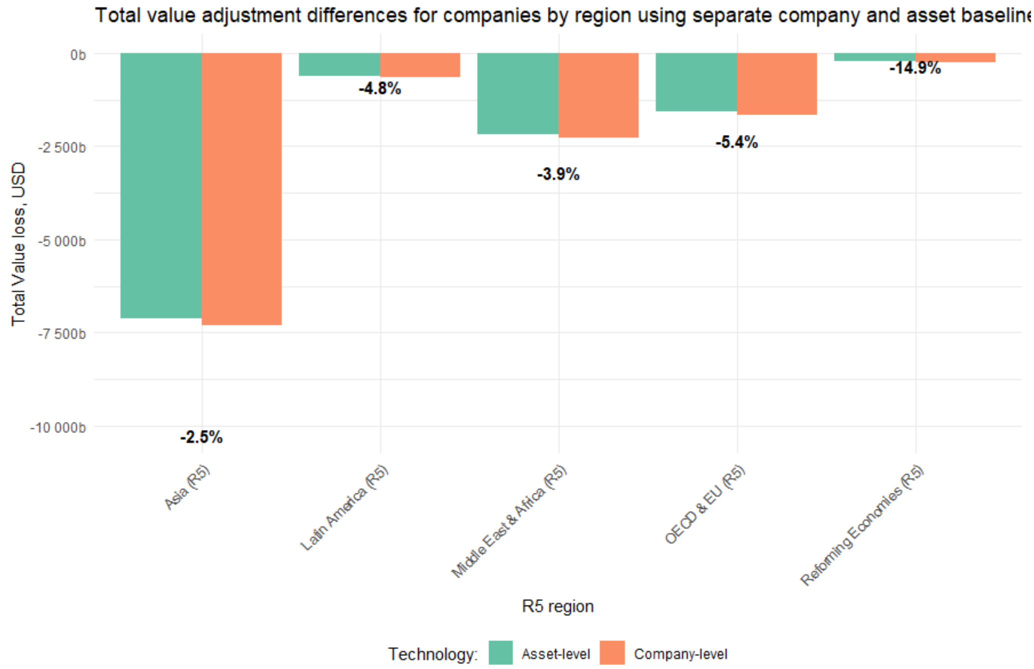


Figure A10: Comparison of power company valuation loss between the baseline and shock scenario using separate company and asset-level baselines, aggregated to R5 region.

This finding is similarly illustrated when comparing valuation adjustment between different baselines when broken down by fossil fuel technology type. Similar to figure A10, the magnitude difference between company and asset–based granularity is smaller than other methods using common baselines.

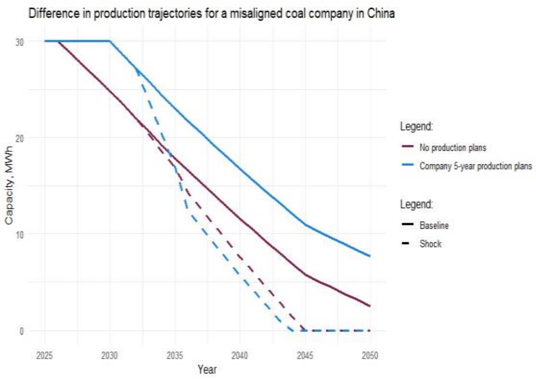
The overall percentage difference using a common asset–level baseline shows 8.6 percent lower losses, representing a difference of 1.1 trillion USD. In contrast, the percentage difference when calculating the baseline and shock valuation adjustment separately is lower, with 4.1 percent lower losses using the asset–based methodology, representing a difference of 500 billion USD. Although there are variations in the magnitude of difference between methodologies depending on the baseline, they do not exhibit a pattern of difference as either being consistently lower or higher across regions or technologies. Therefore, despite these variations, all three methods for calculating the baseline values from which company and asset-level shock values are determined consistently show that an asset–level methodology for estimating valuation change under a shock scenario shows lower losses compared to a company–based method. Consistency in these results across regions and fossil fuel technologies broadly confirms the findings in this paper, and the consistency of the methodology regardless of how the baseline values and adjustment is calculated.

8.5 Appendix: Company granularity

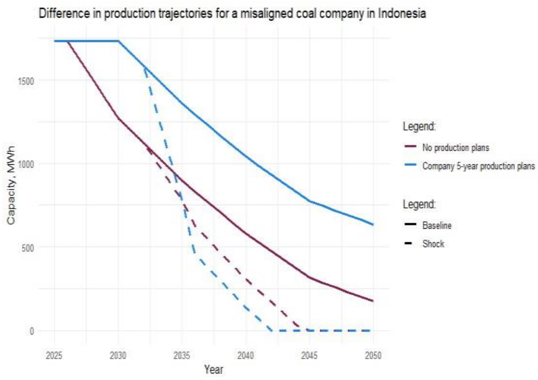
Analysis in the stress test has primarily sought to compare differences in granularity between baseline and shock scenario based on company–level assumptions versus asset–level detail. This paper demonstrates that increased data granularity in a climate stress test shows lower losses to companies compared to a stress test that does not include company–level detail or information. However, this is not always the case.

From the asset database, in addition to information on each specific power asset, we also have specific information on power company's five–year forward–looking production plans up to the year 2030. In running a stress test at the highest level of data granularity, the forward–looking production plans of companies should be included, as these plans have already been disclosed, reported, and incorporated into the company's financial planning and strategy. However, from running a stress test on power companies, we find that company's stated production plans systematically overshoot their production relative to any baseline transition scenario, which equates to higher risk and higher losses than would otherwise be estimated when omitting production plans.

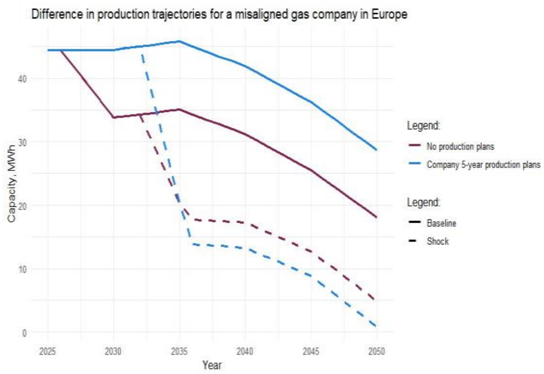
From compiling information on production plans representing different fossil fuel technologies and geographic regions in the asset database, we find that companies systematically overshoot their production when they are incorporated into a stress test, rather than when this information is omitted at the company–level. Figure A12 illustrates the trajectories of four different fossil fuel power companies representing a variety of countries and regions of the world, comparing their production based on generation capacity either only from the start year of the stress test in 2025, or based on the five–year forward–looking production plans under both the shock and baseline scenario trajectory.



(a) Coal company in China



(b) Coal company in Indonesia



(c) Gas company in Europe

(d) Gas company in the USA

Figure A12: Production trajectories for fossil fuel companies under baseline and shock scenario, including and excluding 5–year production plans.

The plots demonstrate that for every company, in every region and for every fossil fuel technology type, future production plans expect either stable or expanding capacity in the next five years, with no company incorporating any reductions. This demonstrates a significant overshoot of a company's fossil fuel production according to even a baseline scenario where there is still an expectation of capacity reductions. Across all regions, the long–run trend shows a decline in production capacity that is fit to the baseline or climate transition scenario. However, by incorporating company production plans, all companies overshoot production, delaying the start of the transition until after the 5-year period.

This enables a company to continue producing fossil fuels for longer, accumulating more profits, before beginning the transition, compared to a stress test that forces companies to begin transitioning immediately at the start of the stress test. Consequently, since all fossil fuel companies overshoot their production relative to a baseline scenario that starts the transition immediately at the beginning of a stress test, this means that the inclusion of production plans increases valuation loss relative to a stress test that omits this information. By overshooting production, companies accrue more profits and higher valuation under the discounted cash flow model, rather than starting reductions immediately.

As a result, this distorts the results of the comparison in NPV change based on the granularity of the stress test, since we consider having more detail in company production and asset information to be more accurate in estimating the cost of transition for companies. However, the omission of company information such as production plans reduces losses, since the stress test assumes an immediate start to the transition for companies, rather than accounting for overshoot production, which imposes higher losses. This is illustrated in figure A13, which compares the total NPV loss adjustment under the asset and company–level granularity including production plans using separately calculated baselines, but also compares this to company–level granularity that omits production plans.[56]

[56] Differences in company and asset-level NPV changes use separately calculated baseline values at the asset and company-level, since the aggregate baseline NPVs change based on the inclusion or exclusion of the 5-year production plans at the company-level. The resulting percentage difference in baseline and company

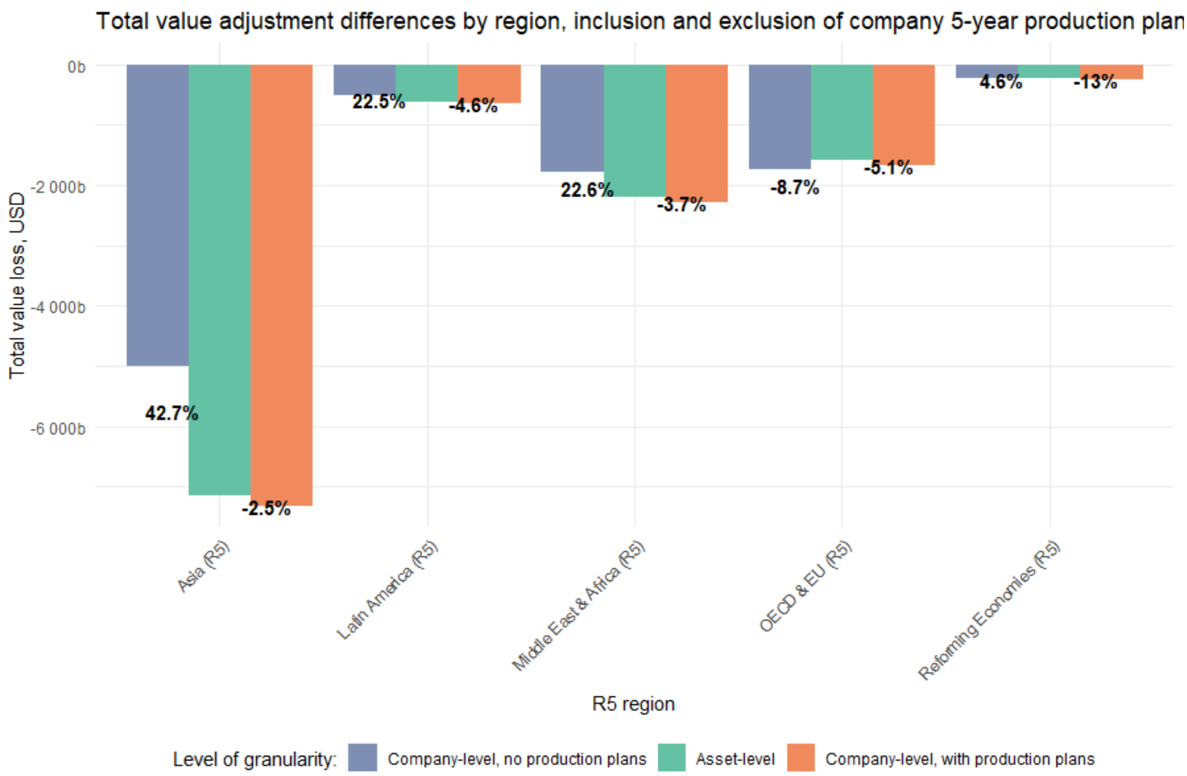


Figure A13: Differences in aggregate NPV loss based on the inclusion and exclusion of 5-year production plans at the company-level granularity.

Since aggregate R5 NPVs are calculated on separate baselines, using the same method as in figure A10, figure A13 has simply added the company-level losses using a separate company baseline where 5-year production plans have been omitted. The resulting valuation loss is illustrated by the first bar for every R5 region in the figure. These losses are consistently lower than estimated valuation loss at both the asset and company–level for all regions when production plans are included.

The only region where losses are still lower with asset–level granularity compared to company–level without production plans is for the OECD and European Union, where losses are 8.7 percent less at the asset–level compared to company-level without production plans. This suggests that this is the only region where fossil fuel power companies have accounted for a reduction in production capacity into their current production plans. The fact that this is not observed for other regions suggest that other companies either estimate future stable or increasing levels of production, and do not account for the energy transition at all.

Hence, evidence from figures A12 and A13 demonstrate that added granularity or detail in a climate stress test does not always reduce transition losses. Since most fossil fuel power companies overshoot their production and delay the start of the transition, this ends up being more costly than if they started transitioning immediately. However, it is

values when including 5-year production plans are the same as in appendix figure A10, but are different with the exclusion of the 5-year production plans.

more accurate to take production plans into account rather than to omit this information in a stress test, so the main results have included production plans in both a more granular asset–based stress test, and in the less granular company–based stress test.

8.6 Appendix: Power companies

The asset database covers 17,398 unique power–generating facilities globally, covering 8,929 companies. Companies include both private, public, and state-owned assets. While state–owned companies have a different cost, profit, and incentive structure compared to public or private power companies, their role in the economy is large. Results from the stress test analysis show that there is an estimated global value of power companies at approximately 52.6 trillion USD, with approximately 18.92 trillion USD at risk based on the valuation adjustment between the climate shock and baseline scenarios.

Although this analysis has not considered the full business operations of companies, but only their operations in thermal power, for several companies, and publicly traded companies in particular, their business would not be limited to only thermal power generation. Companies are likely to diversify in other sustainable or renewable technologies, hence, the estimated valuation adjustments under the stress test do not fully reflect the total value at risk for companies overall. Instead, the stress test focuses on estimating the downside risk to thermal power. However, by including all types of power–generating technologies, the valuation adjustment for companies is likely to be lower.

Despite the lower losses to companies through the inclusion of renewable business units and investments in carbon–capture, there is still significant value at risk for the full operations of power companies. While data is not always available on company size, investment, shares, or ownership in different technologies, information on company size and market capitalisation is available for the largest publicly traded power companies globally. Total market cap for power companies is listed at 2.378 trillion USD, and the market size for thermal power is 1.52 trillion USD, which is expected to grow to 2.13 trillion USD by 2034. This represents a large market with high risk, considering some climate scenarios project a significant phase out of thermal power.