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Delays in Climate Transition Can Increase Financial Tail Risks: A Global Lesson from a Study in Mexico

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ABSTRACT: This paper explores a novel forward-looking approach to study the financial stability implications of climate-related transition risks. We develop an integrated micro-macro framework with a new class of scenario called delayed-uncertain pathways. An additional stochastic financial modeling layer via a jump-diffusion process is considered to capture continuously changing risks, as well as the potential of large/sudden shocks in the financial markets. We applied this approach to study transition risks in the Mexican financial sector. But the implications are global in scope, and the framework is easily adaptable to other countries. We quantify the projections of future distributions of various risk metrics and, hence, the evolving tail risks due to compounding effects from delays in transitioning to a low-carbon economy and the consequent uncertainty of the future policy path. We find that the longer the delays in transition, the larger the future tail financial risks, which could be material to the overall system.

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WORKING PAPERS

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Introduction[1]

Climate change is already generating unprecedented impacts around the world on various segments of the global economy and human society. The Intergovernmental Panel on Climate Change (IPCC), the United Nations body for advancing the science on climate change, highlights that the adverse economic effects attributable to human-induced climate change are increasingly being observed, leading to large-scale losses and damages to nature and human society around the world (IPCC 2022). Physical hazards and their impacts—such as increasing frequency and intensity of extreme climate events (for example, hurricanes, floods, drought, and wildfires)—are projected to increase further with global warming. Limiting global warming requires significant efforts in and commitments to reducing global greenhouse gas (GHG) emissions. Such actions could have a material economic and financial impact on emissions-intensive firms/sectors and also households and governments via different channels. Thus, transition risks arise as the economy moves toward a low-carbon economy, which can impact various segments of the economy and the financial sector.

Worldwide consensus is building on the need to introduce stronger policy actions to limit GHG emissions and transition to a low-carbon economy. During COP26, the 2021 UN climate summit, policymakers around the world made new climate pledges and discussed plans to reduce emissions to avert serious damages to the climate system. At COP26, more than 120 countries, representing about 70 percent of global emissions, pledged to bring emissions to net zero by around 2050. And given the exposure of the financial system to the effects of climate change, global regulators and central banks increasingly recognize the need to assess and minimize those impacts on financial stability.

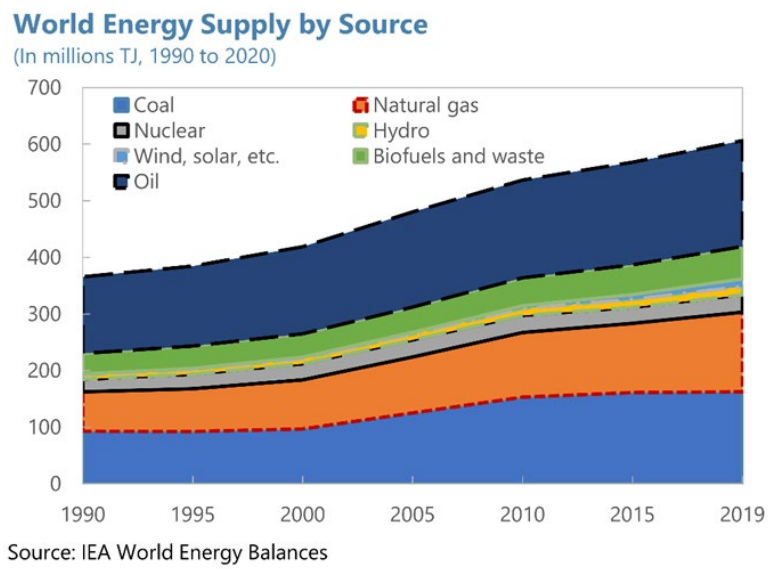
However, despite the warnings from the IPCC on rising global temperatures, more ambitious and decisive actions to limit GHG emissions are still wanting. According to Climate Action Tracker (2022), a non-profit research organization that tracks progress on governments' pledges and actions to address climate change, the global engagement since the COP26 have been weakened, especially in the wake of the Russia-Ukraine conflict. Progress has stalled on more ambitious 2030 climate targets. This was also evident from recent COP27 where stronger global climate ambitions relative to COP26 were largely absent. And without increased policy response, the world could emit significantly more GHGs, potentially increasing the earth's temperature to well above the 2°C upper limit for global warming—with the goal of 1.5°C—established by the Paris Agreement. In fact, global non-renewable-energy- and fossil-fuel-related CO_2 emissions in 2021 bounced back almost to pre-COVID-19 pandemic emission levels (IEA 2021; EDGAR 2022).

The longer the global delays in transitioning to a low-carbon economy, the more stringent the future policy measures might need to be to attain the climate goals. If climate mitigation policy actions are delayed at the present, it is highly likely that future actions required to keep the global temperature well within acceptable limits will need to be even more stringent than they would have been on an earlier transition path. The world is highly dependent on non-renewable energy sources (fossil fuels)—such as coal, oil, and natural

[1]This work developed from climate risk analysis work during the 2022 Mexico FSAP. We would like to thank Vikram Haksar (FSAP mission chief, IMF), Heedon Kang (deputy mission chief, IMF), FSAP team members, and MCM-FS climate group for their valuable comments and discussions. We are grateful to Jean Chateau for providing us with the CGE model outputs. We also thank members of Mexican Financial Authorities for a highly productive engagement, discussions, and feedback.

gas—which dominate the total energy supply (Figure 1), whereas renewable sources, such as hydro, solar, and wind power, constitute a minor portion. In addition to CO_2 emissions from burning oil and natural gas, they are also a significant source of methane emissions, which have significantly more global warming potential than CO_2. In this regard, power generation and transportation are among the key sectors driving emissions: they contributed about two-thirds of total global emissions in 2019 (IEA 2021). This high dependence on non-renewables and the dominance of GHG-intensive sources/sectors, coupled with policy uncertainty and delays in implementing global mitigation efforts, signals the potential for significant transition tail risks to the economy. This risk comes in addition to the continued increase in the frequency and severity of extreme climate-related events.

Figure 1. Sources of Global Energy Supply



Policymakers are increasingly making efforts to assess and quantify climate-related risk exposures and vulnerabilities for the financial systems. This has led to the development of a new and rapidly growing literature on climate-risk-related financial stability and policy analysis issues, as policymakers are increasingly aware of the significant risks posed by climate change. For example, the analysis of climate-related risks with implications for financial stability is a mounting priority of the Financial Sector Assessments Program (FSAP) at the International Monetary Fund (IMF) (see Adrian et al. (2022) for more details).[2] A growing number of central banks and international institutions around the world have started exploring scenario-based analysis and stress testing exercises to assess, quantify, and manage climate-related financial risks. For example, see the studies and reports in De Nederlandsche Bank (2018), Bank of England (2019), Bank of Canada (2020), Bank of

[2] FSAP is an important instrument of the IMF's surveillance and represents a comprehensive and in-depth assessment of a country's financial sector. Since climate risk analysis is at an early stage of development, one of the key goals of the analysis in FSAPs is to raise awareness of the risks and the need for new risk management tools to be developed by the banks and the supervisory bodies. These requirements will be quite different across various jurisdictions, given the unique nature of risks arising from climate change. Recent FSAPs have started addressing both transition and physical risks, for example, in Norway (IMF 2020), Grippa and Mann (2020), Chile (IMF 2021), UK (IMF 2022a), Philippines (IMF and World Bank 2021), Mexico (IMF 2022b), and Uruguay (IMF 2022c).

France/ACPR (2021), and European Central Bank (2021).[3] Baudino and Svoronos (2021) survey and compare bank stress testing practices for climate change risk by central banks and policymakers around the world. Battiston et al. (2021) provide an overview of various methodological developments in advancing our understanding of climate-related financial stability risks and call for continued innovations. This is especially important given the unique features of climate risks, such as ambiguity/deep uncertainty, non-linearities, and so on, rendering traditional approaches largely inadequate. For example, traditional risk analysis tools generally rely on historical data and hence are backward looking. This feature is not particularly well suited to assessing financial stability risks from the ever-complex and evolving nature of climate risks, many of which are expected to materialize in the future, with an uncertain horizon. Further, highly impactful and/or large/sudden negative shocks/events could sharply increase financial stability risks, such as some kind of green swan risks (Bolton et al. 2020) or climate Minsky moment (see United Kingdom (IMF 2022a)). This calls for forward-looking analysis where stress tests and scenario-based methods are generally preferred, given their inherently forward-looking and yet flexible nature.[4]

This paper contributes to the literature on climate-related financial stability analysis by developing a novel forward-looking analytical approach to transition risk analysis. In particular, we build an integrated micro-macro framework and introduce a new class of scenario called delayed-uncertain pathways with a stochastic financial model layer using a jump-diffusion process. It is macro because we use projections of macro-sectoral pathways for various segments of the economy. It is micro because we use micro/firm-level balance sheet information and simulations in projecting risks forward in time. To model the future policy uncertainty regarding when and how globally coordinated actions will take place given current delays, the standard deterministic scenario projection paths (such as those used in stress testing exercises like the Network for Greening the Financial System (NGFS) scenarios) are augmented using a simple but robust binomial tree evolution structure. And to capture the effects induced by the global delays/policy uncertainty in the financial markets, including the potential of large/sudden movements, a jump-diffusion stochastic process is used to model relevant financial variables (here, corporate spreads). To summarize, the future increase in tail risks due to delays in transition coupled with increased policy uncertainty regarding when and how such global actions might take place is largely unexplored in the financial stability literature. This paper contributes by advancing understanding in this regard.

Given the model with the uncertainty structure, we are able to quantify the projections of future distributions of different risk metrics and, hence, tail risk as well. The delayed-uncertain pathways imply that at each point in time in the future, the more accurate way to describe the various risk metrics, such as corporate/sectoral probabilities of default (PDs) and bank capital impact, is via projections of their time-varying distributions. This is in sharp contrast to the illustration of one or more adverse scenario outcomes as deviation from a suitably defined baseline, as done in standard scenario-based stress-testing analysis, which involves point projections of risk metrics one scenario at a time. As such, our approach also takes a cross-sectional

[3] The Federal Reserve Board in the United States also recently announcement the pilot climate scenario analysis exercise for the six largest banks in the country. This is to be launched in early 2023 and concluded by year-end. The stated primary objective is to enhance the ability of supervisors and institutions to quantify and manage climate-related financial risks.

[4] In 2017, the Task Force on Climate-related Financial Disclosures (TCFD) of the FSB published its recommendations on climate-related financial disclosure, in which a key component emphasized scenario-based assessments of the implications of climate-related risks.

perspective to address the critique that a somewhat arbitrary and non-stochastic choice of stress test scenario approach affects the reliability of risk analysis.[5]

We applied the approach to study transition risks in the Mexican financial sector, where the key implications and takeaways are global in scope. The scenarios explored were largely driven by global policy assumptions and actions that generate paths for all the countries in the model, including Mexico (discussed below). Thus, while the specific application is for Mexico, the implications are indeed global, and the framework can easily be adapted for other countries. For this purpose, two sets of scenarios were explored. The first set essentially follows a standard stress testing paradigm, that is, with a baseline and adverse scenario(s) setting, as discussed above. The baseline reflects a current unchanged policies scenario and the adverse is an orderly transition scenario (similar in spirit to that of the NGFS), broadly in line with limiting the global temperate increase to within 2°C by the end of the century (called "global action") with countries acting early and gradually to implement climate policies. However, despite the global consensus on the need to take strong policy actions, it is uncertain when and how such global actions would materialize. Delays give rise to future policy uncertainty, which can have important economic effects, as future risks could be compounded. Thus, the second set helps capture such future policy uncertainty and associated risks, as it consists of a disorderly and uncertain transition environment (called "delayed uncertain"). This is characterized by a simple binomial tree evolution and an embedded layer of stochastic model of corporate spreads via the jump-diffusion process to capture continuously changing risks as well as large/sudden movements in the financial markets. This is a simplified but robust way of modeling uncertainty. The key distinction is that such an uncertainty structure allows us to quantify distributions of various risk metrics, which is generally not possible in a standard stress testing setting, unlike the first set, which consists of a deterministic path of early global action.[6]

The analysis flagged important sectoral heterogeneity of the exposure to transition risks and increased downside tail risks to the corporate and financial sectors from delays. Under the global action scenario, where all countries act early, the aggregate impact on the financial sector is modest, though some sectors and banks appear more exposed. However, the delayed-uncertain pathways revealed the potential for significant risks to corporates and banks. For example, from the sequences of time-varying distribution of PDs across sectors, given the uncertainty in future periods, the analysis found that the right tail of the PD distribution could become significantly heavier with increasingly longer delays. Specifically, the chemicals and non-metallic segments of the manufacturing sector in Mexico seemed the most vulnerable despite their sound initial-state corporate distress metrics relative to many other sectors. Interestingly, even though some sectors are not as emission intensive in their production, like the construction sector, they could still be negatively affected

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[5] Note that in the context of a fully stochastic analysis, the usual characterization regarding discussing outcomes as deviations from baseline (or as different adverse scenarios) is not as meaningful. This is because one is able to characterize the entire distribution where different features of the tails can be discussed, that is, a more probabilistic perspective can be explored. This is generally not possible with usual scenario analysis setting by construction. Our two sets of scenarios (discussed above) also serve to highlight the differences in outcomes that one could expect from a stochastic versus non-stochastic setup.

[6] Note that while the scenario under consideration involves economy-wide carbon prices for all GHGs, there could also be various alternative transition policy instruments to reduce emissions, such as emission trading systems, subsidies to renewable energy etc. In this regard, carbon prices can be seen as a modelling tool that allows for a tractable and parsimonious way to study financial sector impact of a general decarbonization scenario. Hence, the carbon prices implicitly reflect the degree of overall policy ambition and the equivalent effects of various policies mixes. Further, given the flexibility of the model, impact of various policy mixes can also be used in our approach since these macro/CGE model outputs are taken as given scenario paths and are used directly as an input in policy related financial stability analysis (such as stress testing).

depending on their initial financial conditions, as the analysis revealed. Further, whereas the bank capital impact appeared somewhat modest under the global action, delayed-uncertain analysis also revealed non-trivial increases in the tail risk of the bank capital impact, suggesting the potential for material impact in the future.

A key insight of the analysis is that the longer the delays in transition, the larger the future tail risks. In our setup, future policy uncertainty generates material risks from the financial markets channel. Delays in transition generates a need to catch up with stronger future policy action to contain global warming. The risk is compounded due to the uncertainty of when and how such a future policy would be implemented. This could lead to a reassessment of risks in corporate sectors around the world, including in Mexico, with increased market risk and volatility. This could further lead to disruptions in equity and debt capital markets, and a sharp rise in corporate spreads, risk premium, and so on, thereby amplifying risks to the system and increasing tail risks to financial stability. Even in the absence of strong transition-related policy actions, risk from financial markets could materialize, given the forward-looking nature of global investors coupled with increasing awareness of climate change issues. The analysis supports the case for an early and orderly transition to a low-carbon economy, to mitigate the tail risk of larger action on future measures to achieve climate goals.

The analysis abstracts away from considerations of physical risks, which implies that delays in transition could further affect the valuations of wide-ranging assets given the potential future increase in the frequency and severity of various physical hazards. Further, the analysis also does not capture the potential general equilibrium effects which could lead to feedback effects from financial sector to the real economy. Given this limitation, our results could also be potentially underestimating the impact transition delays and resulting likelihood of higher impact of physical risks.

The framework developed is general with global implications, but specific results need to be interpreted with caution. Because the early versus delayed actions at the global level (where Mexico is one of the countries) are key drivers of the scenarios and shocks, the Mexico-specific outcomes point at the potential for larger climate-related transition risks to countries across the globe. While the Mexico-specific results did not find imminent systemic risk to the country, the relatively mild results need to be interpreted with caution, given various data limitations, simplifying assumptions, and other uncertainties not accounted for in the Mexico-specific analysis. In particular, the analysis in Mexico covered only the corporate loan portfolio of the commercial banking sector, where the data limitations precluded a more granular analysis.[7] Nevertheless, the analysis discovered areas of vulnerabilities in the corporate sector, suggesting that there could be other risks that still need to be fully explored. However, the methodological approach itself is not constrained by data limitations. As such, our framework can be easily adapted whenever better and/or more granular data are available. The approach and many of the channels/mechanisms we explored are generalizable and, therefore, the argument on the potential for significant downside tail risks to financial sectors across countries worldwide, depending on their exposures and vulnerability to transition risks, remains valid.

[7] Even though the Mexico-specific exercise mainly relates to the corporate credit risk effects, this is arguably one of the most important channels, because the corporate portfolio constitutes the largest banking portfolio exposures. Further, transition policies generally have immediate consequences for corporates. However, future analysis could consider other channels as well, such as market risks, effects on consumer portfolios, and so on. Note that due to the heterogeneity, each country will be affected differently from global transition policies, given the economic structure, policy ambitions, and so on. Thus, while the framework is general, there would be differential impact across countries-sectors.

The insight from our paper is directly relevant to informing climate-related policy around the world. Our framework can be readily integrated into existing policy frameworks to better inform climate-related risk assessment. Because tail risks get larger the longer the delay toward a low-carbon economy, continued vigilance is required at the global level. This is especially important because despite covering only limited channels of risks in our specific application, we were able to detect the potential for material future downside tail risks.[8]

The rest of the paper is organized as follows. Section II provides a brief overview of transition policy risks in Mexico. Section III presents the modeling framework and the context of application in Mexico. Section IV reveals the results, and section V concludes.

Climate Policy Risks in Mexico

Mexico has signaled its commitment to emissions reduction targets, but more effort will be needed. According to Climate Action Tracker, a non-profit research organization that tracks progress on governments' pledges and actions to address climate change, further steps beyond the current policies of and commitments by Mexico will be needed to adhere to the global warming limit of 1.5°C based on the Paris Agreement. Nevertheless, Mexico made strides to expand its climate goals at COP26 (and updated its commitments at the recent COP27), where the country joined the Global Methane Pledge and the Declaration on Forests and Land Use. The Global Methane Pledge aims to reduce global methane emissions by at least 30 percent by 2030 relative to 2020 levels. This is important because the global warming potential of methane is about 28 times higher than that of CO_2. The Declaration on Forests and Land Use is a commitment to halt and reverse the issues of deforestation and land degradation by 2030. Mexico has also pledged to accelerate the transition to renewable energy sources, such as wind, hydro, and solar power, to support its commitments under the Paris Agreement.

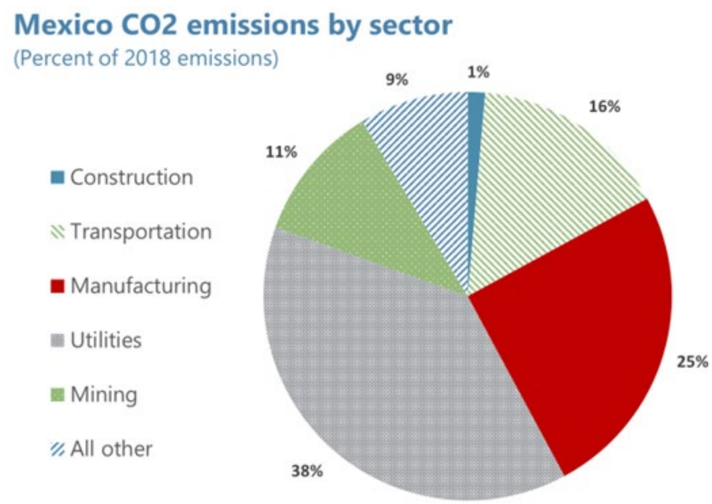
The high dependence on carbon-sourced energy and commitments to reduce emissions raise transition-related risks for Mexico. The country is the second largest emitter of GHGs in Latin America, after Brazil, with one of the highest per capita emissions levels, and a significant portion of that can be attributed to the energy sector. Further, Mexico is highly dependent on non-renewable energy sources, as its total energy supply is dominated by fossil fuels and other non-renewable energy sources, as is the global supply (Figure 1). Oil and natural gas amounted to about 85 percent of the total energy supply in Mexico in 2020).

A large portion of total CO_2 emissions in Mexico is concentrated in the power generation industry, followed by manufacturing and transportation (Figure 2, top panel). About 38 percent of the total CO_2 emissions in 2018 was attributable to the utilities/power generation sector, about 25 percent to the manufacturing sector, and about 16 percent to the transportation sector. The mining sector, which includes oil,

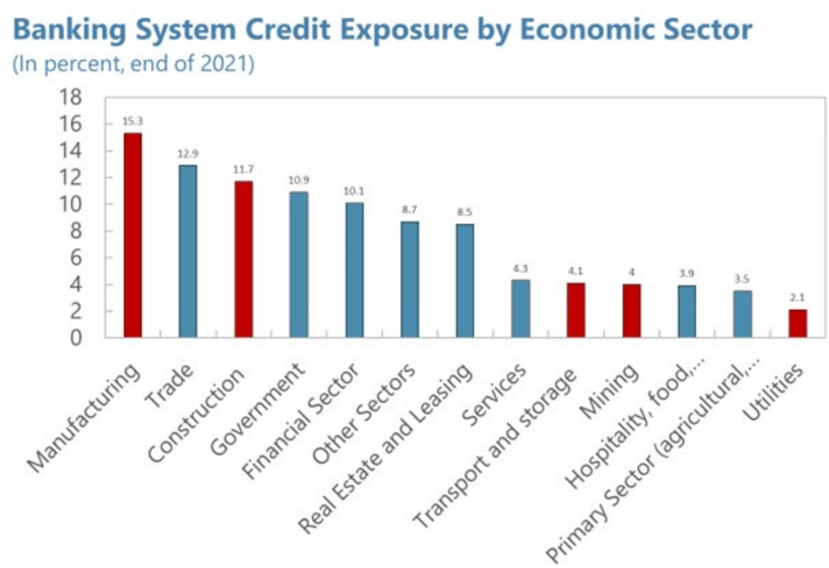
[7] Note that additional risks and ensuing fattening of tails in the delayed-uncertain cases are largely driven by shocks in the financial markets layer. This is because the binomial tree evolution was constructed using the deterministic sectoral paths from the CGE model. However, if such pathways were to be generated from a stochastic model, one could also directly affect the uncertainty of these paths (for example, by affecting the volatility of paths that could generate larger dispersion of sectoral pathways). This would naturally lead to even heavier tails of various risk metrics in addition to those due to the financial markets channel alone. Fully exploring stochastic macro-sectoral pathways is an intriguing and challenging future research topic on its own. As such, it is not yet a regular part of the policy analysis toolkit. In this regard, our analysis effectively lays out a conceptual framework that showcases, via a simple binomial uncertainty structure, how such a full-fledged stochastic analysis can be set up to obtain a more distributional perspective for financial stability policy analysis.

gas, and coal extraction, accounts for only about 11 percent of overall CO_2 emissions, because this sector is not as emission intensive during the extraction phase. Instead, the sector faces risks mostly from other channels, such as demand, because the products are highly emission intensive during the combustion phase. This could significantly affect the sector as the world transitions away from fossil fuels. All other sectors combined constitute about 10 percent of total CO_2 emissions.

Figure 2. Carbon Dioxide (CO_2) Emissions and Financial Sector's Sectoral Credit Exposure



Sources: OECD and IMF staff calculations.



Sources: Banxico and IMF staff calculations

Note: The emission-intensive sectors are shown in red.

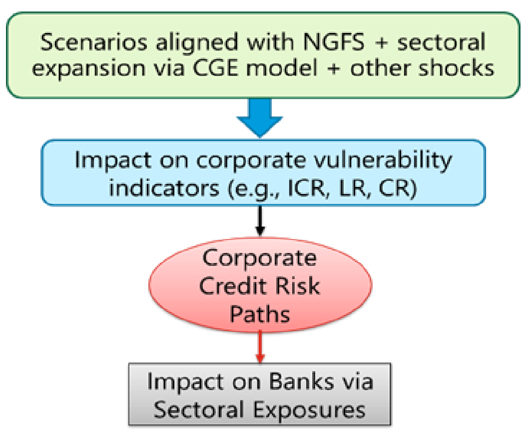
The Mexican financial sector also has sizable credit exposures to transition-vulnerable economic sectors (Figure 2, bottom panel). About 37 percent of the commercial banking system's corporate credit is concentrated in emission-intensive sectors. The largest exposure is concentrated in the manufacturing sector, accounting for about 15 percent of total credit. Exposures to the mining sector, which includes the oil, gas, coal extraction segments, is relatively small, at 4 percent of total credit.

Modeling Framework

A. Micro-Macro Approach

The modeling framework for transition risk analysis can be broadly described as an integrated micro-macro approach. Figure 3 presents the schematic of the overall framework that takes transition risk scenarios for various economic sectors as inputs and allows for adding/exploring other shocks, such as those from financial markets. The paths of these scenarios are structurally linked to firm-level corporate vulnerability indicators. Finally, the impact on these indicators is translated into corporate credit risk paths using an estimated bridge equation, which is then eventually translated into impact on bank capital based on a bank's credit exposures to various sectors. Thus, the framework is flexible enough to take input from various sources and external modeling frameworks such that all the modules are brought to interact together in an internally consistent way.

Figure 3. Transition Risk Analysis: An Integrated Micro-Macro Framework



Source: IMF staff.

We obtained transition risk scenarios using a computable general equilibrium (CGE) model to obtain granular macro-sectoral pathways. This model (the IMF-ENV model) was recently developed by the IMF research department and is documented in Chateau et al. (2022). It is a recursive-dynamic, multi-regional, multi-sectoral model. Given its sectoral granularity, this class of CGE models largely study long-run dynamics and allocation of resources across various sectors. Thus, CGE models are highly suitable for studying the long-run impact of climate mitigation and decarbonization policies. The IMF-ENV model covers 25 regions (including Mexico) and groups countries into high-, middle-, and low-income countries. The model has 37 distinct sectors, allowing for a granular analysis of sectoral impacts of transition policies. The scenarios are also broadly anchored to the high-level NGFS scenario narratives (of orderly and disorderly scenarios) and aligned with IPCC temperature/emission targets.[9] Section C provides more details.

These policy scenarios are applied to generate multi-year projections of firm-level probabilities of default (PDs), which are further aggregated into scenario-dependent sectoral PD paths. These PD paths are then translated into banks' aggregate PD paths weighted by their credit exposure to vulnerable sectors. Details of various components of this approach, summarized in Figure 3, are discussed in what follows.

The corporate micro data used in the analysis mostly consisted of a sample of large/listed Mexican firms. The data sample was sourced from DataStream and S&P Capital IQ, and the sample period covers balance sheet data from 2002 to 2020. On average, there are about 100 total firms in the sample each year. The sample of firms selected for the analysis belong to the sectors that are most emission intensive (Figure 2). In general, limited usable/reliable data are available on other Mexican firms, especially for small and medium size enterprises (SMEs), which constitute a large number of Mexican corporates. This data limitation constrains the scope of the analysis and the ability to generalize results. However, as mentioned before, the framework itself does not depend on the data limitations, because larger/more granular datasets, whenever available, can always be used to increase the precision and granularity of the analysis.

Large corporates dominate the banking credit portfolio, allowing for meaningful analysis. Only 2 percent of the entire universe of firms with outstanding loan facilities across 44 commercial banks are considered large firms, based on the historical maximum loan amount (a standard criterion used by the Mexican central bank, Banxico. The rest are SMEs. However, these large firms account for more than 65 percent of outstanding bank credit.[10] Thus, there is a disproportionate representation of large corporates in the banking system, with a high concentration of these among the largest 10 banks considered in the analysis. As such, it is possible to obtain important insights regarding the anticipated overall impact one would expect across various segments of the economy.[11]

The corporate data sample contains key balance sheet and profit and loss (P&L) items required for the framework. These include earnings before interest and taxes (EBIT), sales revenue, cost of goods sold, interest expenses, average/effective interest rates, total debt, total assets, current assets, and current liabilities. These are some of the commonly used variables for analyzing the financial health of the individual firms and economic sectors as these are used for constructing various indicators of corporate distress, discussed below.

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[9] Note that the CGE model is based on a neoclassical framework and deals with real values/economy and is ideal for studying structural transformations, trade, decarbonization, development, and so on, which are long-run issues. Thus, the focus is on the long-term reallocation of resources across different sectors/regions. However, they are not adapted to study business-cycle, financial, and monetary issues. Given the absence of money and financial market variables, the team was able to explore an additional financial modeling layer within the framework (see section C).

[10] The sample of firms in the analysis represent about 42 percent of the total outstanding debt of the nonfinancial corporate sector.

[11] Some of the economic sectors of the CGE model were manually mapped to aggregated sector names. These names mimic as closely as possible the sectors in the two-digit North American Industry Classification System (NAICS) to eventually map the sectoral impact into impact on the banks. This last step is needed because Mexican banks identify the sector for a given loan to a company based on NAICS codes. Table A1 in Appendix I provides more details on this mapping.

Corporate sales revenues constitute the main structural link to the sectoral output and carbon price paths generated by the CGE model under different scenarios. The following recursive evolution for the EBIT is used to map the scenario-dependent sectoral pathways output of the CGE model for each firm based on its sectoral affiliation (firm and sector indexes omitted for notational simplicity):

$$EBIT_t = EBIT_{t-1} + F_t * [Sales_{t-1} - G * COGS_{t-1}] - Carbon\,Tax_t$$

where F_t is related to the sensitivity of sales to the gross output/gross value added (GVA) paths per-industry, G is the elasticity of cost of goods sold (COGS) to sales revenues (Sales), and $Carbon\,Tax_t$ is the direct additional operating cost due to firm-level emissions projections and scenario-dependent carbon prices, estimated as carbon price times emissions (in tCO2eq).[12]

The factor F_t is different for each sector (and common for firms in the same sector) since it is linked to the projected transition pathways from the CGE model, which is different across sectors. These sectoral paths are then mapped into impact on the sales revenues of each firm based on sectoral affiliation. This ideally requires first estimating the elasticity of sales to the output/GVA of each sector based on regressing historical sector level sales on sector-level GVA. However, given the lack of sufficiently granular data required at the sectoral level, an elasticity of 1.5 was assumed. This was informed by similar estimations in Gross et al. (2022), who analyze similar estimations across many sectors for emerging economies where the related elasticity averaged about 1.5. This implies that in the present analysis, the differences will be driven by the sectoral pathways since elasticities across sectors are fixed. The elasticity G was obtained by panel fixed effects regression of changes in the cost of goods sold to sales growth, estimated to be 0.97.

A carbon tax, capturing the cost of emissions, was considered as an additional operating costs item at the firm level, which would further reduce net earnings. We used projections of firm-level GHG emissions data from Urgentem (a private data vendor) under the three categories of NGFS scenarios (hot house world/business as usual, orderly, and disorderly), because the CGE model scenarios were made consistent with these categories of NGFS scenarios. These data were merged with the corporate data sample. Given the unique carbon price paths for each scenario (discussed further in section B, on transition scenarios), the additional cost for each firm is simply carbon prices times the GHG emission projections of each firm, thus capturing granularity in the analysis. So, the carbon tax captures the direct effects of carbon pricing policies, whereas the equilibrium effects would be captured by the impact on the sales revenues.[13] These two channels used for mapping the impact of climate transition policies into impact on firms strikes some balance between the data limitations and the requirements of a full-fledged micro-macro framework.

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[12] Note that carbon tax here is a simplifying expression that is meant to represent the operating cost component of the EBIT and not to represent the formal notion of tax (since EBIT by definition excludes taxes). Thus, carbon prices effects are captured via EBIT elasticity and not any specific tax elasticity. More details are provided below.

[13] Note that only scope 1 emissions were used to be consistent with viewing carbon tax as additional direct operating cost. Urgentem dataset contains current/starting point emissions as well as projections of emissions for firms in our sample, aligned with the three NGFS scenario categories (hot-house-world, orderly, and disorderly) which were used together with the projection of carbon prices from the CGE model. In absence of such granular firm level emissions datasets, it is possible to also use the projections of sectoral emission intensity from CGE or other suitable model to obtain the overall carbon tax pathways as we have in our analysis.

The direct impact on the sales component feeds into other firm-level variables during the firm-level micro simulation of key corporate variables and the effects can potentially accumulate. The initial impact from sectoral pathways to corporate sales (with consideration of other shocks, for example, to interest rates, discussed below) can accumulate over the periods and potentially be compounded. This is because of the dynamic, recursive relation between various corporate variables during the multi-year simulation/projection. This relation is based on an accounting identity (described in Table A2 in Appendix I). These simulations assume constant business models and technology over the projection horizon where the effects are due to changes in sales, cost of goods, and carbon taxes induced by transition scenarios, as discussed above. The additional shock to the interest rates and hence, cost of debt capital, is considered only in the delayed-uncertain scenario, as that is directly linked to the outcomes in the financial markets, which are not covered in the CGE model.

The simulation of the relevant corporate variables forward in time conditional on transition scenarios allows for constructing scenario-dependent paths of the main corporate vulnerability indicators of interest. These are (i) the interest coverage ratio (ICR), defined as the ratio of EBIT to the interest expenses, which relates to the solvency as well as short-term liquidity conditions of firms; (ii) the leverage ratio (LR), defined as total debt to total assets, a metric relevant for solvency conditions: and (iii) the current ratio (CR), defined as current assets to current liabilities, which represents short-term liquidity conditions. The accounting identity and recursive relations used for projections eventually (as shown in Appendix I) help construct scenario-dependent paths of these vulnerability indicators). The horizon of the analysis is five years (till 2026), which is typical of the three- to five-year horizon generally considered in standard stress testing analysis, such as those in the IMF's FSAPs.

The corporate vulnerability indicators show the heterogeneous risk characteristics of various corporate sectors at the start. Figure 4 (top panel) shows that the median of the ICR and CR indicate potentially diverse impact of the scenarios on various sectors. In particular, the construction sector stands out with significantly low levels of solvency and liquidity metrics. This implies that this sector might be sensitive to even small shocks. Figure 4 (bottom panel) also shows the leverage ratio, which illustrates the potential impact of capital structure and cost of debt capital. For example, the chemicals and non-metallic segment and utilities have relatively higher leverage ratios

The starting interest rates represent another source of risk embedded into the vulnerability indicator. The initial median interest costs across sectors (Figure 4, bottom panel) highlights another important channel of risk propagation because it is related to the cost of debt capital. It is directly linked to risk premia that firms need to pay in order to compensate investors in financial markets for taking on risks. For example, due to a sudden shift in investor risk aversion, for a variety of reasons (for example, uncertain policy regime, potential lingering effects of geopolitical conflicts around the world, downside risks to the economy, and so on,), there could be sudden and large increases in credit risk premia driving higher corporate spreads. While extreme discontinuous movement in fixed-income markets, such as bonds, are relatively rare compared with those in the equity markets, they do occur occasionally during market distress periods, such as the global financial crisis or the COVID-19 crisis. This motivates the exploration of a jump-diffusion model of corporate spreads, discussed below.

A bridge equation was used to establish a structural link between the corporate vulnerability indicators and default risks and formed the basis of projecting firm-level PDs. This structural relationship was estimated following the panel fixed effects regression with logit-transformed firm-level PDs:

$$logit(PD)_{i,t} = \alpha_i + \beta_1 ICR_{i,t} + \beta_2 CR_{i,t} + \beta_3 LR_{i,t} + \epsilon_{i,t}$$

The PDs are obtained from Moody's EDF database for Mexico. This measure is a forward-looking default risk measure. The right-side variables are the corporate vulnerability indicators that attempt to capture the relation between corporate financial health condition and the implied default risks. The logit transformed PD is used to make sure that the projected PDs lie within the unit interval. The summary of this estimation (Table A3 in Appendix I) shows that PDs are most sensitive to leverage ratio, followed by current ratio and interest coverage ratio.

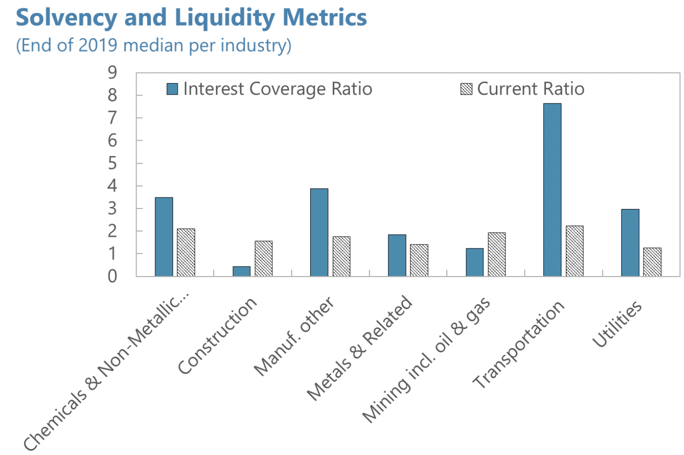
The sensitivity of PDs to the vulnerability indicators are driven by various factors. First, the coefficients of the bridge equation are quite different across these indicators. Second, the paths of these indicators are also affected by the CGE model's sectoral pathways and carbon prices along those paths during simulations. Thus, due to multiple factors affecting the dynamics of the projected paths of PDs (hence a full-fledged micro-macro framework), care needs to be taken in interpreting the outputs of the framework.

It is important to note that the right-hand side variables of the bridge equation do not contain any macro-financial variables. This is because the right-side indicators are already affected by the state variables of the economy consisting of various macro-financial variables in the historical data used for estimating the panel regression. This means the projection of these indicators is driven by the CGE sectoral outputs, carbon prices, and other shocks, such as those to interest rates. For example, the changes to sales revenue for each scenario, as discussed above, would affect the EBIT. This consequently affects the projections of the ICR ratio. Hence, the projections capture the structural links from macro-sectoral transition scenarios to the default risks of the firms.

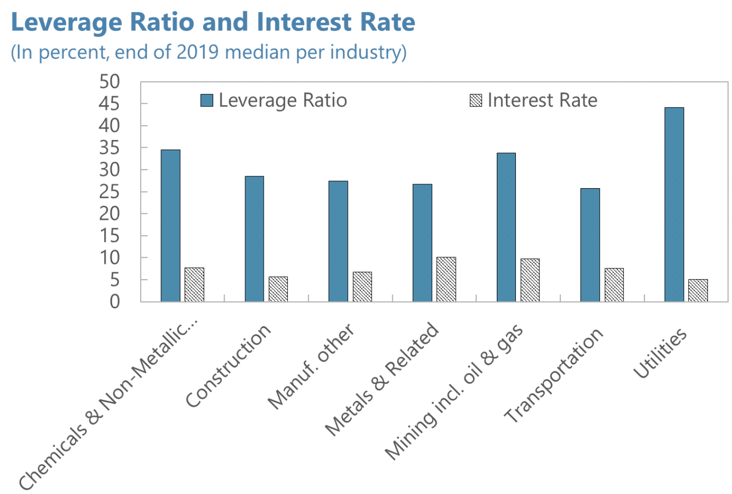
The bridge equation helps generate scenario-dependent PD paths for each firm, all of which are then aggregated to exposure-weighted sectoral PD paths. The exposure of banks cannot be mapped to individual firms using the data that were available, as only aggregated credit exposures data by broad economic sectors were available. This necessitated constructing an exposure-weighted projection of sectoral PDs for each scenario considered. Nevertheless, such granular exposures information, whenever available, can always be used to enhance the output of our framework.

The weighted sectoral PD paths facilitate computing scenario-dependent delta PDs for each bank, weighted by each bank's sectoral credit exposures. We had data with decomposition of credit exposures by sector for each bank but did not have initial starting PDs of banks by each sector. Further, the initial PDs computed from the bridge equation is not necessarily an estimate of each bank's realized starting point PiT PDs. For each scenario, first the delta PDs for each sector was computed as the difference between projected PDs in each year from 2022 to 2026 and the starting PDs in 2021. Second, for each bank, the previously calculated delta PDs for the projection horizon were weighted by the bank's credit exposures to the particular sector. This generates paths of delta PDs for each bank, weighted by its sectoral credit exposures, for each scenario. This computation assumed that the sectoral credit exposures remain constant as at the starting point.

Figure 4. Heterogeneous Corporate Risk Characteristics



Sources: DataStream, S&P Capital IQ, IMF staff calculations



Sources: DataStream, S&P Capital IQ, IMF staff calculations

The calculation of changes to bank capital followed a simplified approach, considering the impact from the expected credit losses only under a static balance sheet assumption. We did not have sectoral breakdowns of non-performing loans and performing loans. Given the data constraint, a simplified approach was used that captured the capital impact only from the expected losses to the overall corporate credit portfolio. In this regard, risk-weighted assets (RWAs) were also held constant at the starting value and, in the absence of sector- and bank-specific loss given default (LGD) rates, a common value of LGD was used across all banks.[14] Tax and dividend payout impact was also ignored. This resulted in estimates of impact on bank capital ratios driven just by loan impairment charges. Once again, these are the limitations of the data and granular data when available and reliable can always be used to augment the analysis.

[14] The system average corporate portfolio implied the LGD from the coverage ratios of non-performing corporate exposures was found to be 53 percent.

To summarize, we developed an end-to-end fully structural, internally consistent framework. Importantly, this framework is also flexible, as it allows for exploring additional layers of risks where relevant and as data permit. The transition scenarios are first applied to generate multi-year projections of firm-level vulnerability indicators that are aggregated into sectoral PD paths using the estimated bridge equation. The sectoral PD paths are then translated into banks' aggregate PD paths weighted by their credit exposure to vulnerable sectors, generating impact on bank capital.

B. Transition Scenarios and Stochastic Financial Model

We explored two main classes of climate policy scenarios: (i) global action (reflecting an orderly transition category analogous to the NGFS "below 2 degrees" scenario); and (ii) delayed-uncertain (reflecting a disorderly transition category analogous to the NGFS "delayed transition" scenario).[15] As discussed earlier, to capture sufficient sectoral heterogeneity required to quantify transitions risks across various segments of the economy, a CGE model (IMF-ENV) was used to obtain sectoral output pathways that are tailored to Mexico. An additional jump-diffusion stochastic financial modeling layer of corporate spreads is then added to the delayed-uncertain scenario.

In the global action scenario, there is a global mitigation effort, including by Mexico, to limit warming to below 2°C. In this scenario, countries act early and gradually to implement climate policies and reach various levels of the carbon price floor by 2030, depending on their development level. Carbon price floors are as follows: $25 tCO2e for low-income countries, $50 tCO2e for middle-income countries, and $75 for high-income countries. As such, in this orderly transition scenario, global mitigation measures are enhanced with moderate economic costs and international burden sharing.

The sectoral transition pathways in Mexico under global action show heterogeneous impact across sectors. Figure 5 (top panel) shows the sectoral impact of the scenario. Consistent with the structural-shift nature of transition, relatively carbon-intensive sectors are more affected than others. For example, the chemicals sector (a sub-segment of the manufacturing sector) shows a decline in the level of output of about 10 percent, and the fossil fuel sector (dominated by extractive/mining segments such as oil, gas, and coal) sees a decline of 12 percent. Similarly, non-metallic, transportation services, and utilities sectors see notable impact. However, some other sectors, such as transportation equipment, are positively impacted by 2030.

The carbon prices paths in Mexico under global action show highly dispersed patterns around the world, highlighting the burden-sharing nature of the scenario. Figure 5 (bottom panel) illustrates these paths for various economies worldwide, depending on their development level. As seen, this scenario models Mexico facing significantly lower carbon prices relative to, say, the United States and the United Kingdom in helping to achieve the below two degrees 2°C global warming goal. Because Mexico is a middle-income country, the carbon prices also reflect the international burden sharing tailored to Mexico's capacity and commitments.[16]

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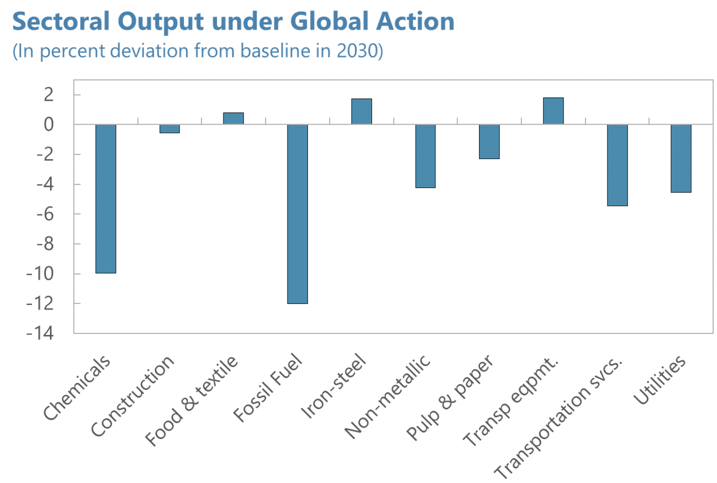
[15] The current policies scenario (that is, no additional action/business-as-usual) serves as the baseline, which is a standard practice.

[16] We emphasize that the carbon prices discussed here do not constitute hard recommendations but simply reflect the exploratory nature of the climate risk analysis with the objective to understand channels and mechanisms through which transition policy actions affect the broader economy and the financial system.

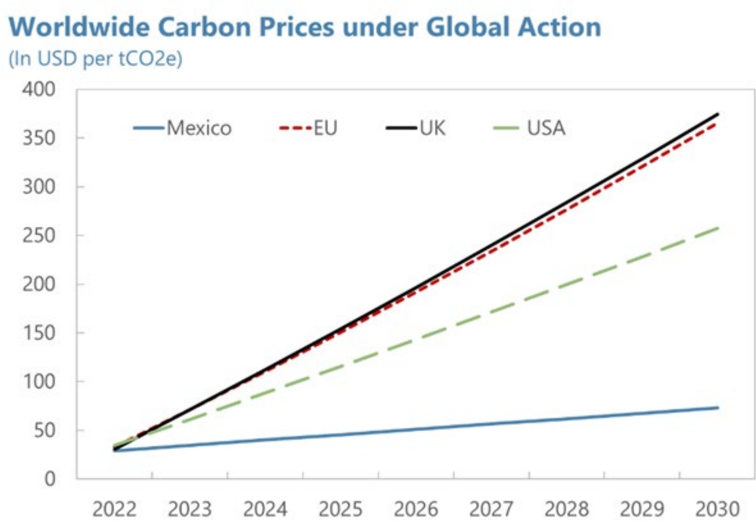
However, the inherently uncertain nature of climate risk has led to policy uncertainty, with highly dispersed responses around the world. Despite the global momentum and consensus building toward strong mitigation efforts and policy actions, delays in climate policy implementation raise uncertainty as to when and how global action would take place, which could have significant economic effects.

The longer the delay in reducing emissions, the stronger future mitigating actions might need to be. In order to achieve the same climate goals, if no action is taken today, future actions would need to be even larger than under an early course of action. For example, the impact on the sectoral output by 2030 could be much more severe.

Figure 5. Sectoral Impact under Global Action and Corresponding Carbon Prices



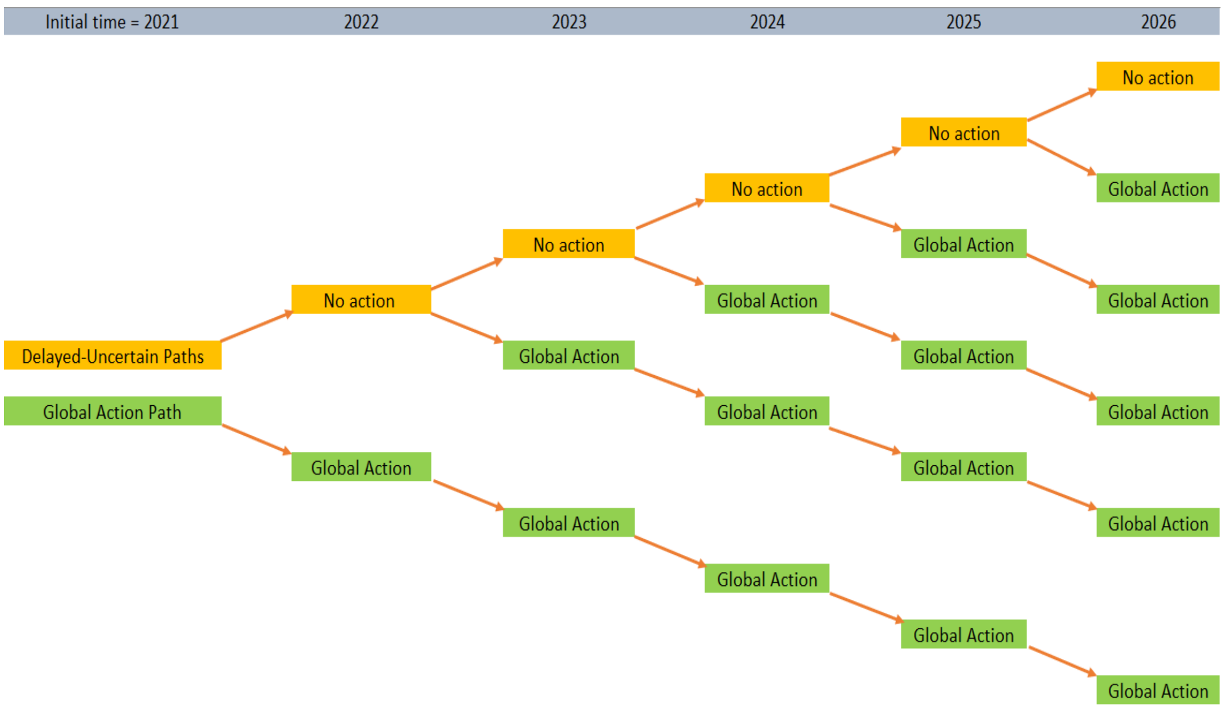
Source: IMF staff calculations.



Source: IMF staff calculations.

To capture this uncertainty and consequent risks, we explore a new "scenario", the delayed-uncertain pathways. Figure 6 shows a schematic of delayed-uncertain pathways while contrasting with the deterministic path of the global action. This binomial tree structure is a simplified but robust way of modeling uncertainty that necessarily implies multiple states of the world and hence, multiple pathways branching out into the future, as opposed to a single deterministic path of global action. Under the delayed-uncertain paths, no global action takes place in 2022 and generates uncertainty regarding when such an action might take place. This means that in 2023, there could be a global action or there could be no such action, that is, business as usual, hence the uncertainty. If global action takes places, the world stays along that trajectory into the future. If there is no action in 2023, the world again would face the same decision in 2024—either continue delaying action or act and branch out. This sequence continues (theoretically indefinitely) into the future.[17]

Figure 6. Transition Policy Scenarios: Schematic



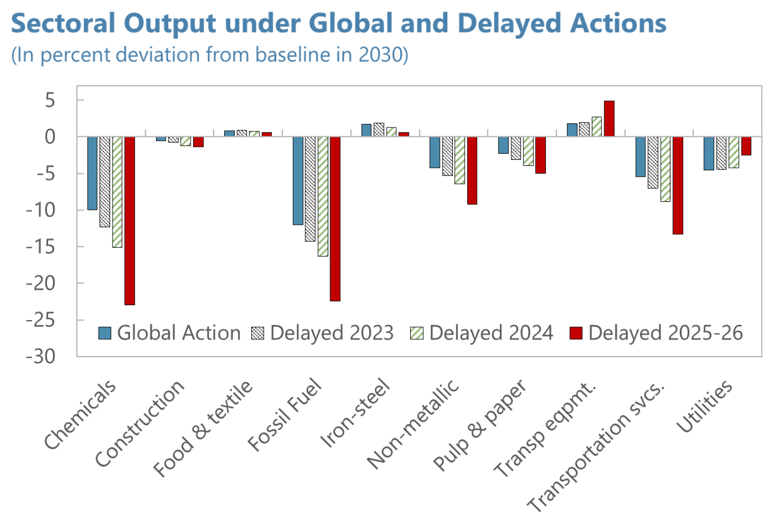
Source: IMF staff.

The various pathways can be effectively viewed as paths of a simple stochastic Monte Carlo simulation. The macro CGE model produces deterministic scenarios generating only one linearized-average path at a time. Capturing the notion of uncertainty from delayed transition requires running the CGE model multiple times under different delayed scenarios and eventually "stitching" them into a binomial tree structure to generate the proper notion of an uncertain policy environment. Thus, from Figure 6, it is evident that in a stylized setting, there are effectively five possible paths that the world could take through 2026. Otherwise, in principle, the number of paths could continue as far into the future as required. But the setup considered here, which mimics a stochastic Monte Carlo simulation, conveniently allows for analyzing the distribution of outcomes such as PDs and bank capital impact, which is not possible with a single/deterministic path by construction. The intuition follows immediately from Figure 6, where under the binomial tree structure, at each

[17] The construction mimics the binomial lattice model used for modeling the stochastic evolution of asset and price derivatives underlying such assets, such as options. For example, it can be used as a discrete time approximation to the well-known continuous time Black-Scholes-Merton option pricing model. However, in this analysis, the binomial structure is only used to generate forward evolution of sectoral outputs to reflect uncertain evolution of pathways.

point in time (2023, 2024, 2025, 2026), there are multiple possible states of the world corresponding to multiple paths. Thus, even though the number of constructed macro-sectoral pathways are limited due to the multiple non-stochastic runs of the CGE, it is still possible, albeit in a somewhat simplified way, to coherently highlight the distributional impact and the tail risks, given the number of economic sectors delivering enough sectoral PDs at each point in time.[18]

Figure 7. Sectoral Impact under Delayed Actions vs. Global Action



Source: IMF staff calculations.

The differential impact on sectoral output can be increasingly material the longer the policy actions are delayed. Figure 7 contrasts the sectoral output under various delayed scenarios accounting for all possible paths as deviation from business as usual, that is, the no-action pathway (Figure 6) by the end of the CGE model horizon in 2030. For example, the impact on sectoral output in the chemicals sector more than doubles, from 10 percent in the global action to 23 percent by 2030, if the global action is delayed to 2025/26. The same is true for other vulnerable but economically important sectors, such as fossil fuel (which includes the oil and gas sectors) and transportation services. As evident, the longer the delay, the more severe the negative impact on some sectors, implying the need for increasingly stringent measures in the future to achieve the same climate goals. This sharply highlights economic impact and potential risks to the financial sector, from a disorderly transition relative to the modest economic impact from orderly nature of early global action.

[18] Ideally, the macro model itself would have to be constructed to produce full equilibrium dynamics consisting of stochastic steady states. But this is generally not available in the majority of policy analysis models, especially CGE models that are already quite computationally intensive. As such, we had to run the model multiple times to mimic the Monte Carlo simulation and hence the uncertainty setup (with the computational time of almost one week for the CGE model to generate these paths).

Box 1. Overview of Jump-Diffusion Model of Corporate Spread

Let the randomness in the financial market be characterized by a filtered probability space $(\boldsymbol{\Omega}, \boldsymbol{\mathcal{F}}, \mathbb{F}, \mathbb{P})$ where $\mathbb{P}$ is the statistical probability measure and $\mathbb{F} = \{\boldsymbol{\mathcal{F}}\}_{t\geq 0}$ is the filtration of sigma field $\mathcal{F}$. The market is assumed to be arbitrage free, which implies the existence of a martingale measure $\mathbb{Q}$ (from the first fundamental theorem of asset pricing) associated with the corporate spread process $\boldsymbol{r_t}$, whose dynamics are given by the following stochastic differential equation:

$$\boldsymbol{dr_t = \kappa(\mu - r_t + s_t)dt \ + \sigma\sqrt{r_t}\ dW_t + dJ_t}$$

$\boldsymbol{\kappa} > \boldsymbol{0}$ is the rate of mean-reversion, $\boldsymbol{\mu} > \boldsymbol{0}$ is the long-run mean, $\boldsymbol{\sigma} > \boldsymbol{0}$ is the volatility parameter, $\boldsymbol{W_t}$ is a standard Brownian motion, and $\boldsymbol{J_t}$ represents a pure jump process that arrives at some intensity and with jump size drawn from some distribution. The Feller condition $\boldsymbol{2\kappa\mu} \geq \boldsymbol{\sigma^2}$ is assumed to ensure that the spreads stay non-negative. The square root term $\boldsymbol{\sigma\sqrt{r_t}}$ generates increasingly higher effective volatility when rates/spreads are higher. The drift factor dominates when spreads are low. The mean-reversion property has practical relevance because rates (just like volatility) do not stay elevated for long periods (as opposed to, say, equity prices) and tend to fluctuate around some long-run level. Such behaviors of this process are consistent with observed dynamics in the financial markets, rendering this model suitable for the analysis of spreads. An additional random variable, the scaling factor s_t, is constructed from sectoral outputs to map the impact of climate risks into the evolution of corporate spread in a simplified way (see Appendix I for more details).

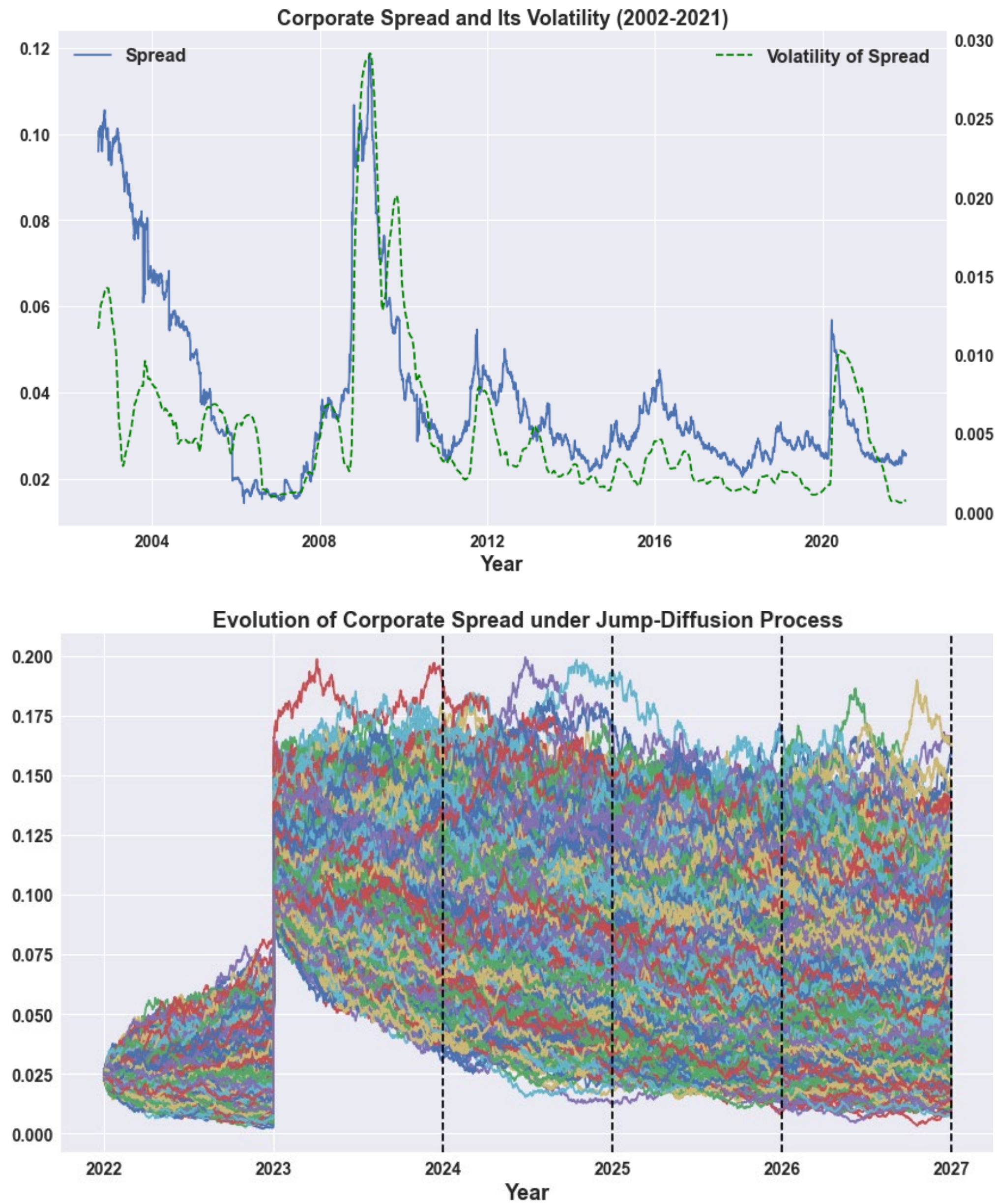
This model is also popularly known as Cox-Ingersoll-Ross or square root process with jumps. This stochastic model belongs to the class affine jump-diffusion family. This constitutes one of the most advanced and powerful sets of financial modeling frameworks. These classes of models are actively used by both researchers and financial markets practitioners to model interest rates, credit risks, currencies, commodities, volatility dynamics, and a wide range of derivatives, among others.

Thus, this model is well suited to analyzing the impact of large/sudden movements in financial markets (coupled with usual smooth randomness) and consequent rise in heightened volatility/uncertainty. Diffusion term captures continuously changing smooth risks, while jump term captures large/sudden and discontinuous shocks. Jumps are important because they could signal highly volatile times ahead (for example, the global financial crisis, the COVID-19 crisis, the Russia-Ukraine conflict), which are effectively captured by the square root term $\boldsymbol{\sigma\sqrt{r_t}}$ after a large jump/shock sharply increases the spread (Figure 8, top panel).

Note: Given the scope of the paper, for more technical details and applications, see the literature and related texts on stochastic processes and their applications, for example, Duffie et al. (2000), Lando (2004), Cont and Tankov (2004), Jarrow (2018).

To consider risks from the financial markets channel, the delayed-uncertain pathways are augmented with an additional layer of jump-diffusion stochastic financial modeling of corporate spreads. Box 1 provides the details of the model. This is consistent with the delayed-uncertain narrative. In particular, the analysis models corporate spreads (or equivalently risk premium) of the Mexican financial markets. For example, due to a sudden shift in investor risk aversion from lingering global uncertainty and the possibility of having to take increasingly drastic measures in the future due to longer delays, there could be a large/sudden increase in corporate spreads. This implies increasing risk premium and cost of debt capital for the Mexican corporate sector. This motivates the exploration of a jump-diffusion model.

Figure 8. Historical Corporate Spreads and Simulation via Jump-Diffusion Process



Sources: J.P. Morgan CEMBI and IMF staff calculations.

The evolution of the corporate spreads is mapped into the micro-simulation of the firms' balance sheet and P&L items as time-varying interest rates in order to capture effects from debt capital markets. Figure 8 (bottom panel) shows the full stochastic Monte Carlo simulation of Mexican corporate spreads consisting of 20,000 paths simulated at daily frequency till end-2026. This means, at each point in time in the future, it is possible to obtain the distribution of the spreads, thereby allowing the flexibility of exploring different parts of the distribution, which would be impossible by construction in a deterministic model. After the jump at the end-2022 (driven by lingering policy uncertainty, as discussed earlier), the corporate cost of debt capital also changes. Appendix I contains details on the implementation of this financial model.

While, in principle, it is possible to model a variety of other market variables (equity, derivatives, and so on), it was most practical to focus on corporate spreads. In particular, it was not possible to calibrate the corporate spreads to individual companies in the sample because most firms do not have liquid corporate bond and/or credit default swap markets data, nor does a coherent set of indexes representing various corporate segments exist for Mexico. In this regard, the Corporate Emerging Markets Bond Index (CEMBI) was deemed a suitable choice to represent an aggregate corporate bond spreads index. The CEMBI is widely used to track the performance of corporate debt markets in emerging economies. Given this, the model was calibrated to this index. Nevertheless, individual firm-level data can always be used to calibrate the model as data permits.

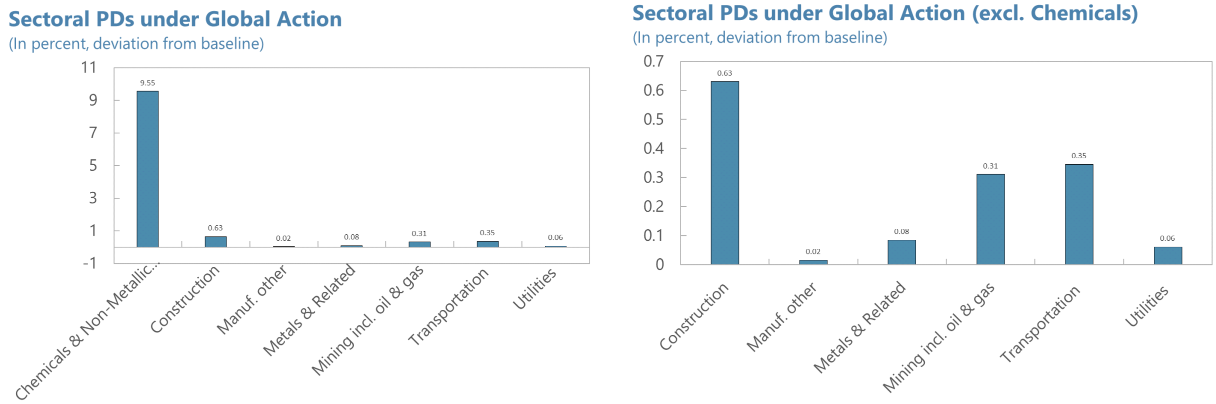
IMPACT ON CORPORATE AND FINANCIAL SECTORS

To better understand the results, it is important to recall heterogeneous drivers of risks that affect firms, corporate sectors, and eventually the banking system. First, the initial risk characteristics and financial health of the firms in different sectors used in the analysis are quite diverse, as seen in Figure 4, together with their individual GHG emissions, as exemplified by sectoral emission shares in Figure 2. Second, the heterogeneous sectoral impact in Figures 5 and 7 from the, CGE model maps into firms' sales revenues and consequently into the vulnerability indicators differently. Third, the sensitivity of firm-level PDs, the coefficient betas in the bridge equation used to project climate scenario-dependent PD paths (and later aggregated to weighted sectoral PDs) are themselves different. Last, the credit exposure of the banking system, which is directly responsible for the materiality of bank capital impact, is also diverse across sectors.

Under the global action scenario, some sectors see a larger rise in credit risk than others, as seen from the impact on sectoral PDs (Figure 9). For example, PDs for the chemicals sector and the non-metallic sector (a sub-segment of the broader manufacturing sector) are material, as the difference between the maximum PDs in the global action scenario and the average in the baseline over the analysis horizon reaches almost 10 percent. This is largely driven by the negative impact on the sectoral output relative to other sectors under the global action scenario. Credit risks in other sectors are also notable, even if relatively small compared with those in the chemicals and non-metallic sectors. For example, deviation in PDs in the construction sector is around 0.65 percent, and those in mining and transportation are also notable. The reason for high risk in the construction sector relative to other sectors, such as mining and transportation, with significantly higher emission profiles, is its initial weak solvency and liquidity metrics, that is, interest coverage ratio and current ratio (Figure 4). This generates high sensitivity to even small shocks.

The above asymmetric result highlights an important point regarding unintended consequences of transition delays and uncertainty. Despite low emissions and hence low direct exposures to transition risks, some firms and sectors might still face heightened risks if there are weaknesses in their existing financial standing summarized for key vulnerability indicators. This renders them vulnerable to transition risks because of additional strain on their already precarious financial conditions. This also reflects the limited scope of the analysis, because it does not capture additional constraints and indirect channels and spillover effects that firms and sectors, despite their relatively low emissions, could face (for example, reduced demand for their products due to production, supply-chain linkages, and so on that could further amplify the effects). As such, the relatively benign PD impact in many sectors above needs to be interpreted with caution.

Figure 9. Sectoral Credit Risk under Global Action Scenario



Sources: Moody's and IMF staff calculations.

Sources: Moody's and IMF staff calcuations.

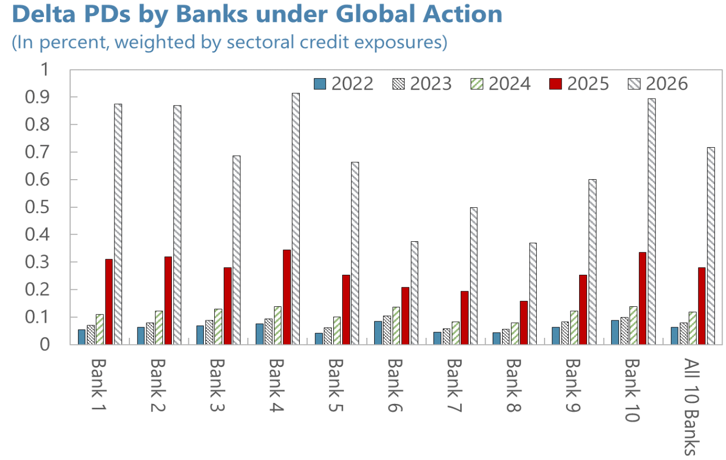
The delta PDs across banks, weighted by their exposures to the vulnerable sectors, show a significant rise in risks in the corporate credit portfolio for some banks under the global action scenario. Figure 10 shows that delta PDs for some banks reach almost 1 percent and the system-wide delta PD rises to above 0.7 percent by 2026. Thus, evaluating the results on the basis of credit risk, and not exposures, the impact is non-trivial even if modest at the system level when compared to impacts one would generally obtain in standard (non-climate) stress testing of bank's sectoral credit risks

The mapping of sectoral PD paths into bank capital under global action generates relatively small effects (Figure 10) and again needs to be interpreted with caution. The cumulative impact on the bank capital due to expected credit losses from exposures to these sectors, under static balance sheet assumption, is about 0.35 percent. This is due to the diversified exposures of the banking system across these sectors (Figure 2). Even though about 37 percent of the banking sector portfolio belongs to these sectors, which is sizable, most banks have diversified exposures to these sectors, thereby containing the impact of sectoral credit risks on the bank capital.

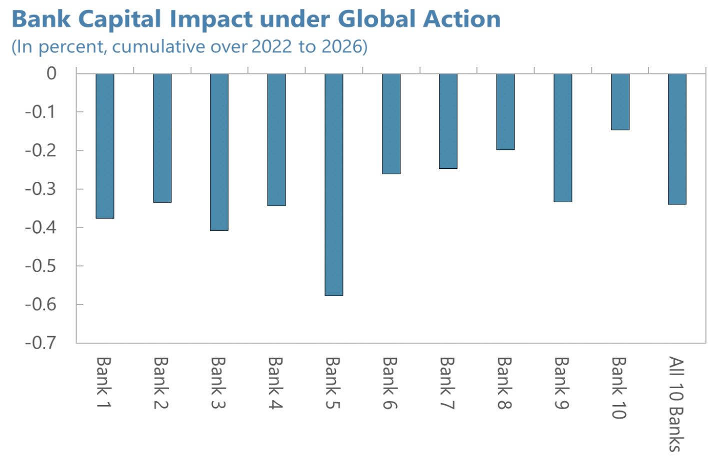
The channels of risk propagation under delayed-uncertain pathways are largely similar to that in global action, but the risk metrics (sectoral PDs and capital impacts) at each point in time are now better characterized by corresponding distributions. The delayed-uncertain pathways consist of increasingly stringent variants of the effects in the early global action path. However, the uncertain nature and narrative of the delayed pathways implies that at each point in time in the future, the more accurate way to describe the risk metrics of sectoral PDs and bank capital impact is via their distributions. Further, these distributions are also time varying (just like corporate spread distributions at each time slice in Figure 8). This is in sharp contrast to the illustration of outcomes as deviation from a fixed baseline in standard scenario-based analysis.[19]

[19] The intuition follows immediately from Figure 6, where under the binomial lattice structure, at each point in time (2023, 2024, 2025, 2026), there are multiple possible states of the world associated with multiple pathways. The full stochastic simulation of spreads in Figure 8 sharply illustrates why this is the case.

Figure 10. Corporate Portfolio Risk and Bank Capital Impact under Global Action



Sources: Banxico and IMF staff calculations.



Sources: Banxico and IMF staff calculations.

The time-varying sequence of distribution of PDs across the corporate sectors highlights the potential of a significant rise in credit risk associated with longer delays in transition (Figure 11, top panel). The entire distribution of the PDs significantly shifts to the right the longer the global delay in transition to a low-carbon economy. This is also accompanied by a sharp increase in the mass of the tail of the distribution.[20] For example, relative to acting in year 2023, where the maximum possible credit risk is around 3 percent, under delayed 2026, the risk could increase to as high as 14 percent. As such, the support of the distribution, which

[20] The intuition follows mainly from the jump part of the financial model (Box 1), which generally captures sudden/discontinuous large shocks. This implies that the tails of the distribution are reached more often in the presence of jumps than otherwise. For example, assume that in the absence of jumps, we observe a large (tail) shock to the spreads, say, 500 basis points, just 1 percent of the time, that is, with 1 percent probability. Then, in the presence of jumps, we would observe the same shock more often, say, 5 percent of the time, that is, with 5 percent probability. Because increasing the probability means an increase in the area of the tail of the distribution, jumps thereby increase the mass of the tail. Additionally, the square root in the diffusion part increases the effective volatility because of increased levels of spread after the jump, thereby further contributing to the tail mass increase. These features are directly mapped into the micro-macro framework together with sectoral impacts (CGE model outputs for delayed scenarios), which subsequently results in heavier tails in the distribution of sectoral delta PDs.

represents the corporate credit risk profile (as measured by PDs), increases by more than four times under climate action in 2026 relative to acting in 2023. The message is unequivocal: the longer climate actions are delayed, the larger the future actions might have to be to achieve the same climate goals.

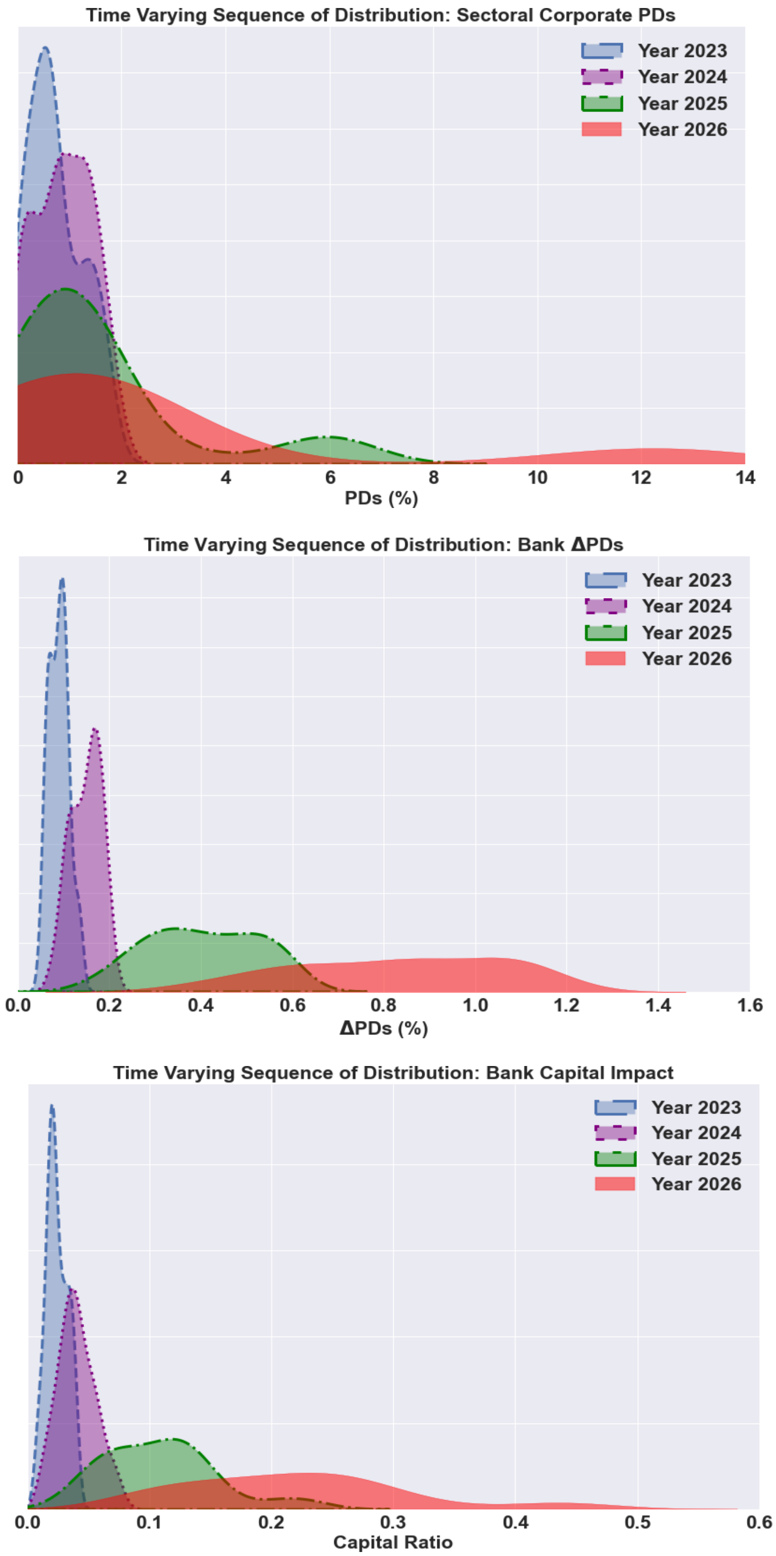
The distribution of bank delta PDs shifts significantly to the right, where the tail gets increasingly longer and heavier (Figure 11, middle panel). Under the early action in 2023 (albeit slightly delayed), the maximum delta PD across banks was around 0.2 percent. However, considering the uncertain future pathways coupled with longer delays in global action, the delta PDs in the banking system could rise to as high as 1.5 percent if the actions are delayed till 2026. This constitutes a more than seven-fold rise in the maximum tail risk, with significantly higher mass near the tail. These effects, as measured in terms of exposure-weighted delta PDs, are significant and could have material impact on the capital buffers of the banking system.

The distribution of bank capital ratios also shifts to the right as the tail becomes increasingly longer and heavier, but the absolute impact appears modest (Figure 11, bottom panel). As discussed above, since the negative impact on capital ratios is determined by expected credit losses from sectoral exposures under static balance sheet assumption, the impact (shown in absolute terms in the figure) appears modest. However, judging by the relative increase, the maximum range of the distribution increases by almost five times if the actions are delayed till 2026 versus 2023. The cumulative bank capital impact under the delayed-uncertain path could reach as high as 0.8 percent with non-trivial probability relative to a maximum impact of around 0.3 percent under global action. Considering this, caution is required in interpreting these relatively benign system-wide capital impacts. The analysis shows that, once additional sources and channels of risks are allowed, the probability and size of impact to the financial system could, in principle, significantly increase with a longer delay in the action.

We also conducted an additional sensitivity analysis with the mean reversion feature of the stochastic model. As highlighted in Box 1, rates/corporate spreads generally do not stay elevated for long periods in the markets but fluctuate around some long-run average. In this regard, the mean reversion parameter $\boldsymbol{\kappa}$ governs how fast spreads drift back to the long-run level. The smaller the κ, the slower the rate of mean reversion. As such, slow mean reversion means the spreads continue to remain higher for longer, which implies that the effective volatility in the markets continues to remain higher given the square root term $\boldsymbol{\sigma\sqrt{r_t}}$. Thus, for the sensitivity analysis, we set the mean reversion parameter as small as possible. In this regard, we use the Feller condition $\boldsymbol{2\kappa\mu \geq \sigma^2}$ to obtain the lower bound value of the mean reversion parameter. The key motivation behind this sensitivity test is to explore the effects of a highly persistent uncertain market environment characterized by extremely slow reversion to long-run levels and hence relatively prolonged and sustained periods of elevated risk in the market.

The time varying sequence of distribution of corporate PDs in the mean reversion sensitivity analysis found even more heightened rise in overall credit risk associated with longer delays in transition. Relative to Figure 11, the distributions of the risk metrics further shift significantly to the right the longer the global delay toward transition to a low-carbon economy. Consequently, the increase in the tail mass of the distribution is even more pronounced than that in Figure 11.

Figure 11. Significant Tail Risks under Delayed-Uncertain Pathways



Sources: Moody's, Banxico, and IMF staff calculations.

Note: Bottom panel shows decrease in bank capital ratios in absolute terms.

CONCLUSION

This paper develops a novel forward-looking transition risk analysis approach consisting of an integrated micro-macro framework with delayed-uncertain pathways with a stochastic financial modeling layer using a jump-diffusion process. The inherent uncertainty structure in the model allows us to quantify the projections of future distributions of risk metrics, and hence tail risks. This framework is then used to assess the impact of delayed transition paths on climate tail risks implications for the corporate and financial sectors. Our approach contributes to the growing literature on financial stability from climate-related risks and was recently applied in Mexico, where the implications are global in nature. While the global action scenario found relatively modest effects overall, the delayed-uncertain pathways revealed potential for significant risks. For example, from the sequences of time-varying distribution of PDs across sectors given the uncertainty in periods 2023 to 2026, the analysis found that the right tail of the distribution could become significantly heavier. The chemicals and non-metallic segments of the manufacturing sector seemed the most vulnerable despite their sound initial-state corporate distress metrics relative to many other sectors.

A key insight of the analysis is that delays in transition coupled with future policy uncertainty increases the future tail risks to financial stability. The analysis supports the case for an early transition to a low-carbon economy to mitigate the tail risk of larger action on future measures to achieve climate goals. While the Mexico-specific results did not find imminent systemic risk at this stage, it sharply highlights the potential for significant downside tail risks to economies and financial sectors worldwide, given the global driving forces behind the model. Despite the data and other limitations in the case of Mexico, including coverage of limited channels of risks, the analysis nevertheless discovered pockets of vulnerabilities in the corporate sector, suggesting that there could be other risks that still need to be fully explored. As such, further application of the framework could be conducted in a more rich/granular data context, as the framework is flexible enough to be scaled up and adapted.

The insights from our paper can help inform climate-related policy around the world. Our framework can be readily integrated into existing policy frameworks to better inform climate-related risk assessment. Since tail risks become larger the longer the delay in transition to a low-carbon economy, continued vigilance is required at the global level. This is especially important because despite covering only limited channels of risks in our specific application to Mexico, we were able to detect potential for material downside tail risks in the future.

Appendix I. Mapping CGE Model Sectors to Corporate Sectors and NAICS Sector Classification

The corporate data used in the analysis still largely depends on the SIC codes classification, as is common for reporting corporate data by many commercial data vendors. It is similar to NAICS classification, but some minor differences exist between the two systems. Considering this, first the firms were grouped into sectors based on their SIC codes, matched as closely as possible to the sectors in the CGE model. Given the small sample size of firms, this necessitated aggregation of some sub-segments of the manufacturing sector in the CGE model to match the sectoral affiliations of the firms based on four-digit SIC codes. Hence, not all sectors of the highly granular CGE model could be used. Then, these aggregated sectors were mapped into corresponding two-digit NAICS sectors. Despite the limitations, finally a coherent set of aggregated sectors of corporate data were created to broadly correspond to the NAICS sectors, with minimal discrepancy. The main reason for this exercise was to allow for consistently translating the sectoral PD paths into corresponding impacts on bank credit exposures based on the NAICS codes.

Table A1. Mapping of Sectors from CGE Model to Two-digit NAICS Sectors

CGE Sector Names	Aggregated sector names in the analysis	Approx. NAICS sector and two-digit code equivalent
Fossil fuel	Mining incl. oil & gas	Mining, 21
Utilities	Utilities	Utilities, 22
Construction	Construction	Construction, 23
Food & Textiles and Pulp & Paper	Manuf. Other	Manufacturing, 31
Chemicals and Non-Metallic	Chemicals & Non-Metallic Minerals	Manufacturing, 32
Iron-steel and Transp. eqpmt.	Metals & Related	Manufacturing, 33
Transportation svcs.	Transportation	Transportation, 48

Table A2. Projection of Corporate Variables and Vulnerability Indicators

- Interest Coverage Ratio (ICR):

$$ICR_t = EBIT_t / Interest\ Expense_t$$

- $Interest\ expense_t = R_{t-1} * Total\ debt_{t-1}$

- $Carbon\ Tax_t = Emissions_t * Carbon\ Price_t$

- Leverage Ratio (LR) and Cash and Equivalents (CE):

$$LR_t = Total\ Debt_t / Total\ Assets_t$$

$$CE_t = \max(0, \quad CE_{t-1} + EBIT_t - Carbon\ Tax_t - Interest\ Expense_t)$$

- $Total\ Debt_t = Total\ Debt_{t-1} - \min(0, CE_{t-1} + EBIT_t - Carbon\ Tax_t - Interest\ Expense_t)$

- $Total\ Assets_t = Total\ Assets_{t-1} + CE_t - CE_{t-1}$

- Current Ratio (CR):

$$CR_t = Current\ Assets_t / Current\ Liabilities_t$$

- $Current\ Assets_t = Current\ Assets_{t-1} - CE_t - CE_{t-1}$

- $Current\ Liabilities_t = Current\ Liabilities_{t-1} - \min(0, CE_{t-1} + EBIT_t - Carbon\ tax_t - Interest\ expense_t) * (1/2)$

Note: Accounting identities based on a similar set of relations between corporate variables, as in Chile FSAP (2021).

Table A3. Panel Regression Estimation of Firm-Level Default Risk

Variables	logit(PD)
Interest Coverage Ratio	-0.002
	(-4.366)
Current Ratio	-0.255
	(-4.166)
Leverage Ratio	2.10
	(3.871)
Firm-Level Fixed Effects	Yes
R-squared	0.54
Observations	762

Sources: Moody's EDF, DataStream, Capital IQ, and IMF staff calculations.

Note: t-values are reported in parentheses. Intercept is set to equal to the average of fixed effects across firms, because firms that are used in the projections are a subset of the firms used in the panel regression.

Mapping Stochastic Model Outputs to the Micro-Macro Framework

A key assumption in the delayed-uncertain analysis is that because no action takes place by end-2022, corporate bond markets sharply react, anticipating heightened uncertainty into the future. To simplify the analysis, only one jump is considered at end-2022, with jump size magnitude calibrated to be as large as shocks seen during past crises episodes. In particular, jump size is set equal to the 99th percentile of rolling two-year changes in the corporate spread. Such large shocks were seen during the 2007-2009 global financial crisis period, where the spreads increased from around 2 percent to almost 12 percent in the height of the crisis.

This is a conservative assumption. However, it is the heightened and persistent uncertainty generated after such shocks that are of utmost importance, not necessarily the large initial magnitude of the shocks market reaction, as evident from stochastic process in Box 1. It is possible to allow random jumps before or after 2022 as well, which would significantly increase the risks. However, such sustained jumps in the fixed-income markets are relatively rare compared with those in other market segments, such as equity. It is also unnecessary for this analysis because the large jump increases the uncertainty significantly due to the square root process that renders the effective volatility higher, as evident from the equation in Box 1 and from the historical time varying-volatility (rolling six months) in Figure 8, top panel.

Thus, the following scheme is followed to arrive at increasingly higher funding costs in the debt markets. For the delayed-2023 path, the average across all the possible paths between each time slice (the vertical lines between years in Figure 8, bottom panel) are computed. This gives a dynamic path of interest rate shocks. For the delayed-2024 path, the 75th percentile is used instead of the average. Similarly, for the delayed-2025 and delayed-2026 paths, 90th and 95th percentiles, respectively, are used. This scheme helps capture the increasingly higher funding costs along the delayed paths. From this sequence, the initial value of the corporate spread is subtracted. As such, the constructed time varying spreads are mapped into each of the uncertain pathways (Figure 6) as shocks to the interest rates in the micro-simulation of the firm-level variables and vulnerability indicators.

This approach strikes a balance between practical data constraints and the narrative of a delayed-uncertain pathways and is a consequence of attempting to reconcile the fully stochastic modeling into a manually constructed simplified delayed-uncertain pathways to mimic the impact of uncertainty. Nevertheless, because financial markets are assumed to be embedded into the broader macro-uncertain environment (Figure 6), this approach is conceptually consistent while sufficiently flexible. For example, because the financial model delivers a full set of distributions at each day into the future five-year horizon (Figure 8), it is possible to experiment with different parts of the distribution in a variety of ways. In the present analysis, the average, 75th, 90th, 95th percentiles were chosen to highlight increasing draws from the tail of the distribution.

Last, the scaling factor in Box 1 is a random variable that is constructed to link the sectoral outputs to corresponding impacts on the spreads in a simple manner. In particular, a uniform random variable between zero and the weighted average of sectoral outputs as deviations from the baseline by 2030 (as in Figure 5) is constructed. In principle, other distributions could also be fitted. However, because the CGE model is not run in a stochastic mode, the simplest assumption that is consistent with the multiple delayed-uncertain pathways (Figure 6) is the uniform distribution. The range of this distribution is then multiplied by the elasticity of corporate spreads to changes in the aggregate output in Mexico (which was about 0.30 percent). As such, the random variables representing the scaling factor can be simply interpreted as mapping the impact of overall macro randomness, induced by the uncertain pathways of the macro policy environment, into corresponding effects on the corporate spreads, whereas the jump term captures a one-time large shock due to the sudden rise of macro policy uncertainty. Thus, this scaling factor links the climate policy scenarios to the evolution of corporate spreads, in a simple but internally consistent and coherent manner.

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