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The ENV-FIBA Model for Climate Risk Analysis

Framework, Model Details, and Guide

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ABSTRACT: We present the ENV-FIBA macro-micro model framework that can be used to analyze the climate-macro-financial consequences of climate scenarios and related policy counterfactuals. The model consists of a multi-country Computable General Equilibrium (CGE) core and a connected micro simulation module for an economy's individual nonfinancial firms and banks. The climate-macro-financial scenario simulations are anchored in future temperature and emission pathways, alongside policy assumptions regarding carbon taxation, fiscal revenue recycling and reinvestment, optional carbon border adjustment mechanisms, and others. We illustrate the use of the model for Japan. We emphasize, exemplify with the model, and recommend in general: (1) that physical and transition risk effects be modeled jointly to a maximal extent (given their intertwined nature); (2) that it is important to consider bank balance sheets that are dynamic (not static), to capture the differential growth of emmission intensive industries that may shrink, opposed to those that may flourish; and (3) related to the latter, that such dynamically evolving lending has primary impacts on bank solvency via interest income, along with quantitatively often smaller impacts through loan losses from borrower defaults.

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WORKING PAPERS

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Contents

1. Introduction

The increasing urgency of addressing climate change necessitates comprehensive model analyses to understand and mitigate both climate physical and transition risks. Physical risk materialization, through the rising frequency and severity of weather events as a result of structural climate change pose a threat to humanity. Losses of an economic kind are just one consequence of this. Transition risks, arising from a shift toward a low-carbon economy, to mitigate such physical risk materialization, imply the potential to disrupt economies and their financial systems, if policies are not well designed.

We develop a micro-macro simulation-based climate-economic model—called the ENV-FIBA model—that is meant to help analyze the implications of such physical climate risks and to design transition policies to counter them. "ENV" denotes the involvement of the IMF's multi-country dynamic computable general equilibrium (CGE) model with explicit links between economic dynamics and greenhouse gas (GHS) emissions (Chateau et al. 2024). "FIBA" abbreviates firms and banks, to refer to the firm-bank micro simulation layer of the model. The model's inputs include temperature and emission targets (pathways) coupled with policy assumptions, for example, regarding carbon taxation, fiscal revenue recycling and reinvestment, and others. The model's outputs include the trajectories for carbon prices (model-implied, so that the desired emission targets are met), alongside the paths for macroeconomic variables at the industry and economy level, and numerous metrics related to bank lending (default rates, loss given default, interest rates, credit spreads, etc.) all for individual nonfinancial firms and at the sub-aggregated industry level, capital impacts for individual banks, and the underlying drivers and contributions to the bank capitalization along a scenario horizon.

The model relates to three clusters of climate-economic models with financial elements in the literature. These include (1) network-based methodologies (e.g., Battiston et al. 2017, Stolbova et al. 2018, Roncoroni et al. 2021), (2) stock-flow consistent models (e.g., Dafermos et al. 2017/18, Bovari et al. 2018, Monasterolo and Raberto 2018, Dunz et al. 2021), and (3) macro-financial model suites with embedded bank stress test methodologies (Vermeulen et al. 2018/21, Allen et al. 2020, Alogoskoufis et al. 2021, Emambakhsh et al. 2023, Laliotis and Lamichhane 2023, Lee et al 2024). Our model falls into the third category. For a general overview of micro-macro model approaches with a transition risk focus see Adrian et al. (2022). In addition to these relatively new model developments, there is a sizeable and well-established preceding literature pertaining to integrated assessment models (IAMs), which do not include financial components. Examples include the pioneering work of Nordhaus's (1992) DICE model, Anthoff & Tol's (2014) FUND model, Luderer et al.'s (2015) REMIND model, Calvin et al.'s (2019) GCAM model, and various others.

We formulate three recommendations that we think would be instrumental for enhancing the value of climate economic models. These include:

(1) Physical and transition risk effects should be modeled in an integrated manner. Physical and transition risk cannot be separated. Transition risk would not exist without physical climate risk. Transition policies imply costs and benefits. Their benefit is to mitigate physical risk and thereby avert the otherwise detrimental humanitarian and economic impact of physical risk materialization. The economic cost stems from certain ("brown") industries vanishing as a result of policy, while other ("green") industries would flourish. We integrate the cost and benefit components, including the link to physical risk, in our model suite.

(2) Dynamic bank balance sheet dynamics should be considered. Models that comprise banks, referenced above, treat bank balance sheets as static so far, i.e., they assume a constant bank lending portfolio size and composition[1]. One reason for this is the perceived complication and possible non-robustness of a dynamic balance sheet scheme—a valid concern *ex ante*. This notwithstanding, we recommend moving to a dynamic balance sheet scheme, however, because the assumption of static balance sheets does not square with the differentially moving industry sizes which are at the core of transition-focused climate risk analysis. The non-robustness concern can and should be overcome, by designing the dynamic balance sheet scheme in a sufficiently simple, yet economically meaningful and robust manner. One such simple solution we embed in our model is to let the debt stock to economic output (flow) ratios for the various industry segments in the model be constant. When economic output of an industry falls (rises), the debt stock shrinks (grows) proportionally.

(3) Related to the latter point, interest income effects should be accounted for, and the focus not lie solely on default risk. As a consequence of dynamic balance sheet dynamics, interest income effects for banks are important and to be taken into account. When lending to vanishing (brown) industries falls, it generates less interest income over time. Conversely, flourishing (greener) industries will generate more interest income over time. These interest income effects are quantitatively important, as we will illustrate in the paper. Meanwhile, credit risk effects, i.e., defaults of borrowers across industries, are often found to be not so sizeable. This is because even climate scenarios of a more "disorderly" kind are designed to evolve over a long period, spanning 10-20 years or longer. Hence, outright defaults of firms in "brown" industries may not be that relevant for banks, as they rather let outstanding debt still be repaid, and then not renew it.

A separate, complementary recommendation concerns loss given default (LGD) metrics as one credit risk component, in a climate risk model context, which ought to be improved. Various climate models do not account for LGD effects yet. We implement and embed an LGD module to let them move endogenously, i.e., they deteriorate under more adverse climate scenarios. It is still a rather simplistic way of modeling them, however. More work is needed going forward, to improve the link of LGDs to physical damage dynamics.

In this paper, we present an application of the model to Japan. The results are documented in IMF (2024), in the context of the Financial Sector Assessment Program (FSAP) for Japan (the empirical results in the paper here mirror those shown in IMF 2024). [2] The example application comprises 22 industries, 270,000 Japanese nonfinancial firms, and 22 Japanese banks. The primary questions posed for Japan included: What will be the impact of climate mitigation policies (carbon taxation etc.) on firms and their banks in Japan by 2040? How heterogeneous will these impacts be across firms, industry segments, and banks?

The paper is structured as follows. Section 2 presents the model framework. Section 3 shows the application to Japan. Section 4 concludes. Two annexes hold more details regarding some model components and an overview of the model code package, respectively. The codes for the ENV-FIBA model are available from the authors on request.

[1] By "composition," we mean the relative size of sub-portfolios such as lending to corporations from different industry segments, retail lending (mortgages, consumer credit), etc.

[2] The model was developed at the IMF in 2020 and applied to other countries since (whose results were not published). The CGE model is useful for multi-country applications, with an account for trade. It was, therefore, employed for IMF-internal analyses over the past years also for country cases where a carbon border adjustment mechanism (CBAM) was relevant. A CBAM policy entails the imposition of import levies of one country on another, from which it imports, and which does not impose carbon taxes on its goods that it exports. A CBAM thereby serves to correct for competitive distortions due to some countries imposing carbon taxation and others not, and to incentivize other countries to impose carbon taxes, as it is beneficial for them to collect and reinvest the carbon tax proceeds themselves. The analysis for Japan in this paper does not include a CBAM-related analysis.

2. The ENV-FIBA Model

2.1 Overview

ENV-FIBA is an integrated micro-macro model framework that can be used to analyze the macro-financial consequences of climate scenarios and related policy counterfactuals. The framework is depicted in Figure 1, using a high-level schematic. Figure 2 summarizes the model setup and its features in more detail.

The model framework entails linking a multi-country, multi-sectoral CGE model with a micro simulation layer for firms and banks. The latter is called FIBA, abbreviating "firms" and "banks." As the first layer of this framework, the IMF-ENV model is used to derive scenario-conditional paths for macroeconomic and sectoral variables, including carbon taxes. The micro simulation layer is technically connected to the CGE model to project financial flow variables, i.e., income and expenses, and the subsequent balance sheet dynamics of both firms and banks, all contingent upon some self-defined climate risk scenarios, along a multi-decade horizon.

The outputs of the model include the macroeconomic impacts in terms, for example, of economic output for all industries, alongside bilateral trade effects. For firms, it will include numerous individual firm balance sheet and profit and loss components, and their implied paths for default probabilities, loss given default, and their credit spreads. For banks, the eventual objects of interest will be their capitalization metrics, measured, for example, in terms of regulatory capital over risk weights assets.

Figure 1. Integrated Micro-Macro Simulation Model Framework for Climate Risk Analysis

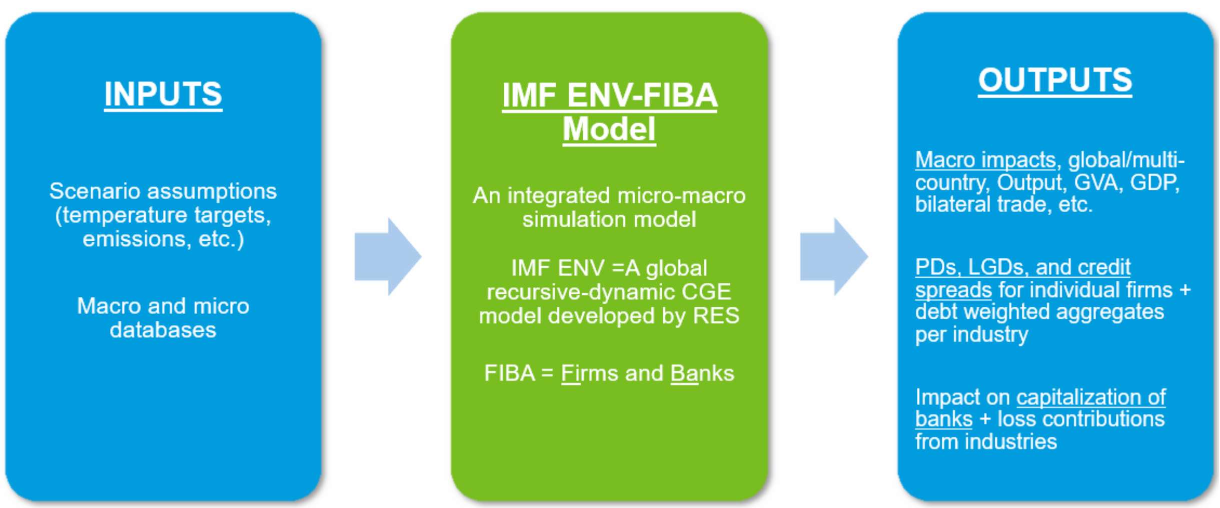
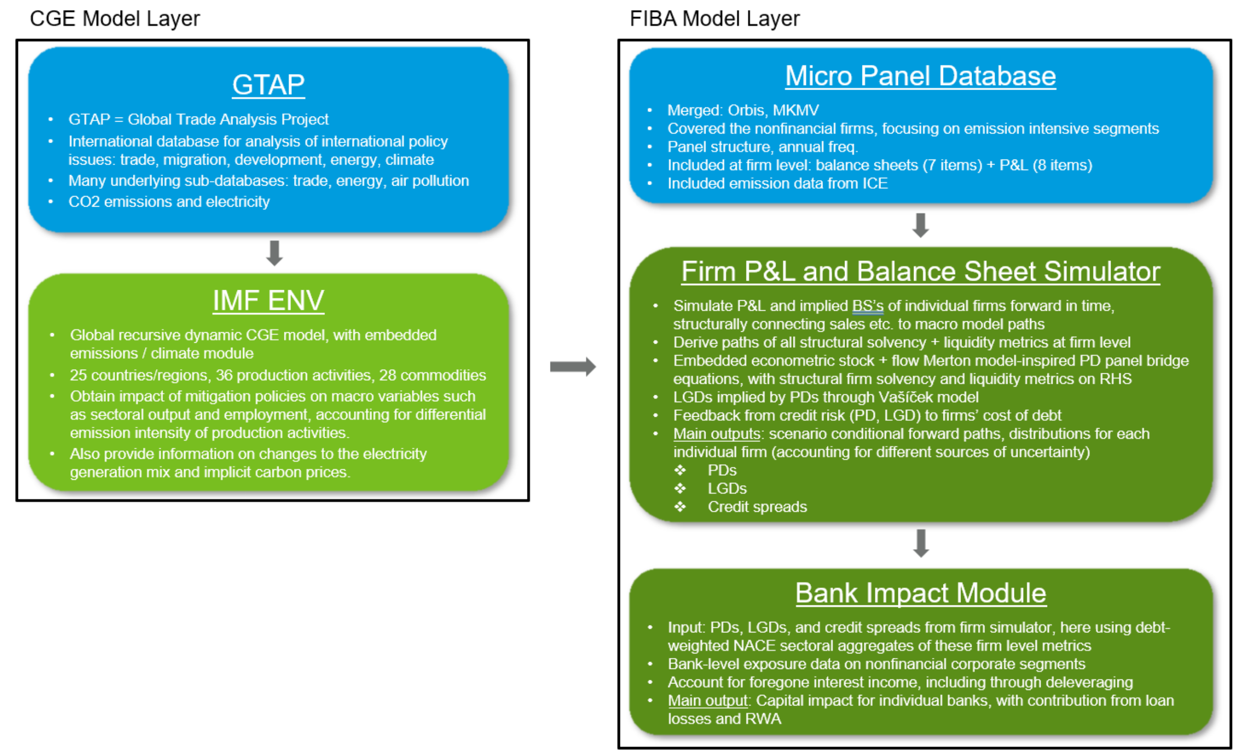


Figure 2. The ENV-FIBA Model Framework in Detail



2.2 CGE Model Component

IMF-ENV is a global recursive CGE model operated by the IMF's Research Department.[3] Dynamic CGE models are well suited to analyze the medium- and long-term macroeconomic effects and structural changes generated by climate mitigation and energy policies. The model distinguishes between more than 30 economic activities that are linked to GHG emissions and includes eight electricity generation sources, which allows a detailed modeling of the energy transition.

The model has a neo-classical economic structure, which entails utility maximizing households and profit maximizing firms. It follows a "circular flow of the economy" rationale, involving the activities of firms and households through markets on which they interact. Firms purchase inputs (from other firms) and primary factors (from households) to produce goods and services. Households receive income from being employed at firms, and purchase goods and services produced by firms. Markets determine equilibrium prices for factors, goods, and services. Factors of production are almost perfectly mobile across sectors (capital excluded) but not across countries.[4] Countries also exchange commodities and capital on international markets. International trade is modeled using the so-called Armington specification where demand for goods is differentiated by

[3] See Chateau et al. (2024) for a detailed technical description of the model.

[4] An important feature of IMF-ENV is that capital stocks have vintages such that firms' production and behavior are different in the short and long run. New capital stock (i.e., net-investment) is allocated without frictions such that the return to new capital across sectors is the same for all sectors, while old (i.e., installed) capital is given and cannot be reallocated without high transfer costs (a "putty-clay" specification captures this in the model).

region of origin. The general equilibrium nature of the model assures that all domestic and international commodity and factor markets are cleared simultaneously.

IMF-ENV creates direct linkages between all economic activities and the corresponding source of emissions of different GHGs. This allows the introduction of mitigation policies that can be GHG- and activity-specific but can also be employed to strengthen energy and emission regulations. Hence, the model allows incorporating and analyzing detailed carbon taxation schemes, multi-country emission trading systems (ETS's), as well as other types of mitigation policies (feebates, feed-in subsidies, regulations, and energy efficiency measures). The model produces impact estimates of these mitigation policies on energy demand and supply, the electricity generation mix, GHG emissions, macroeconomic variables, sectoral outcomes, employment, and trade.

The change in relative prices resulting from shocks to taxes or subsidies determine the macroeconomic outcomes of the model. For instance, carbon pricing directly affects the production costs of activities, proportionally to their GHG emission levels, such that activities that pollute more are more heavily taxed.[5] The increase in production costs is then reflected in higher production and consumer prices, which triggers substitution effects in both supply and demand. From the supply side, resources are reallocated to activities that pollute less. From the demand side, consumers substitute commodities that are relatively cheaper, and hence, consume goods that are on average generating less GHG emissions. Both effects reinforce each other, and carbon pricing reduces the production of polluting activities, but also incentivizes energy efficiency, as the consumption of fossil fuel-based energy is reduced.

Another important feature to account for in climate risk modeling concerns climate-related economic damages. These are usually divided between slow-moving long-term shifts in temperature and precipitation as opposed to extreme weather events. The first set of damages is often referred to as *chronic* physical risks and the latter as *acute* physical risks. There is a large and growing economic literature that estimates the expected global and national damages from different climate change scenarios.

The IMF-ENV model includes several types of climate damages at different levels of detail. First, it can account for chronic physical risks associated with temperature and/or precipitation changes, such as labor productivity reductions for outdoor workers (e.g., in agriculture, construction) and productivity reduction in economic activities and commodities (e.g., country-specific crops). These damages can be modeled broadly as changes in agricultural productivity, or more targeted: worker productivity reductions in specific activities and yield reductions for specific crops. The model can also accommodate changes in energy demand due to changes in heating and air conditioning demand, reduction in available arable land due to higher sea levels, and losses to tourism due to weather changes. Second, the model can include acute physical risks if the data on the country-specific associated damages are available. Finally, the model can incorporate more general climate damage estimations, such as the reductions in overall GDP associated to chronic and acute physical risks. In summary, the IMF-ENV model not only accounts for the economic *costs* of mitigation policies (transition risks), but also the economic *benefits* as a result of the transition policies' positive effect by averting materializing climate-risk induced economic damages (physical risks).

[5] With a carbon border adjustment mechanism (CBAM), an import tariff is imposed proportional to the CO2 emission levels of the traded commodity. This will likely reduce the export of the targeted commodity to the country/region imposing the CBAM, leading to two substitution effects. First, the exporting country can redirect export to another region that is not imposing a CBAM (conditional on relative prices, transportation costs and the overall demand). Alternatively, they reduce production of the traded commodity, and this will reduce emissions. At the sectoral level, the outcome will likely be a combination of both effects, conditional on the tariff level imposed and different substitution possibilities available. At the macroeconomic level, the impacts will be also conditional on the tariff level, but more importantly, on the number of commodities affected.

The model is recursive dynamic in nature, i.e., it is solved as a sequence of comparative static equilibria where the factors of production are exogenous for each year and linked between time periods with accumulation expressions. Agents, however, are not forward looking and investment levels are driven by savings, which in turn is a combination of household savings, the government budget balance, and the current account balance.

The model is built primarily on a database of input-output tables, combined with national accounts and bilateral trade flows. The central input of the model is the GTAP-Power database that contains country-specific input-output tables for 141 countries and 77 commodities and real macro flows. The version of the model used in this study employs 36 activities, 28 commodities sectors and 26 country/regions. Economic activities include several high-emitting and energy-intensive industries, while electricity generation is separated into eight power sources: coal, natural gas, oil (diesel), hydro, nuclear, solar, wind and others (e.g., geothermal, biomass). The regional aggregation includes all G20 countries and five aggregated regions (Latin America, Eurasia, Asia, Africa, and other oil exporting countries).

2.3 Firms and Banks (FIBA) Model Component

The firm level component (i.e., the FI in FIBA) entails a micro simulation structure anchored in firm-level data to derive paths for firm-level risk metrics conditional on some climate scenarios and CGE model outputs. It is divided into three parts.

A first set of equations links macro model sectoral variables to corresponding firm-level variables. This link is established in a structural manner. For instance, a firm's sales revenues are modeled to move proportionally with output growth for the sector that it belongs to (see Annex I. Table 5). Regarding GHS emissions, only a few firms currently make their emissions public, so there is significant uncertainty surrounding individual firm emissions. Capelle et al. (2023) find that the variation in emission intensities among reported firms within the same industries is notable, comparable to or even exceeding the heterogeneity observed in other measures of firms' performance, such as total factor and labor productivity. To address emissions uncertainty at a firm level, we employ a Monte Carlo simulation scheme to simulate the firms' unobserved emissions.

A second part comprises basic accounting equations and equations for dynamic balance sheets. A firm's total periodic cash flow, or earnings after tax, is defined as the sum of all projected income (+) and expenses (-) along the scenario horizon, based on the macro-micro links as hinted to above. The direct costs associated with a firm's direct emissions are accounted for in the calculation of its earnings. Post-tax profits or losses are added to firms' cash and cash equivalents, as well as their total assets, to simulate balance sheet variables period by period forward in time. If a firm's cash holdings fall into negative territory, an amount equivalent to the shortfall is added to the firm's short-term debt. The value of nonfinancial assets is assumed to remain constant by assumption.

The last step that the firm module entails is to derive firm-level risk metrics, that is, their probability of default (PD), loss-given default (LGD), and credit spreads, which have implications for banks' profits and capitalization through the bank lending portfolios that exposure them to the firms. The primary objective of this module is to establish a link between a firm's solvency and liquidity metrics and the likelihood of its defaulting. Based on the rationale of a stock and flow-oriented Merton model, the following variables, among others, are considered as determinants for firms' PDs: the leverage ratio (LEV), defined as the sum of short-term debt and half of long-term debt divided by total assets, which plays an important role in assessing firms' solvency conditions in the conventional Merton model framework; the interest coverage ratio (ICR), defined as EBIT (Earnings Before

Interest and Taxes) over interest expense, relates to flow-type Merton models, capturing firms' short-term liquidity conditions; the EBIT to assets ratio (EBITR) represents a blend of both stock and flow aspects, capturing various facets of firms' financial health; and the cash to short-term debt ratio (CDR) provides valuable information about firms' short-term liquidity coverage capacity. The panel econometric equation can be formulated as follows:

$$logit(PD_{f,t}) = \alpha_f + \beta LEV_{ft} + \gamma ICR_{ft} + \delta EBITR_{ft} + \theta CDR_{ft} + \varepsilon_{ft} \ , \tag{1}$$

where f and n denote a firm and an industry segment, respectively. Equation (1) is estimated as a firm-fixed effects panel regression with the logit transformation, for the listed subset of the firm population (source: Moddy's KMV). The estimated coefficients may differ across industry segments. Importantly, all right hand-side variables are of a structural, firm level kind. This means that the components of the various ratios, their numerators and denominators, are directly linked to specific outcomes from the CGE model. The macroeconomic effects feed structurally through the various variables, which capture profitability, solvency, liquidity, and mixtures of such features, as hinted to earlier.

LGDs are required as input to obtain the impact on bank capitalization (through loan losses). Modeling them, however, is not easy, particularly for nonfinancial firm debtors, since proper account would need to be taken of all physical and financial assets, the legal recourse to those, their value after liquidation accounting for debtor hierarchies, etc. We employ a parsimonious but robust approach to LGD modeling, following Frye and Jacobs (2012). The approach assumes that the default rates and loss rates structurally correlate, and that credit loss and default rates have distributions with common parameters in the asymptotic portfolio. The evolution of LGDs can be derived as a function of the evolution of PDs. When assuming a Vašíček distribution for losses, then the LGD equation is as follows:

$$LGD_{ft} = \frac{\Phi(\Phi^{-1}(PD_{ft}) - k_f)}{PD_{f,t}} \text{ ; where } k = \frac{\Phi^{-1}(\overline{PD_f}) - \Phi^{-1}(\overline{PD_f} \times \overline{LGD_f})}{\sqrt{1-\rho}} \ , \tag{2}$$

where Φ denotes the standard normal cumulative distribution function, k_f is a parameter being driven by through-the-cycle (TTC) PDs and LGDs, and the asset correlation parameter ρ.

A credit risk premium can be computed at the firm level throughout the simulation, including for capturing feedback from firms' credit risk to their debt funding cost. The equation used to this end is derived from a loan pricing equation that mimics the banks' pricing of debt:

$$\underbrace{PD_{ft} \times LGD_{ft}}_{\text{Expected Loss}} + \underbrace{(1 - PD_{ft})i_t^{COF}}_{\text{Expected Interest Expense}} = \underbrace{(1 - PD_{ft})i_{ft}}_{\text{Expected Interest Income}} \leftrightarrow i_{ft} = i_t^{COF} + \underbrace{\frac{PD_{ft} \times LGD_{ft}}{1 - PD_{ft}}}_{Risk\ premium\ \equiv \sigma} \ , \tag{3}$$

where i_{ft} is the cost of debt for firm *f*, and i_t^{COF} is the banks' cost of funding. There is a two-way contemporaneous, endogenous dependence in principle between the firms' cost of debt and PDs. We simplify this two-way relationship by assuming that firms' cost of debt reacts to the PD with a lag, instead of the time-contemporaneous one. Hence, increased PDs at the time t, which in turn leads to an increase in LGDs, gives rise to higher cost of debt for the next period.[6]

[6] Since firms' effective loan rates, which include their implicit credit spreads, are computed at the beginning of the simulation, the change in the credit spread matters during the model simulation.

After computing PDs, LGDs, and credit risk spreads for all firms, we compute firm industry specific weighted averages of the three metrics separately, using the individual firms' level of debt for informing the weights. That is: $PD_{n,h} = \sum_{f\in n} w_f PD_{f,h}$; $LGD_{n,h} = \sum_{f\in n} w_f LGD_{f,h}$; $\sigma_{n,h} = \sum_{f\in n} w_f \sigma_{f,h}$.

The bank module (the BA in FIBA) requires data for the bank sample's currently outstanding loan portfolios, for different industry segments that ideally well match the ones as defined in the CGE model. It should, in particular, allow for separating the emission-intensive sectors. Banks' exposures to less emission-intensive sectors should ideally also be included, for the analysis to reveal not only the effects on emission-intensive, potentially shrinking industries, but also for those industries that may gain.

The analysis employs a dynamic balance sheet approach, which allows for capturing the interest income impacts as a result of changes in the size and relevance of an industry. A bank *b*'s sectoral loan exposures, $L_{n,b,h}$, are assumed to grow at the same rate, $g_{n,h}$, as projected scenario-conditional sectoral GVAs.

$$L_{n,b,h} = L_{n,b,h-1}(1 + g_{n,h}) \ . \tag{4}$$

The assumption reflects that industries that experience a decline (growth), at least in the medium- to long-run, deleverage (leverage). This implies that banks will generate less (more) interest income from shrinking (expanding) industries, all else being equal. The bank impact module further accounts for pricing effects due to changing default risk and LGDs, shown in eq. (3).

The evolution for the nonperforming loan stock for a bank *b*'s exposure to sector *n* at horizon *h* ($NPL_{n,b,h}$) is calculated as follows:

$$NPL_{n,b,h} = NPL_{n,b,h-1}(1 - WROR - CURER) + PD_{n,b,h}\, PL_{n,b,h} \ , \tag{5}$$

where performing exposures ($PL_{n,b,h}$) are computed as a residual of gross exposures and the nonperforming exposure stock ($L_{n,b,h} - NPL_{n,b,h}$). The write-off rate (*WROR*) and the cure rate (*CURER*) are set to 100 percent and zero percent, respectively, for the application of the climate risk model. The cure rate being set to zero reflects the interpretation of PDs as being closer to ultimate bankruptcy rates, not to a 90-day past-due criterion-based default rate. The NPL write-off rate being set to 100 percent is instrumental for not having to design the rate such that NPL ratios, in the long run, do not diverge.

The calculation of loan loss impacts follows an incurred loss concept. Although this model scheme does not explicitly incorporate any elements of an expected loss following IFRS 9 principles, the incurred loss is, in effect, an expected loss by the design and application of the model and will be reported cumulatively over the scenario horizon. Thus, the loss estimates should not fundamentally differ from those generated by a calculation scheme that would explicitly incorporate lifetime provisioning in accordance with IFRS 9 (for where it is relevant). The model-consistent provision stocks for the NPL portfolios, denoted $PROV^{NPL}_{n,b,h}$,, are computed as:

$$PROV^{NPL}_{n,b,h} = LGD_{n,b,h} \times NPL_{n,b,h}. \tag{6}$$

The provision flows, i.e., loan losses ($LL_{n,b,h}$), in turn, are computed as:

$$LL_{n,b,h} = PROV^{NPL}_{n,b,h} - PROV^{NPL}_{n,b,h-1} + WRO \times LGD_{n,b,h} \times NPL_{n,b,h-1}. \tag{7}$$

This loan loss flow, in addition to interest income flow ($i_{n,h} \times PL_{n,b,h}$), impacts bank capital, for the numerator of their capital ratio, period by period.

At the beginning of the simulation, the PDs and LGDs observed at the bank-portfolio level are employed as “anchor points.” Throughout the simulation, the PDs and LGDs for each bank are aligned with the debt-weighted average PD and LGD trajectories for each portfolio, obtained from the firm-level simulation.

With regard to the computation of risk-weighted assets (RWAs), all banks’ risk weights are modeled in accordance with either the standardized approach (STA) or the internal ratings-based (IRB) approach. Under the STA approach, risk weights for the performing and nonperforming categories are held constant. Absolute risk weighted assets in this case change due to migration effects (from performing to nonperforming) and general loan growth. Under the IRB approach, the risk weights are computed using the Basel risk weight formula for the corporate segment, which takes TTC PDs and downturn LGDs as inputs. We assume a complete pass-through from point-in-time PDs to regulatory TTC PDs, which the long-term horizon of the climate risk analysis can rationalize. Changes in RWAs are influenced by loan growth and the changes in PDs and LGDs along the climate scenarios.

2.4 Design of Climate Scenarios and Policy Counterfactuals

The IMF-ENV model analysis compares a business-as-usual (baseline) scenario without future climate policies with a policy counterfactual scenario that includes climate and energy policies. The scenario simulations reveal the impact of the policies on macroeconomic variables (e.g., GDP, sectoral production and employment, bilateral trade), energy variables (electricity generation mix, energy demand), and environmental outcomes (GHG emissions).

The construction of the baseline scenario is based on the GTAP-Power database (with base year 2017), historical data of macroeconomic variables (real GDP, current account balance, government budget and labor supply) and climate-related variables (total GHG emissions, electricity generation mix, energy demand) to project all model variables to the most recent year (e.g., 2023). To project the model variables up to the end of the simulation horizon (2040), we employ the IMF’s macroeconomic projections from the World Economic Outlook (WEO). In addition, external sources for environmental and energy projections are required. These include estimations on future emission paths and their corresponding global temperature effects and associated climate damages, and changes in electricity demand and supply. Technological changes can be included exogenously, such as improvements in energy efficiency and/or emission intensity, implementation of new technologies (CCUS, electrical vehicles, hydrogen) and their associated costs. These external climate-related projections are taken from complex climate risk analyses.

The climate risk analysis requires scenarios for future pathways for GHS emissions and their estimated effect on global temperatures. Common reference scenarios are those developed by the Intergovernmental Panel on Climate Change (IPCC). The IPCC is an intergovernmental body of the United Nations responsible for advancing knowledge on human-induced climate change. The IPCC constructs its scenarios for emissions and temperature by building on a combination of so-called Representative Concentration Pathways (RCPs) that describe paths for future levels of greenhouse gases (covering end-points of 2.6, 4.5, 6.0, and 8.5 watts per meter squared by 2100), and Shared Socioeconomic pathways (SSPs), which look at five different scenarios for how socioeconomic systems around the world might evolve in the absence of policy changes to mitigate climate change.[7] Recognizing the intricate nature of climate risk analysis and the need for common understanding to illustrate the advantages of collective efforts, central banks worldwide joined in 2019 to establish the Network for Greening the Financial System (NGFS). Since then, the NGFS has annually published NGFS climate scenarios for emissions and temperature pathways, along with the corresponding projections for consequent climate impacts.

The IMF-ENV model uses the NGFS scenario outcomes as a reference. We first calibrate the baseline and policy scenarios to the country- or region-specific total GHG emission paths. When available, we also employ projections on electricity demand and supply (i.e., the electricity generation mix), as well as projections on the deployment of new technologies (CCUS, EVs). This implies adjusting the emission intensity of different emission sources and their associated economic activities, as well as changing the implicit electricity generation costs to fit the projected electricity supply mix.

3. Application to Japan

3.1 Context

Climate transition risks are highly relevant for Japan, given its status as one of the world's major carbon emitters. Since the Fukushima nuclear accident in 2011, Japan has mainly relied on fossil fuels as a source of power generation and maintained fossil fuel power generation at levels exceeding 70 percent.[8] Seven emission intensive industries ranging from electricity and gas to basic metal and other non-metallic mineral products collectively contribute to about 80 percent of Japan's total CO2 emissions (Figure 3).

The CO2 emission intensive sectors represent a significant portion of the Japanese economy. The CO2 emission intensity, which quantifies the amount of CO2 released into the atmosphere per unit of output resulting from direct fuel combustion, is a pivotal factor in assessing the impact of mitigation policies on firms' financial performance and the broader economy. In comparison to its G7 peers, Japan stands out with the second-highest output share of sectors characterized by high emission intensity, trailing behind Canada (Figure 3). Beyond the direct emission-intensive sectors shown in the middle bottom panel of Figure 3, there are sectors that rely on emission-intensive inputs throughout their production processes, which are also exposed to transition risks through their supply chains. Together, the direct and indirect emission-intensive sectors represent 13 percent of GDP and account for about 22 percent of total bank lending in Japan. The analysis that follows comprises both the direct and indirect emission-intensive sectors.

The government of Japan has pledged to substantially reduce greenhouse gas emissions in the coming decade. In accordance with the United Nations Climate Change Convention, Japan has set an interim target to reduce GHG emissions by 46 percent from 2013 levels by 2030, with an objective of achieving net-zero GHG emissions by 2050. To realize this ambitious goal, Japan enacted the Green Transformation Promotion Act in

[7] SSP1 is the sustainable development pathway and yields both low emissions and rapid economic growth (Vuuren and others 2017). SSP2 describes the continuation of current trends (Fricko and others 2017). SSP3 describes a world with strong regional rivalry, high emissions, and low economic growth (Fujimori and others 2017). SSP5 describes a world with very fast economic growth supported by fossil fuels (Kriegler and others 2017).

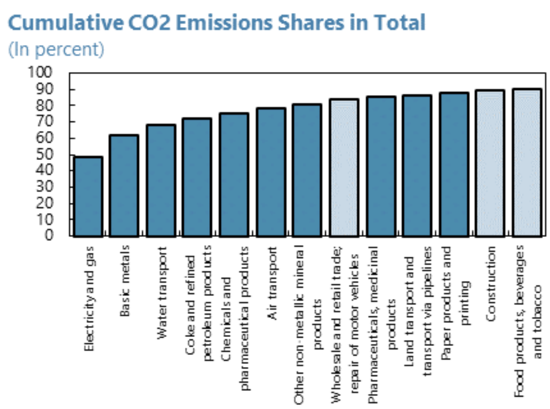
[8] According to Agency for Natural Resources and Energy in Japan, the share of each source in power generation for 2021 is as follows: LNG (34.4 percent), coal (31.0 percent), oil (7.4 percent), solar (8.3 percent), hydropower (7.5 percent), nuclear (6.9 percent), and others (4.4 percent). The current fossil fuel power generation level (73 percent) is lower than in the year of 2012 when it reached its peak at 89 percent.

May 2023 and laid out a strategy to facilitate the transition to a green economy. This strategy emphasizes an upfront investment of JPY 20 trillion over the next decade in decarbonization initiatives, to be largely funded through the issuance of Japan Climate Transition Bonds, along with plans to introduce a carbon levy on fossil fuel supplies from FY2028.[9] Considering Japan's aspirational target of achieving net-zero emissions by 2050 as well as the current low effective carbon rates, a notable increase in carbon tax rates may be needed to achieve its objective.[10]

Against this backdrop, climate risks in Japan were assessed through scenario-based analyses. The IMF-ENV model is used to derive scenario-conditional paths for macroeconomic and sectoral variables, including carbon taxes, tailored to Japan's trajectory up to 2040. The micro simulation layer encompasses about 270,000 nonfinancial firms from Japan, with a particular focus on those operating within emission-intensive sectors. In addition to this extensive firm sample, the bank module comprises 22 banks. Annex I documents in more detail what micro data was compiled for Japan.

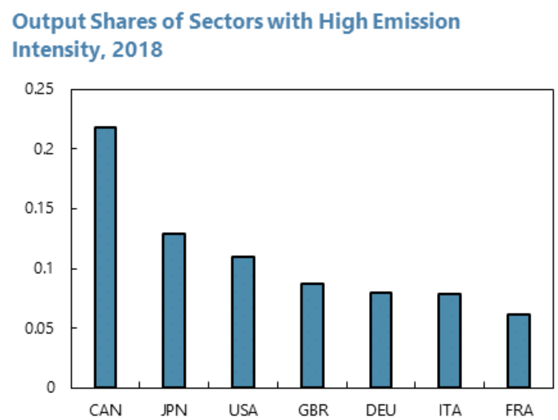
Figure 3. Japan: Climate Transition Risk

Seven emission intensive sectors account for about 80 percent of total Japanese CO_2 emissions.



Direct emission intensive sectors include mining and quarrying, electricity and gas, and water transport.

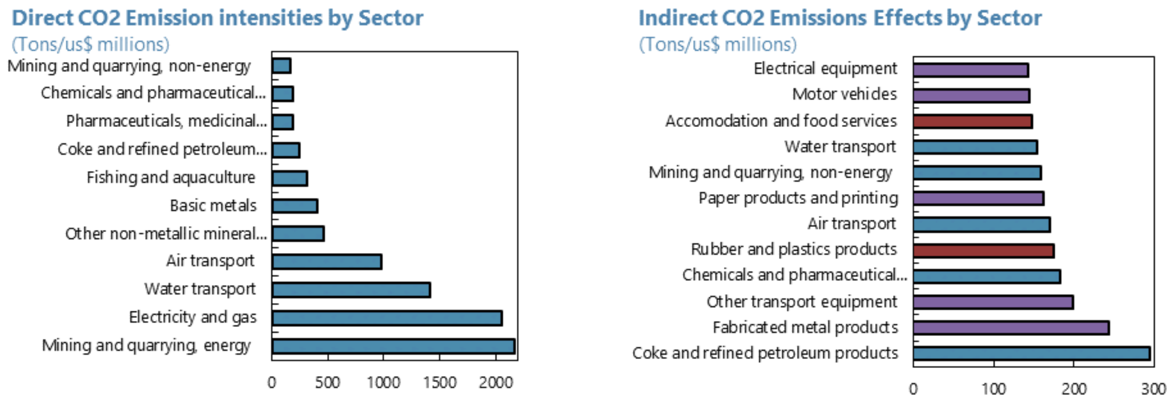
Among the G7 countries, Japan stands out with the second-highest output share of sectors with high emission intensity.



Sectors relying on emission intensive inputs include fabricated metal, transport equipment, and paper products.

[9] In addition to the carbon levy, Japan is set to implement the emissions trading system in high-emission industries starting from FY2026. The allowance auctioning to power generation companies is planned to be gradually phased in from FY2033.

[10] Japan implemented a carbon tax on fossil fuels, known as the Tax for Climate Change Mitigation, in 2012. Currently, the tax is set at JPY 289 (approximately $2) per ton of CO2 equivalent, with certain exemptions granted for competitive reasons. In comparison to its G7 peers, Japan's effective carbon price level is the second lowest, following the United States, according to OECD (2021).



Sources: Global Carbon Atlas; IMF Climate Change Dashboard (Climate Change Indicators Dashboard (imf.org)); BOJ; and IMF staff calculations.
Notes: Direct emission intensive sectors, or sectors with high emission intensity, are defined as those whose emission intensities fall within the top quantile among those of industries in the G7 countries, encompassing (45×7) sectors. In the top left panel, blue-gray bars represent direct emission intensive sectors, with light blue-gray bars indicating non-emission intensive sectors. In the bottom right panel, blue-gray bars denote sectors that are also assessed as directly emission intensive. The remaining bars refer to sectors that depend on emission-intensive inputs downstream, with the purple bars being distinctly considered in the subsequent analyses.

3.2 Climate Risk Scenarios

The scenarios that we employ are aligned with those set forth by the NGFS Phase IV, which are comparable to the scenarios by the IPCC. Our scenarios are anchored in the NGFS scenarios' emission and temperature paths and expected benefits of mitigation policies in the form of a reduction in GDP losses due to chronic physical risks. Three focal scenarios are employed for the analysis, as shown in Figure 4: (1) Net Zero 2050 (NZ), (2) Fragmented World (FW), and (3) Current Policies (CP). Under the NZ scenario, global warming is limited to 1.5°C above pre-industrial levels through stringent climate mitigation policies and innovation, achieving global net-zero CO2 emissions by 2050. The CP scenario maintains only currently implemented policies, resulting in elevated physical risk materialization. The FW scenario entails a delayed and divergent climate policy response among countries globally, characterized by high physical and transition risk materialization. Specifically, currently implemented policies are to be maintained until 2030 (delayed transition); thereafter, countries with net-zero targets achieve an 80 percent reduction only by 2050, while others continue with current policies (divergent transition). The CP scenario serves as the "reference" scenario, relative to which the impacts of the other two scenarios will be presented.

We start with a baseline or business-as-usual scenario that is equated to the CP scenario. We employ the IMF WEO macroeconomic projections until the latest available year (2028) as well as the NGFS projections on overall greenhouse gas emissions and electricity generation by power source. For the period 2029-2040, we assume that growth rates of real GDP and total labor supply are the same as of 2028 and we keep the current account and government balances fixed as a share of GDP.

For the alternative scenarios—that is, the NZ 2050 and the FW scenarios—the model endogenously estimates the carbon tax level that achieves the targeted greenhouse gas emission trajectory for each NGFS scenario. In the context of the NZ scenario, we further assume some progress in green technology development in Japan, which includes an increase in the penetration of electric vehicles and that carbon capture technology (CCUS) absorb 95 million CO2 tons, which is 18 percent toward the total emission reductions for the NZ scenario.

Finally, we account for the economic impact of chronic physical risk materialization.[11] GDP losses from chronic physical risk for Japan, estimated by the NGFS, are incorporated in our model through adjustments in overall total factor productivity (TFP) growth. The CP scenario includes the total value of the estimated chronic physical risk from NGFS, which represents a reduction of GDP levels by 2040 of 2.7 percent in Japan. The alternative scenarios include a reduced value, which reflects the lower risks when global mitigation policies are implemented. These are negligible for the FW scenario but represent a reduction of around 25 percent of the risks for the NZ scenario (or a 0.7 percent higher GDP level in 2040 with respect to the CP scenario).

The model operates under the premise of maintaining fiscal income-expense balances neutral. That is, any revenues generated from carbon taxes must be offset either by increased government expenditures, reduced taxes in other areas, or a combination of both. Two approaches for recycling carbon tax revenues within the CGE model are considered: In the first approach (Rule 1), all generated revenues are transferred to households, while in the second approach (Rule 2), half of the revenues are allocated to feed-in tariffs for the renewable energy sector, with the remaining half directed towards households as transfers. This second rule aims to emulate the Government of Japan's Green Transformation (GX) policy. The analysis reveals that required carbon tax rates are lower when applying Rule 2 as compared to Rule 1, as the green transition of the energy sector accelerates with feed-in subsidies for the renewable sector under Rule 2 (Figure 4).

In terms of the macroeconomic impact by 2040, the NZ scenario exhibits slightly larger adverse effects compared to the FW scenario, though Rule 2 helps to mitigate some of the negative repercussions. The impact on employment remains relatively subdued in the NZ scenario (Figure 4). When analyzing sectoral impacts, significant variations in Gross Value Added (GVA) are observed, depending on the sectors' direct emission intensity and inter-industry linkages (Figure 5). Relative to the CP scenario, emission intensive sectors, such as natural gas, petroleum and coal, chemical products, iron and steel, and air transport, experience a large decline in GVA. The electricity sector thrives, though displaying diverse outcomes among its sub-sectors. While coal and gas power see a reduction in GVA, renewable energy sources experience growth. Labor costs exhibit a similar, albeit less pronounced, degree of variation when compared to GVA.

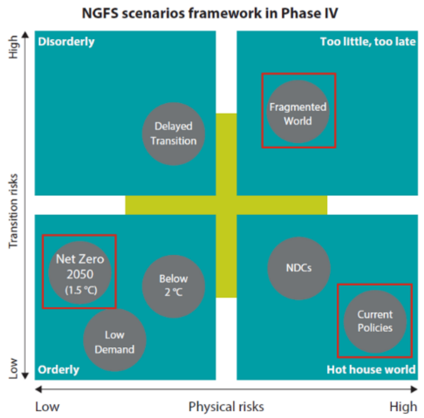
To guide the subsequent micro simulation, the focus centers on scenario-specific sectoral variables that encompass inter-industry relationships and price adjustments stemming from carbon taxes. Sectoral output, intermediate input, and GVA exhibit synchronized impacts, but their magnitudes differ across sectors (Figure 5). In certain sectors such as land transport and business services, output (accounting for both real and price effects) displays positive growth relative to the CP scenario, but GVAs decline due to a more pronounced increase in intermediate input.

[11] The NGFS also provides estimations for acute physical risks, but these were deemed unreliable for Japan, and we did not include them here. The NGFS is expected to provide updated acute physical risk estimates, which can be then included in our analytical framework.

Figure 4. Japan: Climate Macro Scenarios

Three focal NGFS scenarios are employed…

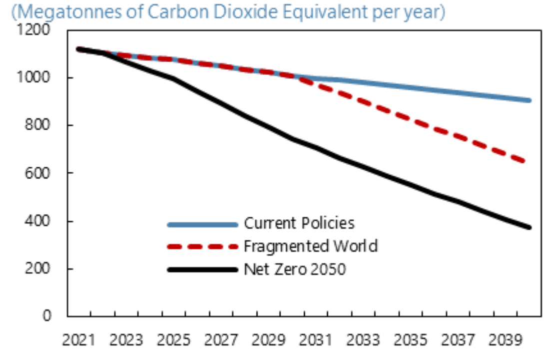
NGFS Scenarios Framework in Phase IV



Total emissions in Net Zero 2050 and Fragmented World are 60 percent and 30 percent lower by 2040, respectively, compared to Current Policies. Mitigation efforts in Fragmented World are designed to start from 2031.

Japan: GHS Emission Paths by Scenario

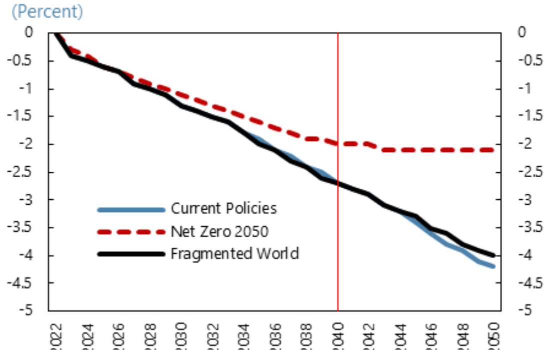
(Megatonnes of Carbon Dioxide Equivalent per year)



GDP losses from chronic physical risk is incorporated via the adjustments in overall Total Factor Productivity growth. The benefit of the orderly transition becomes more visible after 2040.

GDP Losses from Chronic Physical Risks

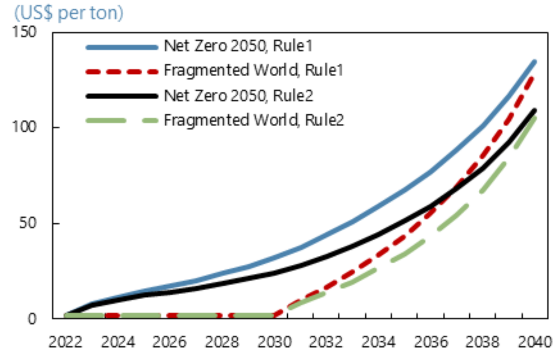
(Percent)



Carbon tax rates are lower in Rule 2, with half of the revenues going to feed-in tariffs for the renewable sector and half to households, compared to Rule 1, where all revenues are transferred to households.

Japan: Carbon Tax Paths by Scenario

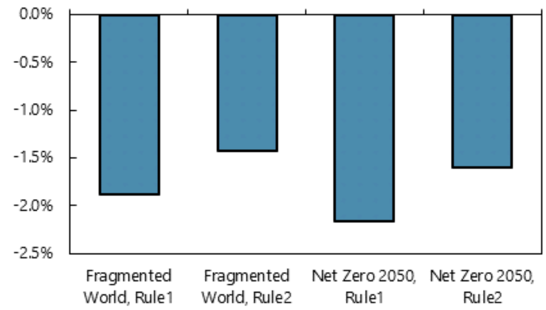
(US$ per ton)



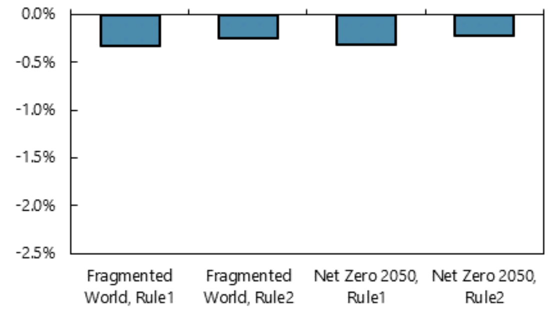
Macro impacts by 2040 are somewhat greater under Net Zero 2050 compared to Fragmented World. Under Rule 2, negative impacts are mitigated.

The influence on employment remains relatively subdued.

Impacts on Real GDP by Scenario
(Percent, level deviation from current policies in 2040)



Impacts on Employment by Scenario
(Percent, level deviation from current policies in 2040)

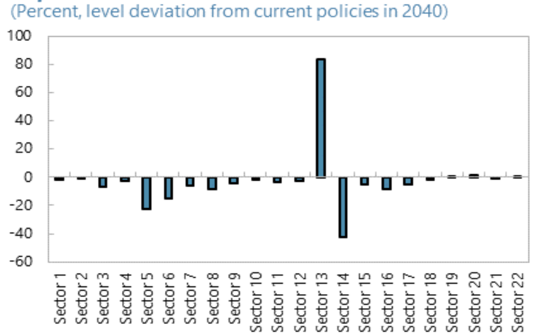


Sources: NGFS; and IMF staff calculation.

Figure 5. Japan: Sectoral Impacts Under Net Zero 2050 vs. Current Policies Scenario

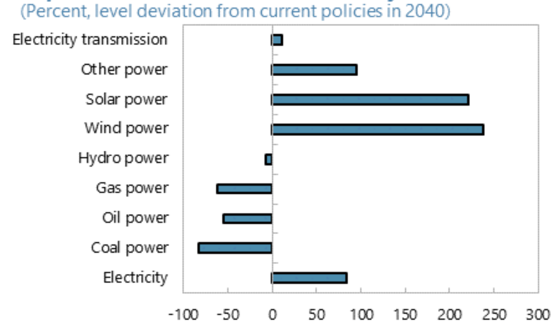
Sectoral GVA impacts vary based on sectors' emission intensity as well as inter-industry linkages, among others.

Impacts on Sectoral Real GVAs
(Percent, level deviation from current policies in 2040)



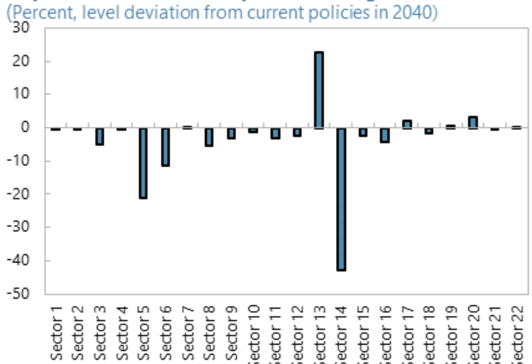
The electricity sector thrives overall, yet outcomes vary across sub-sectors.

Impacts on Real GVAs in the Electricity Sector
(Percent, level deviation from current policies in 2040)



Sectoral output, intermediate input, and GVAs exhibit broadly synchronized impacts…

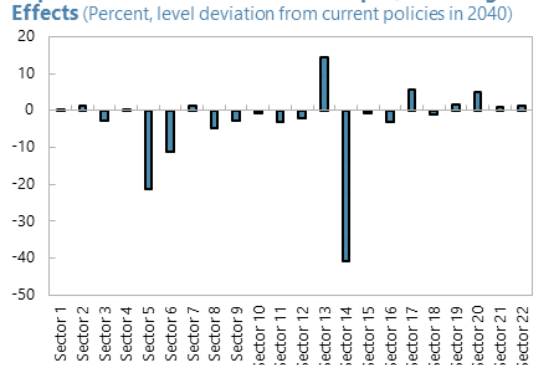
Impacts on Sectoral Output, including Price Effects
(Percent, level deviation from current policies in 2040)



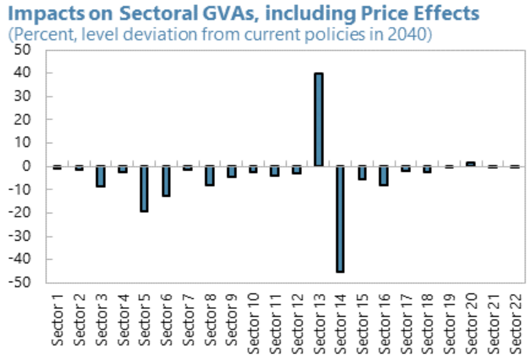
In certain sectors, output and GVAs move in opposite directions due to a larger increase in intermediate inputs.

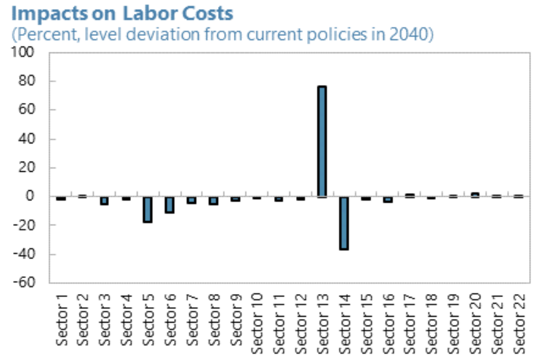
But their magnitudes are different across various sectors.

Impacts on Sectoral Intermediate Input, including Price Effects (Percent, level deviation from current policies in 2040)



Labor costs exhibit a similar degree of variation to GVAs, albeit with a less pronounced response.





Sources: NGFS; and IMF staff calculation

Note: The NZ sceanrio is simulated under Rule 2 where a half of revenues are allocated to feed-in tariffs for the renewable energy sector, with the remaining half to be transferred to households. A mapping table for sectors used in the macro and firm-level micro simulations is as follows:

Sector 1	Agriculture	**Sector 9**	Non-ferrous metals	**Sector 16**	Air Transport
Sector 2	Fisheries	**Sector 10**	Fabricated metal products	**Sector 17**	Land transport
Sector 3	Mining and quarrying	**Sector 11**	Electronic equipment	**Sector 18**	Other manufacturing
Sector 4	Paper products	**Sector 12**	Transport equipment	**Sector 19**	Construction
Sector 5	Petroleum and coal	**Sector 13**	Electricity	**Sector 20**	Water supply
Sector 6	Chemical products	**Sector 14**	Natural gas	**Sector 21**	Collective services
Sector 7	Non-metallic minerals	**Sector 15**	Water Transport	**Sector 22**	Business services
Sector 8	Iron and steels				

3.3 Results

Notable heterogeneity exists in the initial (pre-simulation) solvency and liquidity metrics for Japanese firms (Figure 6). Sectors such as fishery (2), electricity (13), iron and steel (8), other manufacturing (18), and business services (22) exhibit high levels of leverage at the outset, while gas (14), mining and quarrying (3), and chemical products (6) are among the least leveraged. Regarding the ICR, many sectors are characterized by sufficient earnings to cover interest payments, but there are some exceptions such as electricity (13), water transport (15), paper products (4), and fishery (2). Regarding the EBIT to total asset ratio (EBITR), the weakest sectors include agriculture (1), water transport (15), paper products (4), and collective services (21). Regarding the cash debt metric, sectors such as iron and steel (8), non-ferrous metals (9), and paper products (4) appear to have weaker initial positions.

As a result of the heterogenous solvency-liquidity risk metrics, Japanese firms' PDs at the outset exhibit significant variation across and within sectors. Among the emission-intensive sectors, non-metallic minerals (7), iron and steel (8), non-ferrous metals (9), fabricated metal products (10), electronic equipment (11), and water transport (15), exhibit relatively high initial PDs. Among non-emission-intensive sectors, water supply (20) and services (21-22) face elevated PDs at the outset. Substantial variations in initial PDs are observed at firm level within certain industries.

In interpreting the scenario-conditional estimates for both firms and banks, the multiple sources of heterogeneity that contribute to the outcomes should be kept in mind. These include: (1) heterogeneous sectoral impacts across industries, according to differential emission intensity across industries and inter-industry linkages; (2) the initial risk characteristics across different industries, alongside wide variations within each segment; (3) differential loan exposures to different industries; and (4) the varying risk profiles across banks.

Under the policy scenarios compared to the CP scenario, PDs, LGDs, and credit spreads exhibit significant variations across sectors (Figure 7). Notable impacts are observed for firms operating within emission-intensive sectors such as paper products, iron and steel, and fabricated metal industries. Several emission-intensive sectors such as chemical products, and petroleum and coal show only a modest increase in PDs due to favorable initial conditions, despite experiencing a substantial decline in sectoral GVAs. Other services and construction, which are not considered emission intensive, experience a somewhat higher increase in both PDs and LGDs.

The analysis reveals that substantial uncertainty surrounding the firms' emission intensity can have a noteworthy impact on their financial performance. The embedded Monte Carlo simulation scheme around individual firms' emission intensity for those lacking emission intensity information aims to shed light on this source of uncertainty (Annex I Figure 2). The firm risk metrics at the 50th (Q50), 75th (Q75), and 90th (Q90) percentiles of the outcome distributions were investigated and aggregated by sector. No notable differences in outcomes are observed between the 50th and 75th percentiles, while for the 90th percentile, a large increase in both PDs and LGDs results for certain emission-intensive sectors (such as mining and iron and steel). This finding highlights the sensitivity of firms' credit risk to their emission intensity levels.

The impact on bank capital appears not too sizeable at the system level, while it is surrounded by notable heterogeneity in the cross-section of banks (Figure 8). Under the Net Zero 2050 scenario, the aggregate capital ratio for the banking system is estimated to decrease by about 0.6-0.7 percentage points by 2040, translating to a decline of around 0.03-0.04 percentage points per annum when compared to the CP scenario. Under the FW scenario, the banking system's aggregate capital ratio declines by 0.3 percentage points by 2040. However, considering that the mitigation efforts in this scenario are designed to commence from 2031 onward, the decline in capital ratios during the 2030s is estimated to be about 0.03 percentage points per year, which is comparable to the average annual rate observed in the NZ scenario.

The capital impacts vary across banking clusters (Figure 8). Internationally active banks are modestly impacted because of the more favorable risk profiles of their borrowers, while the impact on regional banks—those that are contained in the sample—is more pronounced. The contribution analysis reveals that non-emission intensive sectors, such as other services, account for approximately 30 percent of the shift in the banking system capital ratio.[12] This suggests that spillover effects through macroeconomic channels, the initial risk characteristics of borrowing firms, and individual bank risk parameters all play an important role in determining the results.[13] Furthermore, about one-third to one-half of the capital ratio shift can be attributed to changes in risk-weighted assets (RWAs). This is partly due to rising risk weights resulting from rising PDs and LGDs in emission-intensive sectors. The contribution analysis for individual banks highlights the heterogeneity in terms of the size and composition of the impact on capital ratios.

The substantial uncertainty surrounding firms' emission intensity levels could have a significant impact on bank capitalization. The implications for the shift in bank capital ratios closely align with those observed for the

[12] In the contribution analysis, a shift in bank capital ratios can be decomposed into three parts: a change in interest incomes (ΔII) relative to RWAs, a change in loan losses (ΔLL) relative to RWAs, and a residual change related to RWAs ($\delta RWAs$).

$$\Delta CAPR = {}^{\Delta II}/_{RWAs} + {}^{\Delta LL}/_{RWAs} + \delta RWAs$$

The first two components are summed up by sectors. The average of the initial and end-horizon RWAs are used for normalizing the interest income and loan loss contributions. $\delta RWAs$ represents the combined effect of (a) rising/falling risk weights due to rising/falling PDs and LGDs and (b) loan growth (either positive or negative for the underlying industries).

[13] Abe et al. (2023) also find that an increase in carbon price impacts non-emission-intensive sectors through inter-industry linkages, thereby increasing their credit cost.

underlying firm industry risk metrics. No notable differences are observed in outcomes between the 50th and 75th percentiles of individual firms' risk metrics. However, at the 90th percentile, substantial differences in the impacts on bank capitalization can be observed, primarily driven by increased loan losses incurred in direct emission-intensive segments (Figure 8).

Considering the dynamic evolution of firm debt is important as it allows to capture the shifts in industry size and structure and the potential effect on bank profitability. To illustrate this, two industries were analyzed in more detail: the chemical products and the electricity and gas segments (Figure 9). In Scenario 5 (Net Zero 2050 with Rule 2, considering the 50th percentile of firms' risk metrics) compared to Scenario 1 (Current Policies), a notable loan growth differential can be observed, with the chemical sector experiencing an average annual decrease of 0.8 percentage points in growth, while the electricity and gas sector's growth increases by 1.2 percentage points per annum until 2040. When the chemical sector shrinks, it leads to a decline in interest income for banks, and loan losses become less negative, even though PDs and LGDs rise relative to the CP scenario. Conversely, in the case of electricity and gas experiencing growth, interest income increases, and loan losses become more negative, despite reductions in PDs and LGDs relative to the CP scenario. Additionally, loan growth has a direct impact on RWAs. More positive loan growth puts downward pressure on capital ratios, whereas less positive or negative growth exerts upward pressure on these ratios from this perspective.

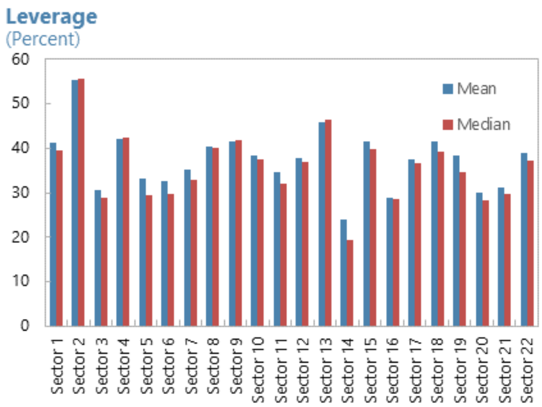
Under a dynamic balance sheet, the banking system's capital ratio in the NZ scenario further declines by 0.1 percentage points compared to a static balance sheet where zero gross loan growth is assumed (Figure 9). This decline results from the foregone interest income from shrinking industries outweighing the increasing interest income from growing industries and the reduction in asset riskiness via deleveraging within the negatively affected sectors. However, when examining the impact on individual banks, capital ratios of several banks improve under a dynamic balance sheet compared to a static balance sheet. These banks benefit from reduced loan losses from shrinking industries and a decline in RWAs, which outweigh the foregone interest income from shrinking industries. Banks with riskier portfolios (e.g., higher through-the-cycle PDs) tend to show better performance under the dynamic balance sheet approach.

The effects of pricing in credit risk outweigh those of adopting a dynamic balance sheet. While taking a dynamic balance sheet approach leads to a modest decline in the aggregate capital ratio, approximately 0.05 percentage points, the increase in lending rates for industries experiencing an uptick in credit risk enables banks to generate a higher interest income relative to RWAs, by approximately 0.15 percentage points. This increase in interest income is three times as large as the impact of moving from a static to a dynamic balance sheet.

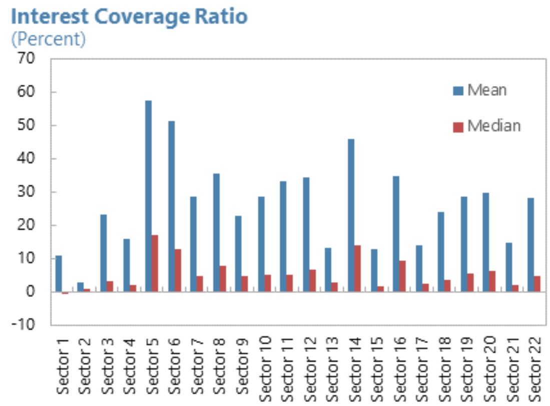
Several caveats should be considered when interpreting the model results. First, the firm module lacks elements related to firm entry and exit dynamics. Second, although several firm-level heterogeneity, including in terms of emission intensity, has been accounted for from a model perspective, the analysis may be affected by additional layers of heterogeneity such as the quality of physical capital and the intensity of knowledge in green technology. Third, more granular bank-industry specific risk parameters would be instrumental for refining the analysis, using models of a kind as employed here, going forward.

Figure 6. Japan: Firms' Risk Characteristics and Initial PDs

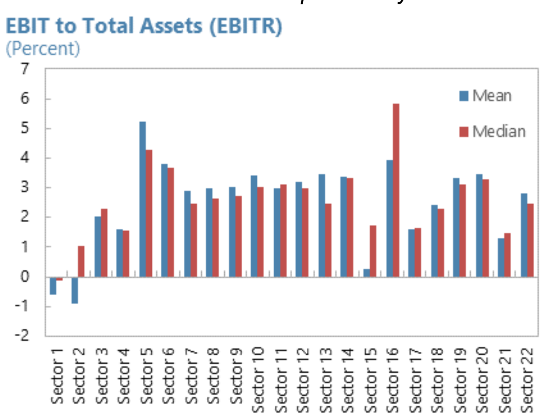
Firms in fishery, electricity, iron and steel, other manufacturing, and business services generally exhibit higher levels of leverage...



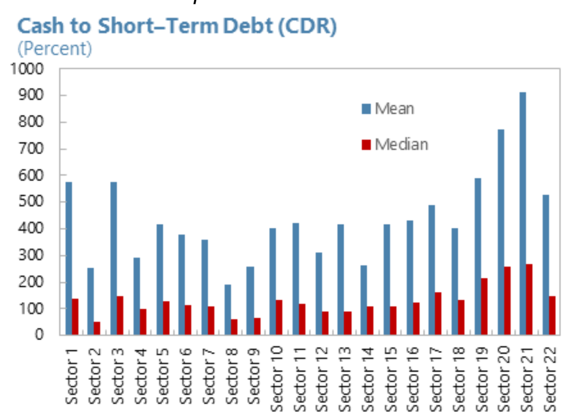
…while firms in electricity, water transport, paper products, and Fishery have weaker initial ICR levels.



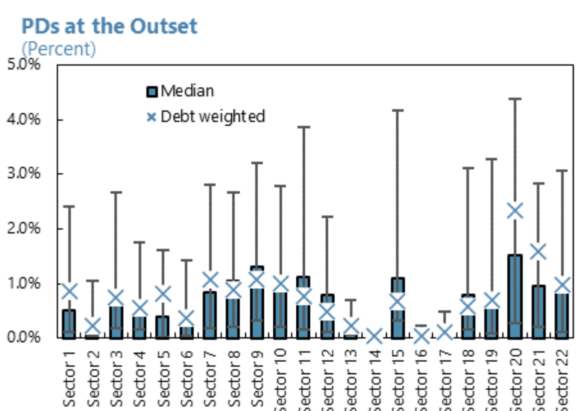
Agriculture, water transport, paper products, and collective services show weak profitability…



Iron and steel, non-ferrous metals, and paper products have weaker cash positions…



PDs at the outset exhibit significant variation both across sectors and within sectors.



Mapping Table for the Sectors in the Figures

Sector 1	Agriculture	Sector 12	Transport equipment
Sector 2	Fisheries	Sector 13	Electricity
Sector 3	Mining and quarrying	Sector 14	Gas
Sector 4	Paper products	Sector 15	Water transport
Sector 5	Petroleum and coal	Sector 16	Air transport
Sector 6	Chemical products	Sector 17	Land transport
Sector 7	Non-metallic Minerals	Sector 18	Other manufacturing
Sector 8	Iron and steels	Sector 19	Construction
Sector 9	Non-ferrous metals	Sector 20	Water supply
Sector 10	Fabricated metal products	Sector 21	Collective services
Sector 11	Electronic equipment	Sector 22	Business services

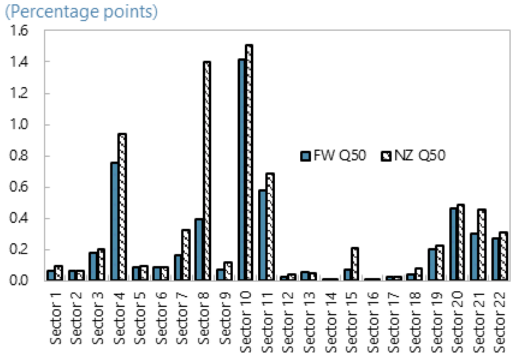
Source: IMF staff calculations.

Note: In the bottom left panel, the error bars represent the 10th and 90th percentiles of initial PDs among firms for each sector.

Figure 7. Japan: Firm PDs, LGDs, and Credit Spread Impacts (22 Sectors)

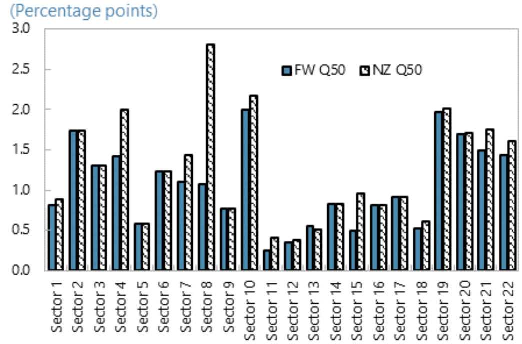
Notable impacts are observed for firms operating within emission-intensive sectors such as paper products, iron and steel, and fabricated metal industries…

PDs – Max(Scenario)-to-Average(Current Policies) Gaps
(Percentage points)



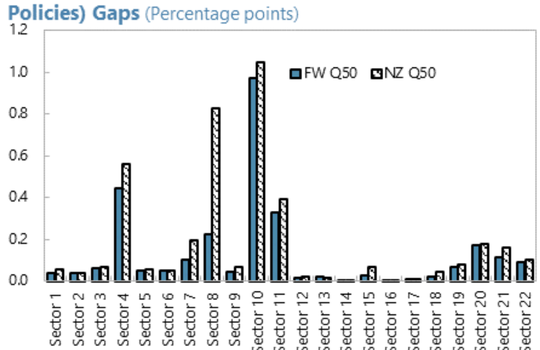
Several non-emission-intensive sectors such as other services and construction experience somewhat higher increases in LGDs…

LGDs – Max(Scenario)-to-Average(Current Policies) Gaps
(Percentage points)



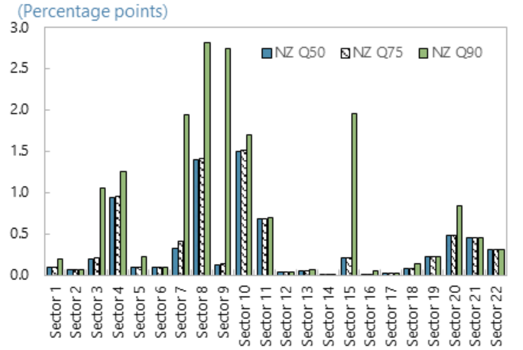
The chart for credit spread mirrors those for PDs and LGDs.

Credit Spread – Max(Scenario)-to-Average(Current Policies) Gaps (Percentage points)



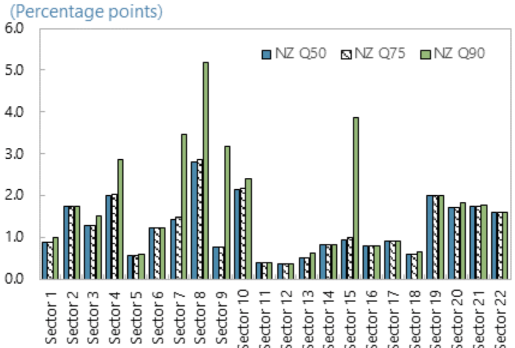
There are no noticeable differences in outcomes between the 50th and 75th percentiles, but for the 90th percentile, a large increase in PDs for certain emission-intensive sectors can be observed…

PDs – Max(Scenario)-to-Average(Current Policies) Gaps
(Percentage points)



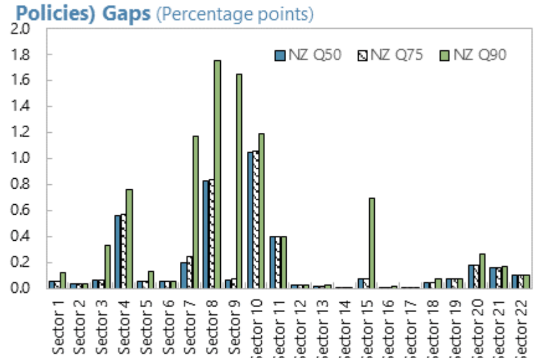
…along with a large increase in LGDs for certain emission intensive sectors…

LGDs – Max(Scenario)-to-Average(Current Policies) Gaps
(Percentage points)



…and a large increase in credit spreads for certain emission intensive sectors.

Credit Spred – Max(Scenario)-to-Average(Current Policies) Gaps (Percentage points)



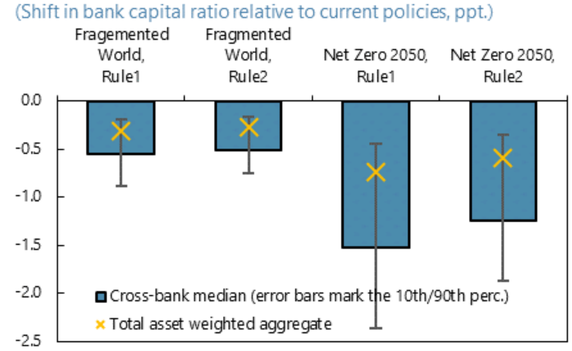
Source: Author calculations.
Note: The sector list can be found in Figure 6. The policy sceanrios are simulated under Rule 2.

Figure 8. Japan: Banking System Capital Impact by 2040

The aggregate impact on bank capital ratios aligns with the macroeconomic impact. Significant heterogeneity among individual banks is observed.

Banking System Capital Shift by 2040

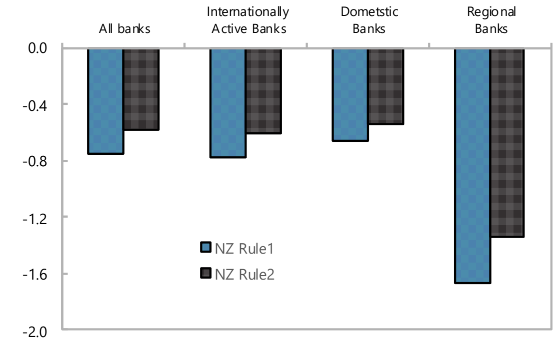
(Shift in bank capital ratio relative to current policies, ppt.)



Regional banks in the sample experience the most pronounced effects.

Banking System Capital Shift by Type of Bank

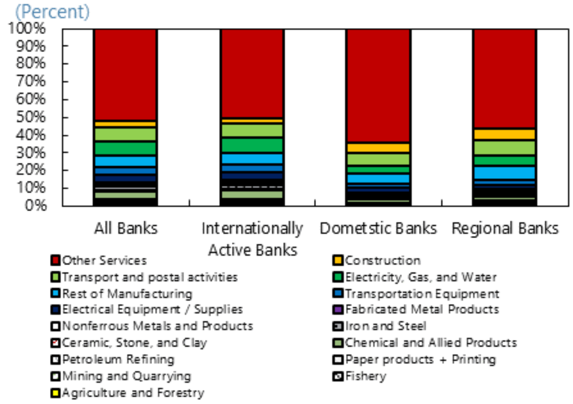
(Shift in bank capital ratio relative to current polices)



Internationally active banks have a notable exposure to emission intensive sectors, but …

Composition of Loan Portfolios by Type of Banks

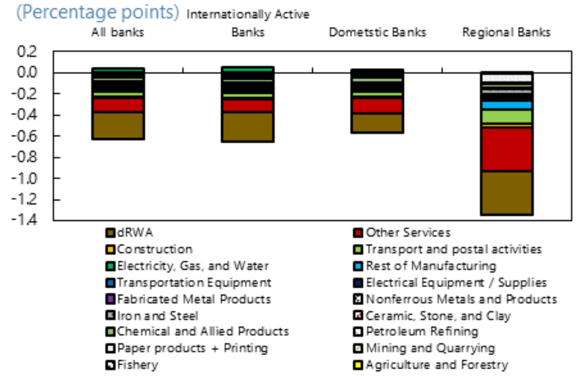
(Percent)



…non-emission intensive sectors account for 30 percent of the shift in banking system capital ratio. One-third to one-half of the capital ratio shift can be attributed to changes in RWAs.

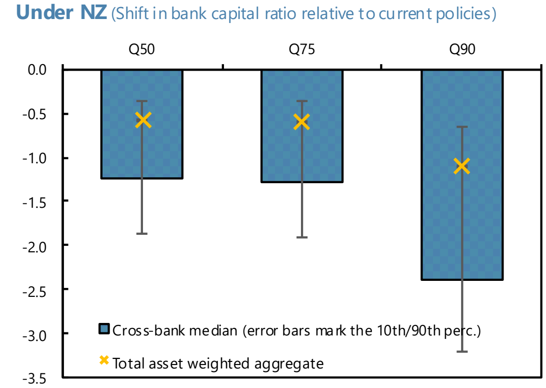
Sectoral Contributions to Banking System Capital Ratio Shift Under Net Zero 2050 by Type of Banks

(Percentage points)



Significant uncertainty in firms' emission intensity may have a substantial impact on banks' capital ratios…

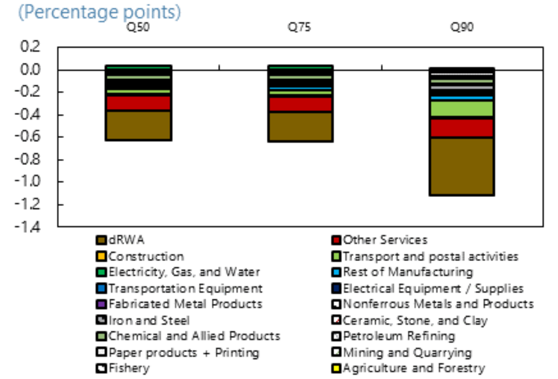
Effects of Firms' Emission Uncertainty on Bank Captial Under NZ (Shift in bank capital ratio relative to current policies)



…. primarily through direct emission intensive sectors.

Sectoral Contributions to Banking System Capital Ratio Shift by Emission Intensity Levels

(Percentage points)



Sources: FSA; and IMF staff calculations

Figure 9. Japan: Effects of Dynamic Balance Sheets under the Net Zero 2050 Relative to Current Policies Scenario

With dynamic balance sheets, shifts in industry structure and their resulting effects on bank profitability can be accounted for.

Industry #6: Chemical (Shrinking in S5 relative to S1)

[JPY million, cumulative flows until 2040, under scenario 5 minus scenario 1]

	Static	Dynamic
Interest income	9,623	-218,213
Loan loss	-29,468	21,322
Sum	-19,845	-196,890

Industry #14: Electricity and Gas (Growing in S5 relative to S1)

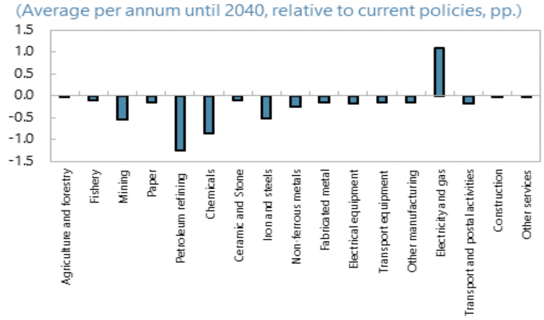
[JPY million, cumulative flows until 2040, under scenario 5 minus scenario 1]

	Static	Dynamic
Interest income	-2,153	598,422
Loan loss	14,963	-348,908
Sum	12,811	249,514

While loans to electricity and gas grow under the NZ relative to the CP, loans to other sectors decline.

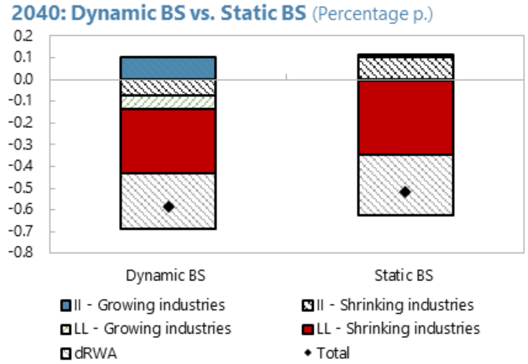
Loan Growth Differentials

(Average per annum until 2040, relative to current policies, pp.)



Under a dynamic balance sheet, the banking system's capital ratio declines by 0.1 percentage points compared to a static balance sheet.

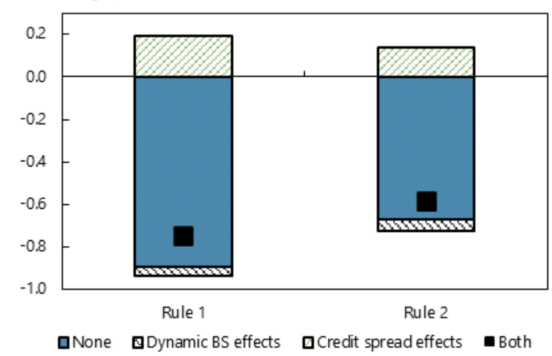
Contributions to Banking System Capital Ratio Shift by 2040: Dynamic BS vs. Static BS (Percentage p.)



It turns out that effects of pricing in credit risk outweigh those of adopting a dynamic balance sheet.

Effects of Dynamic Balance Sheets and Interest Income

(Percentage p.)



Source: Author calculations.

Note: The Net Zero 2050 scenario with Rule 2 is used for this exercise.

4. Conclusions

We have set up an integrated micro-macro simulation model for the purpose of conducting policy-relevant, transition risk-focused scenario analysis. The ENV-FIBA model comprises a CGE macro model core and a micro simulation module connected to it, for a sample of nonfinancial firms and banks. The focal distinguishing features relative to other, related models in the literature include:

(1) the account for chronic physical risk feedback in the otherwise transition-risk focused model;

(2) the use of a dynamic balance sheet mode for firm debt and hence bank balance sheets;

(3) related to the latter point, the emphasis on interest income effects stemming from shrinking vs. growing industries.

Three other noteworthy features built into the model include an endogenous LGD model scheme (albeit still simple), a stochastic drawing mechanism embedded in the model to account for the uncertainty surrounding the individual firms' emission intensities, and the incorporation of all industry segments, not just emission intensive ones, to thereby include in scope and examine the industries that may gain from transition policies.

The model's use is exemplified with an application to Japan. This application involves the CGE model's coverage of 22 industry segments of the Japanese economy, alongside 270,000 individual firms and 22 individual banks in the FIBA model component. Three scenarios are considered: the NGFS's current policies scenario, the fragmented world scenario, and the net zero 2050 scenario.

Accounting for chronic physical risk feedback means that transition policies can exert their intended positive impact through mitigating physical risk materialization. This, in turn, means that the consequent positive economic effects can be better measured, which offset the economic losses induced by only transition policies if seen in isolation. The "current policy" scenario considered for the application to Japan, for example, accounts for the macro impact of the estimated chronic physical risk from the NGFS, which represents a reduction of GDP levels of 2.7 percent by 2040 for Japan. The alternative scenarios, such as the net zero 2050 scenario, then result in *less* detrimental effects, revealing the net beneficial effect of the transition policies at the aggregate level. Underneath that aggregate, emission intensive industries would shrink materially, while others would benefit. The physical risk benefits of the net zero 2050 scenario become increasingly visible after 2040, according to the estimates.

Considering the dynamic evolution of firm debt is shown to be important. It allows to capture any shifts in industry structure and its potential effect on bank profitability. To illustrate this with the application to Japan, two industries are analyzed in more detail: the chemical products and the electricity and gas segments. A notable loan growth differential could be observed for these two industries, according to the model. The emission intensive chemical sector experiences an average annual decrease of 0.8 percentage points in growth, while the electricity and gas sector see an increase of 1.2 percentage points of growth per annum until 2040, both under the net zero 2050 scenario relative to the current policies scenario. When the chemical sector shrinks, it leads to a decline in interest income for banks, and loan losses become less negative, even though PDs and LGDs deteriorate relative to the current policies scenario. Conversely, in the case of electricity and gas experiencing growth, interest income increases, and loan losses become more negative, despite reductions in credit risk parameters relative to the current policy scenario. Additionally, loan growth has a direct impact on risk weighted assets for banks. More positive loan growth puts downward pressure on capital ratios, whereas less positive or negative growth exerts upward pressure on these ratios from this perspective. It is concluded that considering dynamic balance sheets, even in a simple, and therefore robust manner, should be instrumental to account for the quantitatively important interest income effects of shrinking (vs. growing) industries.

The model framework can be further developed in various ways. Three examples include: (1) better integrating the financial components, first and foremost interest rates, in the macro (CGE) model; (2) considering the integration of stock-flow consistent model elements with the macro-financial model structures in a model like the ENV-FIBA model, so as to bring in markets (bond markets, equity markets) and capture their role more explicitly; and (3) improving the LGD model component for the banks and their lending portfolios, to more directly link them to the physical risk implications (as an output of damage functions).

Annex I. Model Inputs and Calibration

Firm Module—Data

The analysis relies on three key sources of micro data, with the primary source being Japanese firms balance sheets and income statements from Moody's/Orbis. The dataset spans the period 2005-2023, and features a panel structure, encompassing between 150,000 to 280,000 firms annually. Entities operating within sectors such as finance and insurance (NACE Rev. 2, 64-66), public administration (84), and activities of households (97-98) are excluded.

A "no double counting" principle is employed when dealing with the consolidation level of nonfinancial firms. This means that firms are included at the highest consolidation level, while excluding lower-level subsidiaries if their parent companies from Japan exist in the database. There are four consolidation codes available in the dataset: "C1," "C2," "U1," and "U2". One consolidation code per firm is to be kept. The preference order is defined as C2-C1-U1 in that sequence (see the Table 1 below for a description of these consolidation codes). The U2 code is not relevant because unconsolidated results are not used when consolidated results are available. The "filing type" is used to remove any remaining duplicates for a given consolidation code per firm and year. "Filing type" references whether the financials are from the annual report or from a local registry filing.

The list of variables required and used for defining the firm sample includes various balance sheet and profit and loss flow metrics. Various filters are imposed to clean the dataset as shown in Table 3 below.

Annex I. Table 1. Moody's/Orbis Firm Consolidation Codes

C2	Contains the consolidated financial statements. The unconsolidated results are also available in Orbis.
C1	Contain the consolidated financial statements. The unconsolidated results are not available in Orbis.
U1	Contains unconsolidated financial statements and assumes that these firms do not have controlled subsidiaries (or it could be that they do have controlled subsidiaries, but that information is not public).
U2	Contains the unconsolidated financial statements, without integrating the controlled subsidiaries, but the consolidated financial statements are available in Orbis.

Sources: Moody's / Orbis.

Annex I. Table 2. Micro-Level Variables Relevant for the FIBA Model Layer

Firm Balance Sheets

Variable	Moody's/Orbis variable name
Total assets	Total assets
o/w cash and cash equivalent	Cash_and_cash_equivalent
o/w non-cash assets	Non-cash assets
o/w current assets excl.cash	Current assets excl. cash
Total liabilities	
o/w non-current liabilities	Non_current_liabilities
o/w long-term debt	Long_term_debt
o/w other non-current liabilities	Other_non_current_liabilities
o/w current liabilities	Current_liabilities
o/w loans	Loans
o/w creditors	Creditors
o/w other current liabilities	Other_current_liabilities
Shareholder funds	Shareholders_funds
o/w capital	Capital
o/w other shareholder funds	Other_shareholders_funds
Number of employees	Number_of_employees

Firm P&L Flows

Variable	Moody's/Orbis variable name
Sales revenue [A]	Operating_revenue_Turnover
Operating expenses [B = C+D]	
o/w Costs of goods sold [C]	Costs_of_goods_sold
Other operating expenses [D]	Other_operating_expenses
o/w Costs of employees [E]	Costs_of_employees
Rest of operating expenses [F = B-E]	
EBIT [A-B]	Operating_P_L_EBIT
Financial revenue [G]	Financial_revenue
Financial expense [H]	Financial_expense
o/w interest expense	Interest_paid
Net profit after net fin. Income, before tax [EBT=EBIT+G-H]	P_L_before_tax
Tax [I]	Taxation
Net profit after tax [P=EBT-I]	P_L_after_tax

Sources: Moody's/Orbis.
Notes: The variables in light grey are not effectively needed as input to the FIBA model layer but shown for completeness to include information on the remaining "of-which" categories. In the P&L category, the grey items are those that do not need to be obtained from the micro database as they can be computed from the other items.

Annex I. Table 3. Moody's/Orbis Variables and Filtering Conditions

Cash_and_cash_equivalent **(≥0)**	Operating_revenue_turnover **(>0)**
Total_assets **(>0)**	Operating_P_L_EBIT **(≠0)**
Debt_holding* **(>0)**	P_L_before_tax **(≠0)**
Long_term_debt** **(>0)**	P_L_after_tax **(≠0)**
	Costs_of_goods_sold** **(≥0)**
	Costs_of_employees ** **(≥0)**

Sources: Moody's / Orbis.
Notes: * Debt_holding = Loans + Creditors + Long_term_debt.
** This filtering is only applied to the construction of the "T0" database.

The "T0" database serves as the initial "anchor" for the microsimulation. To mitigate potential distortions caused by the pandemic in the model simulations, we construct the "T0" database that contains pre-pandemic averages for flow variables, such as revenues, and the latest data for stock variables such as total assets.[14] The year profiles for both flow and stock variables are presented in Figure 1. Furthermore, A filter condition is imposed to retain only active firms, that is, firms that defaulted or merged or were resolved for other reasons in the past are removed. In the final step of our data processing, missing values for two key firm-level variables are imputed: For costs of employees, the industry median wage at the NACE Level 2, in combination with the firm's number of employees is used to estimate missing values for firms representing 9.8 percent of the total sample; Similarly, for interest expenses, the industry median interest rate and the firm's debt holdings are used to impute missing data points for firms that account for 8.2 percent of the total sample.

In the "T0" dataset for Japan, the emission-intensive sectors represent 5.6 percent of the total number of firms, yet they constitute a significant portion, accounting for 42 percent of total assets and 26 percent of total sales

[14] Flow data are averaged over a period of up to three years, whenever data are available.

within the firm sample. According to the Japan Industrial Productivity database, these sectors comprise 13.4 percent of the total GVA.

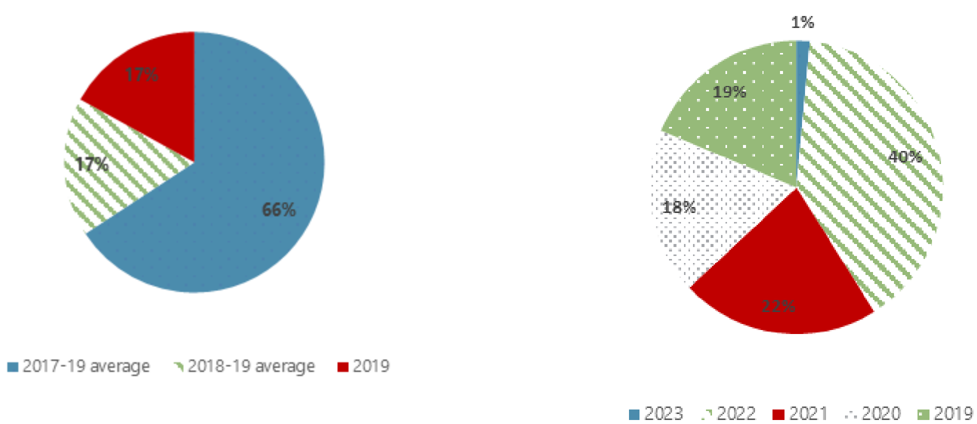
Annex I. Table 4. Japan: Firm Micro Data for the FIBA Model Layer at the Outset (T0)

#	Sector classification		Number of firms per segment (T0)		Total assets per segment (T0), US$ bn		Annual sales per segment (T0), US$ bn		Total sectoral GVA in 2021 (macro stats), Yen bn	
			abs.	% of total	abs.	% of total	abs.	% of total	abs.	% of total
1	Agriculture	A1-2	1,276	0.5%	12	0%	12	0%	5,039	0.9%
2	Fishing and aquaculture	A3	68	0.0%	2	0%	3	0%	637	0.1%
3	Mining and quarrying	B	307	0.1%	93	1%	25	0%	368	0.1%
4	Manufacture of paper and paper products	C17-18	2,078	0.8%	133	1%	121	1%	4,746	0.9%
5	Manufacture of petroleum and coal products	C19	174	0.1%	154	1%	212	2%	6,877	1.3%
6	Manufacture of chemical products	C20-21	1,402	0.5%	786	7%	495	4%	11,834	2.2%
7	Manufacture of non-metallic mineral products	C23	1,569	0.6%	102	1%	81	1%	3,237	0.6%
8	Manufacture of iron and steels	C24_1	734	0.3%	241	2%	206	2%	7,549	1.4%
9	Manufacture non-ferrous metals	C24_2	379	0.1%	68	1%	58	0%	2,490	0.5%
10	Manufacture of fabricated metal products	C25	5,587	2.1%	150	1%	161	1%	5,141	0.9%
11	Manufacture of electronic equipment	C26_1	1,283	0.5%	672	6%	455	4%	8,465	1.5%
12	Manufacture of transport equipment	C29-30	993	0.4%	1,355	13%	1,001	8%	13,456	2.5%
13	Electricity	D351	347	0.1%	559	5%	297	2%	5,950	1.1%
14	Manufacture and distribution of gas	D352	98	0.0%	67	1%	44	0%	884	0.2%
15	Water transport	H50	192	0.1%	90	1%	54	0%	1,346	0.2%
16	Air transport	H51	33	0.0%	28	0%	21	0%	473	0.1%
17	Land transport	H49	5,907	2.2%	474	4%	289	2%	19,314	3.5%
18	Other manufacturing	C-1	31,320	11.6%	1,724	16%	1,569	13%	48,906	8.9%
19	Construction	F	106,828	39.4%	797	7%	853	7%	18,812	3.4%
20	Water supply	E	2,470	0.9%	26	0%	20	0%	8,332	1.5%
21	Collective services	S1	4,735	1.7%	145	1%	125	1%	66,799	12.2%
22	Business services	S2	103,335	38.1%	4,563	43%	4,616	38%	252,826	46.2%
	Total		271,115	100%	10,720	100%	12,239	100%	493,482	90.1%

Sources: Moody's/Orbis; Japan Industrial Productivity database; IMF Climate Dashboard; and IMF staff calculations.
Notes: 1) The total GVA shares in this table refer to aggregate, industry-wide statistics. All others are based on the firm micro data. 2) Direct emission intensive sectors are colored in orange, and sectors that depends more on inputs from emission intensive upstream industries in light orange. The classification of sectors is based on the analysis of sector-level emission intensities mentioned in a note of Figure 3 in the main text.

Annex I. Figure 1. Japan: Year Profiles for Flow Variables and Stock Variables at T0

Flow Variables at T0 **Stock Variables at T0**



Sources: Moody's/Orbis; and author calculations.

The second data source involves PD data from Moody's KMV, covering approximately 1,900 listed Japanese firms from 2005 to 2020. Daily PD data are converted to yearly averages for each firm, while accounting for the time shift in individual firms' financial reporting. Subsequently, the PDs are merged with the Moody's/Orbis dataset based on firms' identification numbers and are employed to estimate a firm-fixed effects panel model.

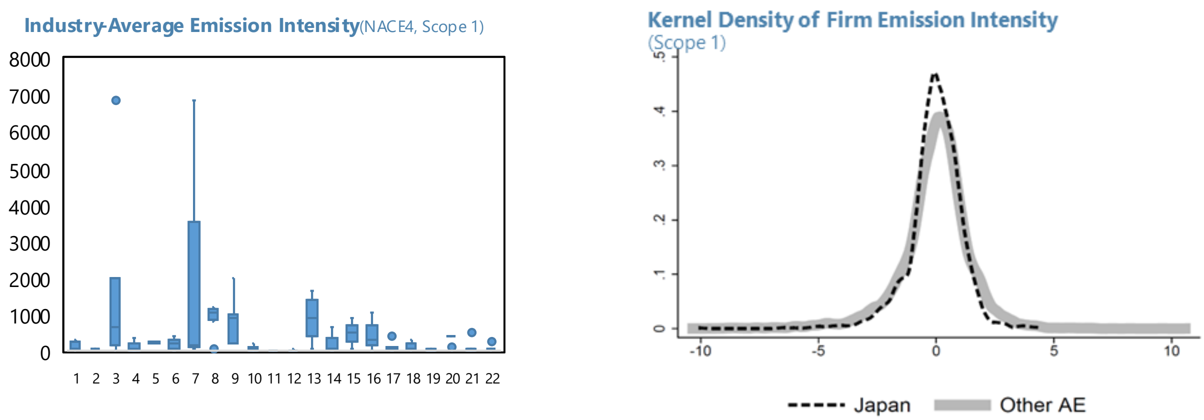
The third data source concerns CO2 emissions. Scope 1 emissions data is obtained from Intercontinental Exchange (ICE) to account for direct emission costs within the FIBA module. The ICE dataset includes firm-level reported emission intensities, measured in ton CO2/USD million revenue, including about 360 Japanese firms. For firms lacking reported emission data, industry-average values for NACE Level 4 industries in the Asia-Pacific region are used, as also sourced from ICE.[15] The data reveal considerable variation among several sub-industries, such as mining (3) and non-metallic minerals (7), as illustrated in Figure 76.

The kernel density distribution of firms' emission intensity estimated by Capelle et al. (2023) is utilized to conduct a Monte Carlo simulation. It is the distribution of residuals in firms' emission intensity (represented as the logarithm of CO2 emissions over revenues in megatons per million USD) after accounting for industry-year fixed effects. A substantial within-sector variation in emission intensities are observed. For Japan, the 75th and 90th percentiles of "residualized" emission intensities are about 2 and 3 times greater than the median in the sample, highlighting the significant uncertainty surrounding individual firms' emissions. The impact of the uncertainty surrounding the emission intensity on individual firm risk metrics are assessed in the analysis based on the 50th, 75th, and 90th percentiles, respectively.

Annex I. Figure 2. Japan: Data on Emission Intensity

There is a considerable variation in industry-mean emission intensity…

Large heterogeneity in firms' emission intensity is observed within a certain industry…



Sources: ICE; Capelle and others (2023); and IMF staff calculations.
Notes: The left chart shows industry-average emission intensities for NACE level 4 industries in the Asia-Pacific region. Please refer to the mapping table for sector numbers in the note of Figure 6 in the main text. In the right chart, emission intensity is measured as the log of emissions over revenues, and residuals are extracted after controlling for industry × year fixed effects.

Firm Module–Calibration and Estimation

[15] A comparative exercise is conducted between the industry-average emission intensity of ICE and 45-sector emission intensity data for Japan, obtained from the IMF Climate Change Dashboard. The median emission intensity is selected from sub-industries corresponding to each of the 45 sectors. The results show high correlation between two emission intensity data, with a correlation coefficient of 75 percent excluding electricity and gas sector.

The firm P&L modeling comprises several structural sub-components, as outlined in Table 5. Firms' sales revenues are modeled to move at the same rate as sectoral output projections from the IMF ENV. Projections for costs of employees are linked to growth of sectoral labor income that is computed by multiplying sectoral employment and equilibrium wage from the IMF ENV. Operating expenses net of cost of employees are linked to sectoral intermediate input, which can be obtained by subtracting GVA from output. It is assumed that a firm's CO2 emissions, the multiplication of its emission intensity and sales revenues, move along with the sectoral emission projections from the IMF ENV. Income tax expense flows during the simulation are computed based on net income before tax using the industry-specific relevant rates. The tax rates are informed by the micro data themselves (Figure 3) and applied when earnings before tax for any given firm and per time period along the simulation horizon are positive. When firms' pre-tax earnings are negative, they do not pay taxes. Tax credits are not considered.

Annex I. Table 5. Japan: Firm P&L Modeling–Overview

P&L Component	Model Approach
Sales revenue [A]	Align with output projections from the IMF ENV
Operating expenses [B=C+D=E+F]	E + F
Costs of goods sold [C] Other operating expenses [D]	
Costs of Employees [E]	Align with labor cost projections from the IMF ENV
Rest of operating expenses [F=B-E]	Align with intermediate input projections from the IMF ENV
Financial revenue [G]	Moving proportionally with sales revenue
Financial expense (interest paid) [H]	Credit spread moving endogenously as function of firm specific PD and LGD
Tax expense [I]	Ratio of tax to EBT constant, zero for firms in periods when EBT<0

EBIT = = [A] – [B] - *Direct emissions costs (a firm's emission (scope1) × carbon price)*

EBT = Earnings after net financial income and before tax = EBIT + [G] - [H]

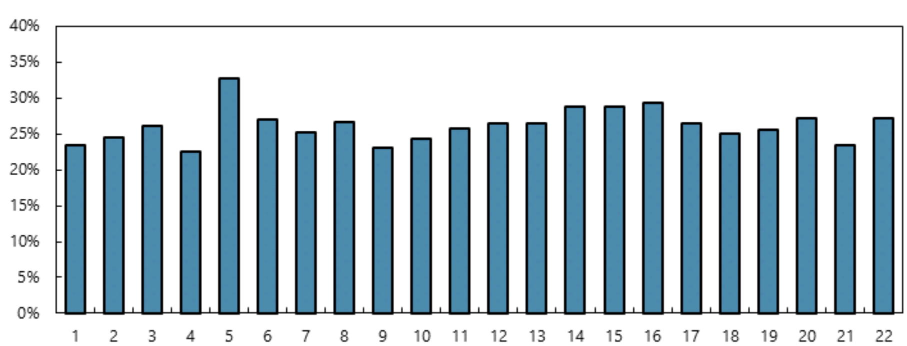
NI = Earnings after net financial income and tax = EBT - [I]

ICR = EBIT / [H]

$$NI_{fh} = rev_{fh} - oe_{fh} + fi_{fh} - ie_{fh} - tax_{fh}$$

Source: IMF staff.

Annex I. Figure 3. Japan: Corporate Tax Rates Across Firm Industries



Sources: Moody's/Orbis; and IMF staff calculations.
Notes: The tax rates were computed as the sum of all firms' tax expenses over the sum of their earnings before tax at T0. Please refer to the mapping table for sector numbers in the note of Figure 6 in the main text.

The PD model is structured as a firm-fixed effects panel econometric equation for the entire nonfinancial corporate sector, featuring logit-transformed firm-level PDs on the left-hand side.[16]

$$logit\,(PD_{ft}) = \alpha_f + \beta LEV_{ft} + \gamma ICR_{ft} + \delta EBITR_{ft} + \theta CDR_{ft} + \varepsilon_{ft}\ .$$

The PD equation is estimated using pre-pandemic data (2005-2019) for listed firms, and the estimates suggest a quantitatively prominent role for leverage. The coefficient estimates (Table 11) are all statistically significant, and their signs are as expected from a theoretical perspective. An increase in leverage implies a rise in PDs, while an increase in the ICR, EBITR, and CDR implies a decline in PDs. The normalized coefficient for leverage, normalized by its standard deviation, is about twice as large as the normalized coefficients for all other regressors combined.

Annex I. Table 6. Estimation Results for the PD Equation

	(1) *logit* (PD)
LEV	3.534***
	(.0917)
ICR	-0.01***
	(0.0002)
EBITR	-0.791***
	(.1568)
CDR	-0.016***
	(.0037)
_cons	-6.031***
	(.0327)
Observations	26,793
Within R^2	.173

Sources: MKMV and IMF staff calculations.
Notes: Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1. ICR, EBITR, and CDR are winsorized at 5 (95) percent, while LEV is winsorized at one.

When embedding the PD equation in the FIBA module, an intercept is adjusted to anchor the model-implied firm PDs. For firms that are not part of the PD model estimation sample—primarily unlisted firms—the industry averages of the estimated firm fixed effects are used. Subsequently, these firms' historical PDs and, based on these, the through-the-cycle (TTC) PDs as long-term averages of the PiT PDs are computed using the estimated panel model and their risk metrics.

Bank Module–Data and Calibration

Establishing the connection to bank balance sheets and their capitalization necessitates access to individual banks' industry exposure data. Industry exposure data as of end-March 2023 are sourced from the individual banks. Focus is placed on emission-intensive sectors and those reliant on emission intensive inputs from 22 banks, following the Bank of Japan classification of Loans and Bills Discounted by Sector. 17 distinct portfolio segments are constructed and used as a starting point for computing the scenario-conditional credit losses and interest income for banks. To align with these 17 loan portfolios, PDs, LGDs, and credit spreads at the firm industry levels are reaggregated, using each firm's debt as the weighting factor.

The composition of the loan portfolios, particularly the loan exposure to emission intensive sectors, exhibits significant variability across banks (Figure 4). Internationally active banks have higher exposure to emission intensive sectors, compared to the other types of banks. On average, the loan exposure to these sectors is roughly 30 percent, which is somewhat higher than the share calculated based on the BOJ's loan statistics (of 22 percent).

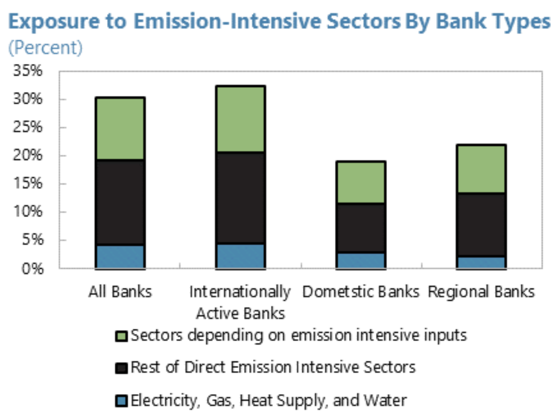
[16] The logit transformation: $logit(PD) = \ln(PD/(1 - PD))$. The inverse calculation to undo the logit is the sigmoid function: $logit^{-1}(x) = e^x/(e^x + 1)$. This transformation scheme guarantees that the predicted default rates remain within the [0-1] interval.

The debt interest rate for the Japanese corporate sector, which stood at about one percent in 2022, is used for the “base” lending rate.[17] Finally, the general loan growth pertaining to gross loans is aligned with a rolling multi-year average of scenario-based sectoral GVA growth for each industry.

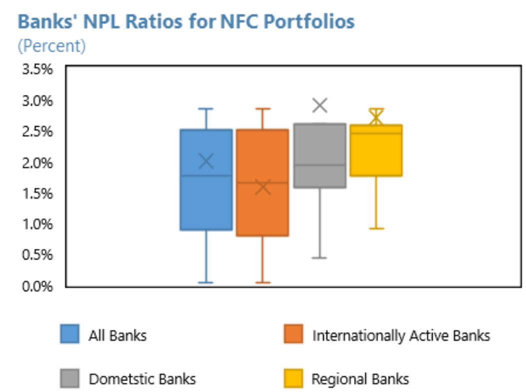
PDs and the LGDs at the bank level for the NFC portfolio are employed as “anchor points” to account for structural cross-bank differences in their risk profile. As depicted in the middle and lower panels of Figure 4, regional banks in the sample tend to exhibit higher risk parameters, including through-the-cycle PDs and LGDs, compared to other types of banks. An alternative approach is to use the PDs and LGDs at the bank-portfolio level if data is available. This was partly tested and yielded quantitatively similar outcomes for impacts on banks’ capitalization.[18]

Annex I. Figure 4. Japan: Banks’ Loan Portfolios by Sector and Risk Profile by Type of Banks

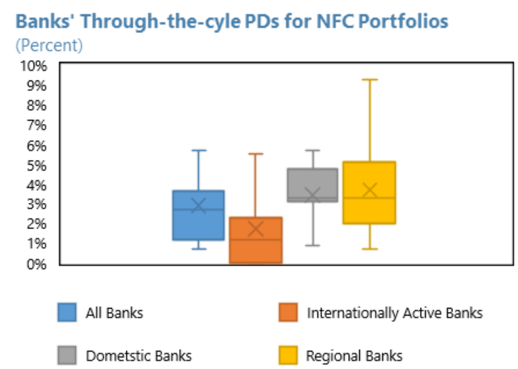
Internationally active banks have higher exposures to emission-intensive sectors, compared to other types of banks.



NPL ratios for NFC portfolios of regional banks in the sample are higher than those of internationally active banks…



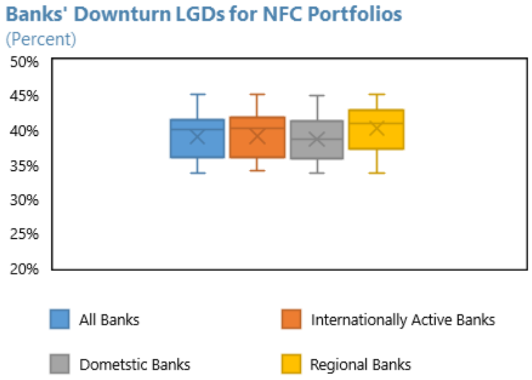
…through-the-cycle PDs are, on average, higher and more diverse…



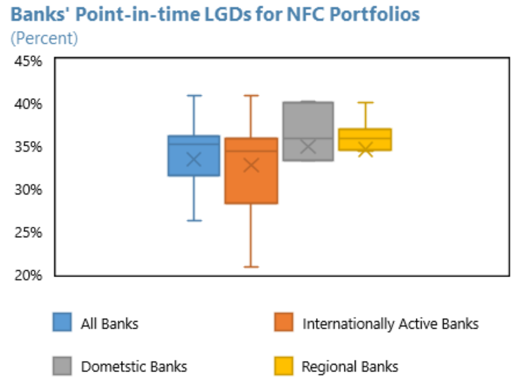
[17] The lending rate is composed of such a “base lending rate” and the “credit spread” component on top.

[18] To estimate LGDs at the bank-portfolio level at the outset, provision coverage ratios (PCR) for nonperforming loans are first computed within three industry clusters, based on aggregated bank data: agriculture and fishery, manufacturing, and the rest of the nonfinancial corporate industries, as well as for the overall NFC total. . Subsequently, the differences between the PCR of each industry cluster and the PCR of the overall NFC portfolio are employed to adjust both point-in-time LGDs and downturn LGDs of individual banks at the outset. This adjustment scheme is employed since LGDs are not available at the detailed industry level at the outset, while NPL provision coverage ratios are.

…as are their downturn LGDs for NFC portfolios…



…and the point-in-time LGDs for NFC portfolios.



Sources: FSA; and IMF staff calculations.
Notes: In the top panels, the loan exposure data is as of March 2023. In the box plots, lines in the middle of the box are medians, box edges are the 25th/75th percentiles, and the ends of the whiskers mark the 1st/99th percentiles.

Annex II. Model Codes

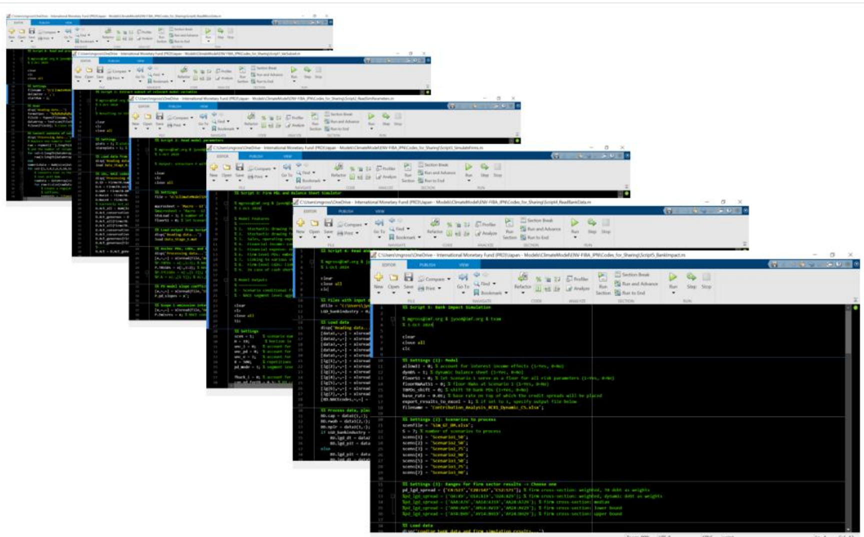
A Matlab model code package—pertaining to the FIBA model component—accompanies this paper. It consists of six scripts and 32 accompanying functions. Its structure is summarized in Table 1 and visually depicted in Figure 1. The script package requires data inputs for nonfinancial firms, banks, scenario inputs that are the outputs from the CGE model component, and other model input parameters.

The nonfinancial firm data as input to Script 0 takes the form as depicted in Figure 2. The content of this data sheet was summarized in Annex 1 (see text and Table 2 therein). Table 2 below summarizes the model parameters that Script 2 requires as inputs. Table 3 below summarizes the inputs pertaining to banks, as input to Script 4. The model codes are available from the authors on request.

Annex II. Table 1. Matlab Code Structure—FIBA Model Component

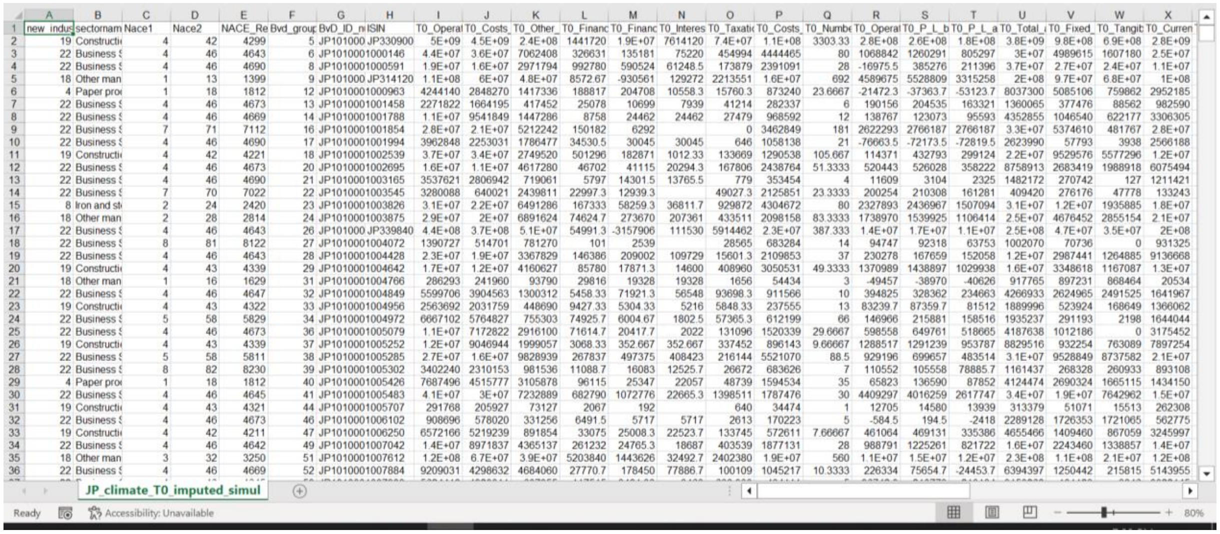
Script	Purpose	Input	Output
Script0_ReadMicroData.m	Process raw micro data from CSV	Firms_T0.csv	Data_Stage_0.mat
Script1_VarSubset.m	Extract subset of relevant model variables	Data_Stage_0.mat	Data_Stage_1.mat
Script2_ReadSimParameters.m	Read model parameters	Data_Stage_1.mat Model_Parameters.xlsx	Data_for_Sim.mat
Script3_SimulateFirms.m	Firm P&L and Balance Sheet Simulator	Data_for_Sim.mat	Data_SimFirms.mat Sim_Results.xlsx Plots
Script4_ReadBankData.m	Read and process banks' T0 data	Global_Solvency_Data.xlsx	Data_Banks.mat
Script5_BankImpact.m	Estimate impact on banks	Data_Banks.mat Sim_Results.xlsx	Bank_Impacts.xlsx Plots

Annex II. Figure 1. Matlab Script Package—FIBA Model Component



Note: The figure provides a visual impression of the FIBA model script package (six scripts).

Annex II. Figure 2. Nonfinancial Firm Micro Data Input—Input to Script 0



Note: The figure depicts the input file that holds the micro data for nonfinancial firms as input to the FIBA model component.

Annex II. Table 2. Model Parameters—Input to Script 2

#	Parameter	Level	Comments
1	PD model coefficients	Industry	Slope coefficients pertaining to logit-PD model component, by industry. They can be homogeneous or heterogeneous across industries. Intercepts (nonfinancial firm fixed effects) are not included in this input file, but in the firm-level input depicted in Figure 2 above.
2	Tax rates	Industry	Income tax rates, by industry
3	Emission intensities	Firm	Emission intensity for individual firms (firm micro data)
4	Anchor point PiT LGDs	Industry	Firm industry-level LGDs, as of most recent. These are needed in the nonfinancial firm micro simulation (Script 3), since firm-level LGDs are not initially observed.

Note: The table summarizes the four parameter inputs that Script 2 requires as input.

Annex II. Table 3. Bank Data Inputs—Input to Script 4

#	Parameter	Level	Comments
1	Capital	Banks	Banks' regulatory capital as of T0, in local currency
2	RWA		Banks' total risk-weighted assets, in local currency
3	NPL ratio		Banks' nonfinancial corporate portfolio-related NPL ratio, at bank-level
4	Industry exposures	Banks & industries	Banks' current credit exposures to the various industries, gross (not net of provisions), performing and nonperforming combined
5	PD TTC	Banks (optionally industries)	Banks' recent historical average (through the cycle, TTC) default rates, pertaining to their nonfinancial corporate portfolio in total or by industry; for those banks with portfolios under IRB

6	LGD PiT		Banks' current PiT LGDs, pertaining to their nonfinancial corporate portfolio in total or by industry
7	LGD DT		Banks' current downturn (DT-) LGDs, pertaining to their nonfinancial corporate portfolio in total or by industry; for those banks with portfolios under IRB
8	NFC IRB shares		Banks' IRB-in-total portfolio shares; either for banks' NFC portfolios in total or for each industry
9	STA RW performing		Effective risk weights for banks (portfolios)' performing portion under the standardized (STA) approach; either for NFC portfolios in total or for each industry
10	STA RW nonperforming		Effective risk weights for banks (portfolios)' nonperforming portion under the standardized (STA) approach; either for NFC portfolios in total or for each industry
11	Gross loan growth by industry, under the climate scenarios	Industry & forward in time	Gross loan growth, by industry, along the scenario horizon; by industry; informed by output of CGE model component
Note: The table summarizes the bank-related parameter inputs that Script 4 requires as input.			

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PUBLICATIONS

The ENV-FIBA Model for Climate Risk Analysis: Framework, Model Details, and Guide

Working Paper No. WP/2025/230