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TECHNICAL NOTE ON CLIMATE RISK ANALYSIS

This Technical Note on Selected Issues on Climate Risk Analysis for the Mexico FSAP was prepared by a staff team of the International Monetary Fund as background documentation for the periodic consultation with the member country. It is based on the information available at the time it was completed in July 2022.

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TECHNICAL NOTE

CLIMATE RISK ANALYSIS

Prepared By

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This Technical Note was prepared by IMF and WB staff in the context of the Financial Sector Assessment Program in Mexico, and overseen by the Monetary and Capital Markets Department, International Monetary Fund, and the Finance, Competitiveness and Innovation Global Practice, World Bank. It contains technical analysis and detailed information underpinning the FSAP's findings and recommendations. Further information on the FSAP program can be found at http://www.imf.org/external/np/fsap/fssa.aspx, and www.worldbank.org/fsap.

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GLOSSARY

Banxico	*Banco de México* (Central Bank)
CAR	Capital Adequacy ratio
CENAPRED	*Centro Nacional de Prevención de Desastres* (National Center for Prevention of Disasters)
CGE	Computable General Equilibrium
CNBV	*Comisión Nacional Bancaria y de Valores* (National Banking and Securities Commission)
CR	Current Ratio
EBIT	Earnings Before Interest and Taxes
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GHG	Greenhouse Gas Emissions
GVA	Gross Value Added
ICR	Interest Coverage Ratio
LGD	Loss Given Default
LR	Leverage Ratio
NAICS	North American Industry Classification System
NGFS	Network of Central Banks and Supervisors for Greening the Financial System
P&L	Profit and Loss
PD	Probability of Default
RCP	Representative Concentration Pathway
RWA	Risk Weighted Assets
SMEs	Small and Medium Size Enterprises
SSP	Shared Socioeconomic Pathway
TFP	Total Factor Productivity

EXECUTIVE SUMMARY[1]

Mexico is exposed to both transition and physical risks from climate change. Mexico's total energy supply is dominated by fossil fuels and non-renewable energy sources. The country is the second largest emitter of greenhouse gases (GHG) in Latin America. Emissions are highly concentrated in a few economic sectors that play an important role in the Mexican economy. The Mexican financial sector has sizable exposures to these emission intensive sectors. As such, the transition to a low carbon economy raises challenges for the economy and financial sector that need to be considered. Meanwhile, Mexico is exposed to a range of physical risks, including acute risks associated with floods and tropical cyclones, by virtue of the exposure to both the North Atlantic and Eastern Pacific hurricane basins, droughts, and heatwaves, and chronic risks.

This FSAP analyzed potential risks to financial stability posed by transition risk and acute physical risks. The transition risk analysis used an integrated micro-macro approach and explored two scenarios motivated by the scenarios developed by the Network for Greening the Financial System (NGFS). In addition to a standard baseline current unchanged policies scenario, these included: (i) a scenario with an orderly transition broadly in line with limiting temperate increase to below 2 degrees centigrade by end of century ("global action") and (ii) a scenario modeling a disorderly transition as in the NGFS delayed transition scenario ("delayed uncertain"). We also develop a novel stochastic financial framework to assess the impact of delayed transition paths on climate tail risks. While chronic risks and other acute risks (e.g., droughts and heatwaves) are also important, the physical risk analysis focused on acute risks associated with tropical cyclones and floods, due to the historical significance of these hazards in terms of frequency, number of people affected, and economic losses. These risks were analyzed for a set of scenarios using a model of direct damages, combined with macroeconomic and financial sector impact modelling.

The analysis flagged the important sectoral heterogeneity of the exposure to transition risks and downside risks 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 disorderly transition scenario flags potentially non-negligible risks to corporates and banks. A key insight of the analysis is that delays in transition—and the resulting need to catch up with stronger policy action to contain the faster rise in temperatures—increase tail risks to financial stability. The impacts get increasingly severe, the longer the delay relative to early action. While there is significant uncertainty underlying this analysis, it 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.

The physical risk analysis suggests that extreme tropical cyclones and floods could have a material impact, though less likely at a scale to generate systemic financial stress. An

[1] This Technical Note has been prepared by Sujan Lamichhane and Dimitrios Laliotis (both IMF), and Michaela Dolk and Dorra Berraies (both World Bank). The IMF team conducted the transition risk analysis section. The physical risk analysis section was jointly conducted by the IMF and WB teams.

innovation in the analysis is to focus on a severe tropical cyclone/flood season, as opposed to single extreme events. A sequence of extreme tropical cyclone and flood events occurring within a single season based on historical climate conditions could lower the level of gross domestic product (GDP) by more than one percentage point within the year. Preliminary modeling that allows for increases in the severity of these events because of climate change—linked to high greenhouse gases emission scenario—would have larger effects. These scenarios suggest specific financial institutions could face material risks. It is important to recognize that the analysis is only limited to tropical cyclones and floods, and that the materiality of the physical risks associated with climate change could be much larger if other risks (e.g., droughts, heatwaves, and chronic risks) are also considered given their considerable potential negative impact and their persistence.

The analysis and results should be regarded as exploratory and interpreted with caution given the uncertainty associated with the scenarios, time horizon and models. Both the transition and physical risk analyses are subject to multiple layers of scenario and model uncertainties. Many of these uncertainties are difficult to quantify. Both analyses are also subject to various simplifying assumptions given data and model limitations. Further analysis is needed to explore the sensitivity of the results to scenario and model assumptions. While the analysis relied on standard stress testing methodologies, it is not a standard stress test and is not focused on quantifying capital needs of the financial sector given the various challenges and the exploratory nature of the exercise. Although there is substantial uncertainty on the quantitative side (i.e., strength of climate change risks), the qualitative effects (i.e., the sign of risk materialization) are increasingly well understood.

The Mexican authorities should strengthen data collection and conduct further analysis to understand the potential impact of climate risks. Disclosure should be enhanced to collect granular data for understanding the carbon footprint of the entire spectrum of firms, not just the listed firms. Additionally, authorities are encouraged to partner further with other government entities, the private sector, and research institutions to leverage their expertise in climate and catastrophe modelling to assess the impact of physical risk in a highly granular and data-driven way, and to incorporate that into the analysis of banking sector resilience to climate-related hazards. This analysis should cover a broad range of physical risks, including both acute and chronic risks.

Table 1. Mexico: Recommendations on Climate Risk Analysis			
Recommendations	**Responsible Authorities**	**Time**[1/]	**Priority**[2/]
Improve and harmonize data collection and modelling to enable more comprehensive and granular analysis of transition and physical risks to the financial system.	Banxico CNBV	MT	H
Strengthen, expand, and accelerate the ongoing development of climate related risk analysis and its integration with financial system analysis, in collaboration with other government entities, the private sector, and research institutions.	Banxico CNBV	MT	M
1/ "I (immediate)" is within one year; "NT (near-term)" is one–two years; "MT (medium-term)" is three–five years. 2/ H: high; M: medium; L: low.			

INTRODUCTION

1. **Globally, climate change is already having unprecedented impacts on communities, economies, and the financial sector.** According to the Intergovernmental Panel on Climate Change, adverse economic impacts attributable to climate change are increasingly being observed and are projected to increase further with global warming (IPCC, 2022). Limiting global warming requires an unprecedented reduction in global greenhouse gas emissions (UNEP, 2021), which will have a significant impact on emissions-intensive firms, with evidence already emerging of impacts on the market value of equities of firms in heavily polluting industries (FSB, 2020). Given the exposure of the financial system to these impacts, there is increasing recognition amongst regulators and central banks, including through the NGFS, of the need to assess the impact of climate change on financial stability.

2. **Climate-related risks can be broadly categorized into transition risks and physical risks.** Transition risks are those related to the process of adjusting towards a low-carbon economy, which can impact the value of financial assets and liabilities. Physical risks include the impacts of increasing frequency and severity of hydrometeorological disasters due to climate change (e.g., tropical cyclones and floods), referred to as acute risks, and risks associated with gradual changes induced by climate change, referred to as chronic risks (e.g., sea level rise). The manifestation of these risks, and the relationship between them, is likely to depend on the pathways of action to mitigate climate change, with a possibility that these risks might interact and crystallize simultaneously (FSB, 2020).

3. **The analysis of climate-related risks is an increasing priority of FSAPs, enabling financial system pressure points from these risks to be identified, and improving understanding of their complexity.** Since climate risk analysis is at an early stage of development, one of the key goals of the analysis 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 needs and

requirements will be quite different across various jurisdictions given the unique nature of risks arising from climate change. Recent FSAPs have started addressing transition and physical risks, for example, in Norway (IMF, 2020), Grippa and Mann (2020), Chile (IMF, 2021), United Kingdom (IMF, 2022), Philippines (IMF and WB, 2021), Colombia (IMF and WB, 2022), and South Africa (IMF, 2022). The Mexico FSAP includes an analysis of both transition and physical risks, with new scenario and modelling and innovations not yet used in previous FSAP analyses.

4. **There is significant heterogeneity across countries in terms of their exposures to transition and physical risks.** Such differences may stem from differences in economies' reliance on fossil fuels, as well as countries' physical exposures and vulnerability to droughts, coastal and inland floods, tropical cyclones, high temperatures, and other hazards that are likely to be worsened by climate change. As such the approach and methodologies to analyzing these risks need to be tailored to the specific country context.

5. **This FSAP analyzes the potential impact of both transition and physical risks on the stability of Mexican financial sector.** A significant portion of greenhouse gas emissions can be attributed to a select few economic sectors that play important role in the Mexican economy. Mexico is also highly dependent on non-renewable energy sources as the total energy supply is dominated by fossil fuel and non-renewable energy sources. This implies potential for transition risks to the economy and the financial sector. In addition, Mexico is exposed to physical risks, including acute risks associated with tropical cyclones and flooding, by virtue of the exposure to both the North Atlantic and Eastern Pacific hurricane basins, droughts, and heatwaves, and chronic risks. The FSAP analysis of physical risks focuses on tropical cyclones and flooding, whilst recognizing that other physical risks may also be substantial.

TRANSITION RISK

A. Overview: Climate Policy Risks in Mexico

6. **Worldwide consensus is building on the need to introduce stronger policy actions to limit GHG emissions and transition to a low-carbon economy**. During the latest UN climate summit held on November 2021 (COP26) policymakers around the world made new climate pledges and discussed plans to reduce emissions to avert serious damages to the climate system. At the COP26 more than 120 countries, representing about 70 percent of global emissions, pledged bringing emission to net zero around 2050. According to IEA (2021) if the new pledges together with previous ones are followed through, it would help limit the rise in global temperatures to below 2 degrees centigrade by the end of the century.

7. **Mexico has signaled its commitment to emission reduction targets, though some observers view that 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 and commitments by Mexico will be needed to adhere to the 1.5 degrees temperature limit based on Paris Agreement.

8. Nevertheless, Mexico has made strides to expand its climate goals in November 2021 COP26. Mexico joined the Global Methane Pledge and Declaration on Forests and Land Use during the COP26. 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 CO2. The declaration on forests and land is a step towards addressing the issue of deforestation and land degradation. Mexico has also pledged to accelerate the switch towards renewable energy sources such as wind, hydroelectric, solar etc. to support its commitments under Paris Agreement.

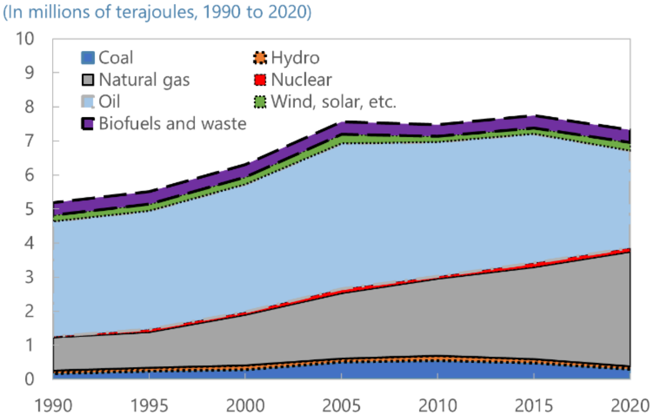
9. The Central Bank of Mexico (Banxico) is also taking active role in helping promote transition to a low-carbon economy. The Financial System Stability Council in 2020 established the Committee on Sustainable Finance (CFS) consisting of various working groups to support sustainable finance in the country. Banxico is an active participant in various workstreams of the NGFS, a consortium of central banks and supervisors around the world helping to strengthen the role of financial sector to address risks and capital allocation as the world transitions towards a low-carbon economy. The central bank also participates in other working groups in standard-setting bodies discussing these topics.

10. 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 GHG's in Latin America after Brazil with one of the highest per-capita emissions and a significant portion of that can be attributed to the energy sector. Further, Mexico is highly dependent on non-renewable energy sources as the total energy supply is dominated by fossil fuel and non-renewable energy sources (Figure 1). Oil and natural gas dominate the total energy supply in Mexico whereas renewable sources such as hydro, solar, wind etc. constitute a minor portion of the energy ecosystem. In addition to CO2 emissions from burning, oil and natural gas are also a significant source of methane emissions which has significantly more global warming potential than CO2. This high dependence on non-renewable and GHG emission intensive sources, coupled with commitments to global climate mitigation efforts signals potential transition related risks.

Figure 1. Sources of Energy Supply

Sources of Energy Supply in Mexico

(In millions of terajoules, 1990 to 2020)



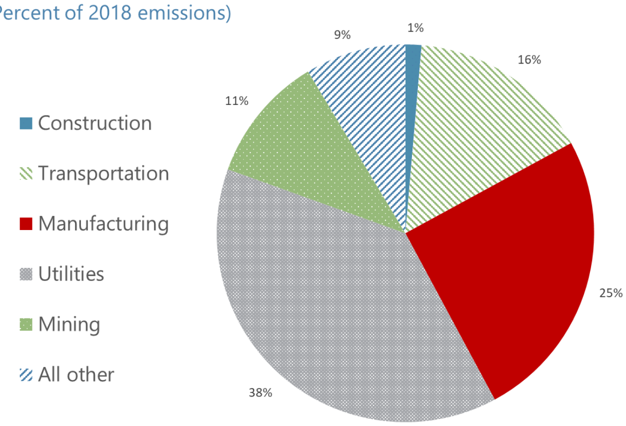
Source: IEA World Energy Balances.

11. A large fraction of total CO2 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 CO2 emissions in 2018 was attributable to the utilities/power generation sector, about 25 percent to the manufacturing sector, and 16 percent to the transportation sector. The mining sector, which includes oil, gas, and coal extraction, only accounts for 11 percent of overall CO2 emissions because this sector is not as emission intensive during the extraction phase. Instead, this 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 the total CO2 emissions.

Figure 2. Carbon Dioxide (CO2) Emissions and Financial Sector's Sectoral Credit Exposure

Mexico CO2 Emissions by Sector

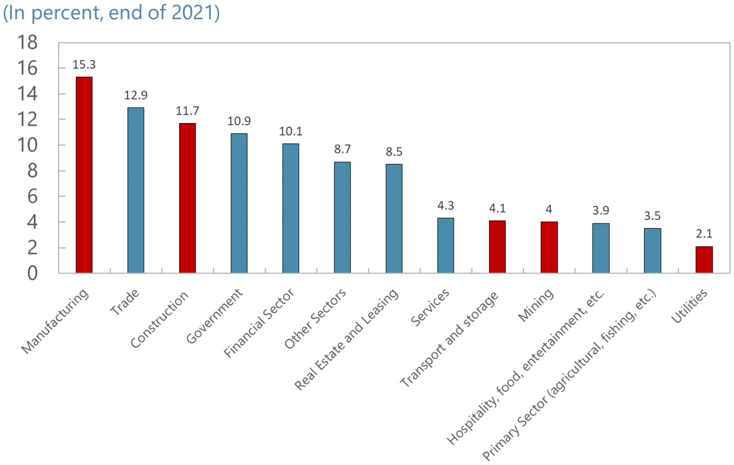
(Percent of 2018 emissions)



Sources: OECD; and IMF staff calculations.

Banking System Credit Exposure by Economic Sector

(In percent, end of 2021)



Sources: Banxico; and IMF staff calculations.

Note: The emission intense sectors are shown in red.

12. 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 total 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.

13. Climate related transition policies could have implications for the financial sector. The impact of transition policies on financial stability would depend in part on when the policies are expected to be implemented. Risks are compounded by uncertainty regarding the implementation of transition in the future in the absence of immediate global coordination efforts. A question to analyze also is the extent to which the financial sector might be well positioned to support the transition to the low carbon economy by boosting its credit to finance green climate projects across sectors.

14. Even in jurisdictions where strong transition related policy actions are not planned, risks could materialize from financial markets channels, given increasing awareness of global investors to climate change issues. Potential policy delays today could require significantly stronger policy steps in the future to contain global warming. This could lead to a reassessment of risks facing corporate sectors around the world, including in Mexico, that remain highly emission intensive. This could lead to disruptions in equity and debt capital markets, sharp rise in corporate spreads, risk premium etc. Further, uncertainty about future policy actions could lead to increased market risk and volatility, generating amplified risks to the system.

15. Thus, implications for financial sector stability could arise from different channels. This note will dive deeper into the issues discussed above and attempt to quantify transition related risks and vulnerabilities in the sections below.[2]

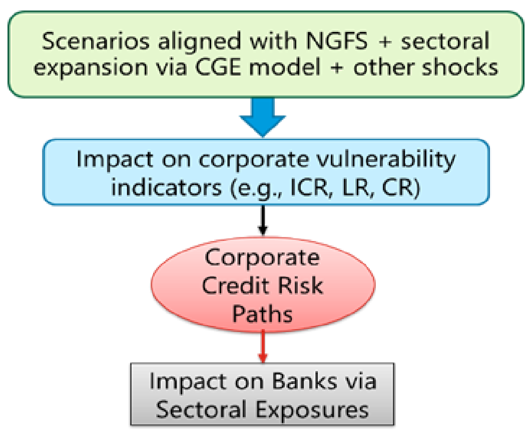
B. Modeling Framework

16. The modelling framework for transition risk analysis can be broadly described as an integrated micro-macro approach. Figure 3 gives 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 bank's credit exposures to various sectors. Thus, the framework is flexible enough to take input from various sources and external modelling frameworks such that all the modules are brought to interact together in an internally consistent way.

[2] Note that the exercise mainly relates to the impact of the transition risk on banking sector through corporate credit risk channel. This is arguably one of the most important channels since transition policies generally have immediate consequences for corporates. Future analysis could consider other channels as well, such as market risks, and effects on consumer portfolios, among others.

17. The FSAP team explored transition risk scenarios using a computable general equilibrium (CGE) model. This model (the IMF-ENV model) was recently developed by the IMF research department, which is documented in Chateau and others (2022). It is a recursive-dynamic, multi-regional, multi-sectoral model. This class of CGE models largely study long run dynamics and allocation of resources across various sectors. Thus, they are highly suitable to study the long run impact of climate mitigation and decarbonization policies. The model covers 25 regions (including Mexico) and groups countries into high income, medium income and low-income countries. The model has 37 distinct sectors, allowing for a granular analysis of sectoral impacts of transition policies. The scenarios are broadly anchored to the high-level NGFS scenario narratives (of orderly and disorderly scenarios) and aligned with IPCC temperature/emission targets. Given the limited country coverage, and lack of sufficient sectoral heterogeneity in the NGFS scenarios, the IMF-ENV CGE model was used to obtain sectoral output pathways tailored to Mexico.[3] More details are provided in Section C below.

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



Source: IMF staff.

18. These policy scenarios are applied to generate multi-year projections of firm-level probabilities of default (PDs) that 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, as summarized in Figure 3, will be discussed in what follows.

19. 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 with the sample period covering balance sheet data from 2002 to 2020. On average there are about

[3] Note that the CGE model is based on a neoclassical framework and deals with real values/economy and are ideal for studying structural transformations, trade, decarbonization, development etc. 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 modelling layer within the framework (see section C).

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 (as shown in Figure 2). In general, limited usable/reliable data is available on other Mexican firms, especially for small and medium size enterprises (SMEs) that constitute a large number of Mexican corporates. This data limitation constrains the scope of the analysis and the ability to generalize results.

20. 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 Banxico). The rest are SMEs. However, these large firms account for more than 65 percent of outstanding bank credit.[4] Thus, there is a disproportionate representation of large corporates in the banking system with 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.[5]

21. 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 asset, and current liabilities. These are some of the commonly used variables for analyzing the financial health of the individual firms and various sectors by construction of various indicators of corporate distress discussed below.

22. 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 their 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 emission projections and scenario dependent carbon prices, estimated as carbon price times emissions (in tCO2eq). [6]

23. 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

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

[5] 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 2-digit North American Industry Classification System (NAICS) classification 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.

[6] Note that carbon tax here is a simplifying expression that is meant to represent the operating cost component of the EBIT and not represent 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.

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 sectoral level, an elasticity of 1.5 was assumed. This was informed by similar estimations in Gross and others (2022) that analyzes similar estimations across many sectors for emerging economies where the related elasticity averaged about 1.5 (see Gross and others (2022) for more details). 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 cost of goods sold to sales growth, estimated to be 0.97.

24. A carbon tax, capturing cost of emissions, was considered as an additional operating costs item at the firm level which would further reduce net earnings. The team had access to 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). This data was merged with the corporate data sample. Given the unique carbon price paths for each scenario (discussed further in transition scenarios section below), the additional cost for each firm is simply carbon prices time 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.[7] 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.

25. 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, e.g., to interest rates, discussed below) can accumulate over the periods and potentially get 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 only considered in the delayed-uncertain scenario as that is directly linked to the outcomes in the financial markets which is not covered in the CGE model.

26. 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) 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

[7] 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.

conditions of firms; (ii) leverage ratio (LR) defined as total debt to total assets, a metric relevant for solvency conditions: (iii) current ratio (CR) defined as current assets to current liabilities, 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 3 to 5 years horizon considered in FSAP analysis.

27. 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 quite sensitive to even small effects. 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.

28. 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 sudden shift in investor risk aversion, for a variety of reasons (e.g., uncertain policy regime, potential lingering effects of geopolitical conflicts around the world, downside risks to the economy etc.), 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 to those in the equity markets, they do occur occasionally during market distress periods such as the global financial crisis (GFC) or the covid-19 crisis. This motivates the exploration of a jump-diffusion model of corporate spreads that will be discussed below.

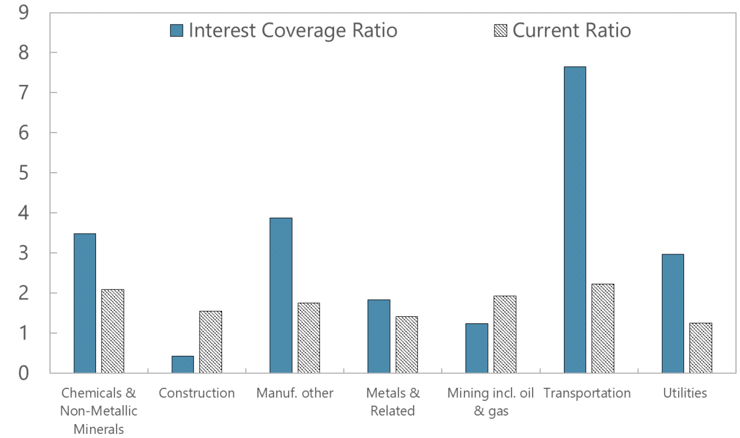
29. A bridge equation was used to establish a structural link between the corporate vulnerability indicators and default risks and formed the basis of projecting firm level PDs. This structural relationship was estimated following the panel fixed effects regression with logit-transformed firm-level PDs:

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

The PDs are obtained from Moody's EDF database for Mexico. This measure is a forward-looking default risk measure. The right-hand side variables are the corporate vulnerability indicators that attempts 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.

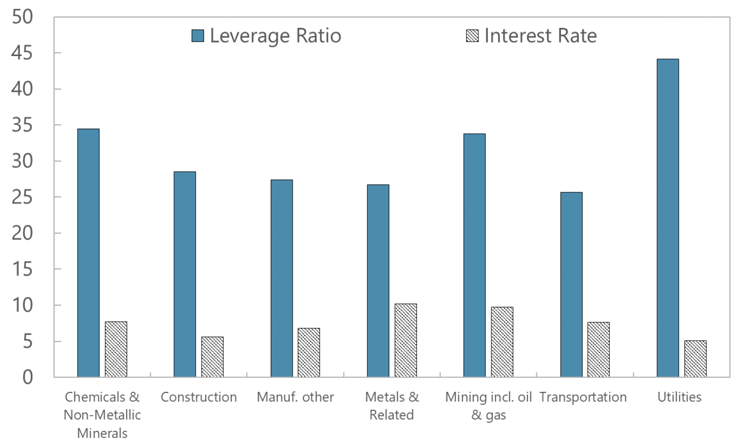
Figure 4. Heterogeneous Corporate Risk Characteristics

Solvency and Liquidity Metrics
(End of 2019 median per industry)



Sources: DataStream; S&P Capital IQ; and IMF staff calculations.

Leverage Ratio and Interest Rate
(In percent, end of 2019 median per industry)



Sources: DataStream; S&P Capital IQ; and IMF staff calculations.

30. 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 macro-micro framework), care needs to be taken in interpreting the outputs of the framework.

31. 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 ICR ratio. Hence, the projections capture the structural links from macro-sectoral transition scenarios to the default risks of the firms.

32. The bridge equation helps generate scenario dependent PD paths for each firm which are then aggregated to exposure-weighted sectoral PD paths. The exposure of banks cannot be mapped to individual firms in the available data and only aggregated credit exposures by broad economic sectors is available. This necessitated constructing an exposure-weighted projection of sectoral PDs for each scenario considered.

33. The weighted sectoral PD paths facilitate computing scenario dependent delta PDs for each bank, weighted by each banks' sectoral credit exposures. The team had data with decomposition of credit exposures by sectors 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 difference between projected PDs in each year from 2022 to 2026 to the starting PDs in 2021. Second, for each bank, the previously calculated delta PDs for the projection horizon were weighted by each bank's credit exposures to the particular sector. This generates paths of delta PDs for each bank, weighted by their sectoral credit exposures, for each scenario. This computation assumed that the sectoral credit exposures remain constant as at the starting point.

34. 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. The team 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 (RWA) were also held constant at the starting value and, in absence of sector and bank specific loss given default (LGD) rates a common value of LGD was used across all banks.[8] Tax and dividend payout impact was also ignored. This resulted in estimates of impact on bank capital ratios driven just by loan impairment charges.

35. To summarize, the team developed an end-to-end fully structural, internally consistent framework. Importantly, this framework is also quite flexible as it allows for exploring additional layers of risks where relevant and as data permits. 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, which are then translated into banks' aggregate PD paths weighted by their credit exposure to vulnerable sectors, generating impact on bank capital.

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

C. Transition Scenarios and Stochastic Financial Model

36. The team explored two climate policy scenarios motivated by the NGFS scenarios: (i) global action (reflecting an orderly transition as in the NGFS "below 2 degrees" scenario) and (ii) delayed-uncertain (reflecting a disorderly transition as in the NGFS "delayed transition" scenario).[9] 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 modelling layer of corporate spreads is added to the delayed-uncertain scenario.

37. In the global action scenario, there is a global mitigation effort, including by Mexico, to limit the warming below 2 degrees. 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 (LICs), \$50 tCO2e for medium income countries (MICs) and \$75 for high income countries (HICs). As such, in this orderly transition scenario, global mitigation measures are enhanced with moderate economic costs and international burden sharing.

38. The sectoral transition pathways 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 other. 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 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, utilities sectors see notable impact. However, some other sectors like transportation equipment, are positively impacted by 2030.

39. The carbon prices paths under global action shows 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 price relative to say, the United States and the United Kingdom in helping reach below two degrees climate goals. Since Mexico belongs to the middle-income countries group, the carbon prices also reflect the international burden sharing tailored to Mexico's capacity and commitments to burden sharing. The team emphasizes 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 of understanding channels and mechanisms by which transition policy actions affect the broader economy and the financial system.

40. 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

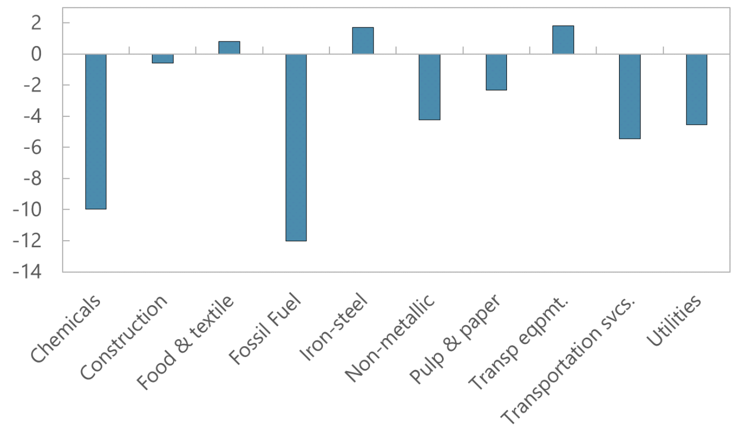
[9] As discussed earlier, the current policies scenario (i.e., no additional action/business-as-usual) serves as the baseline which is a standard practice.

building towards strong mitigation efforts and policy actions, it is uncertain when and how such global policy action would materialize. Importantly, delays in implementing climate policies raises uncertainty regarding when and how such a global action would take place in the future, which can have important economic effects.

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

Sectoral Output Under Global Action

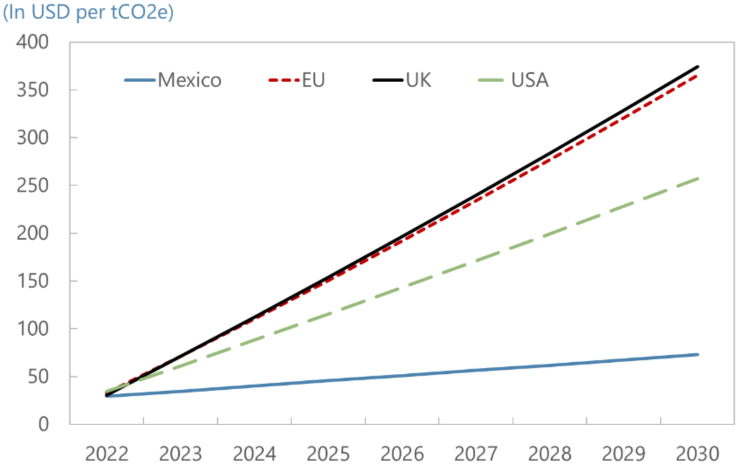
(In percent deviation from baseline in 2030)



Source: IMF staff calculations.

Worldwide Carbon Prices Under Global Action

(In USD per tCO2e)

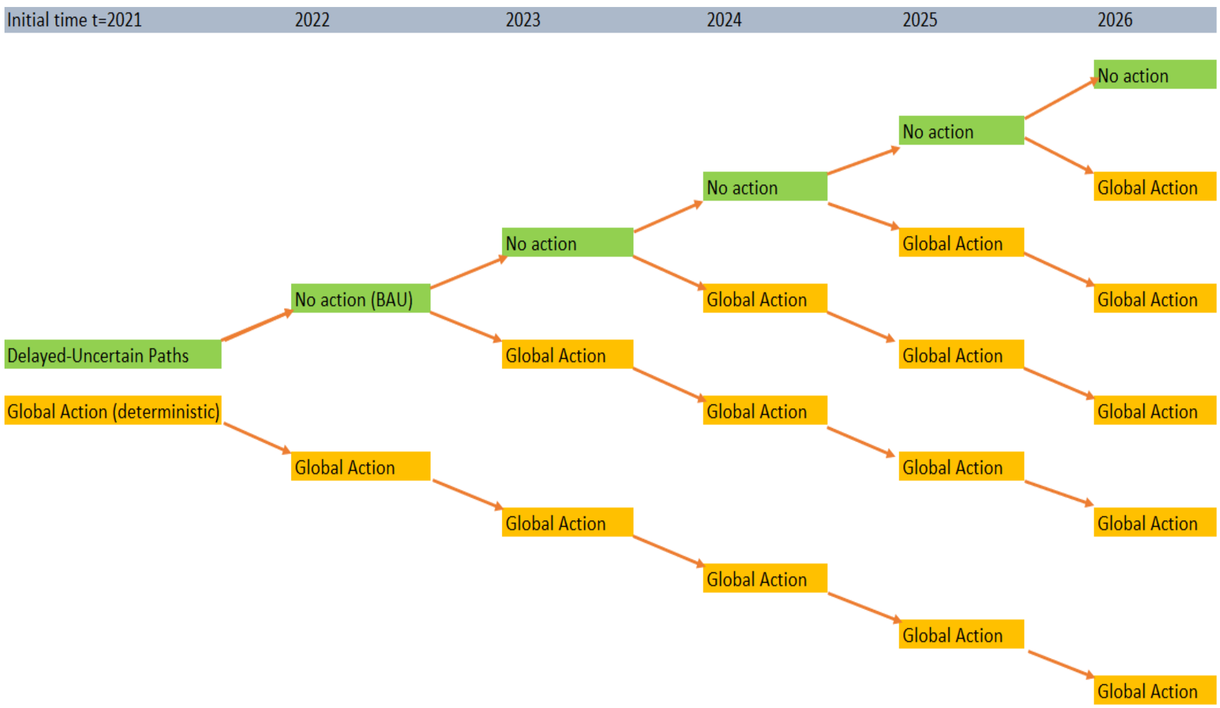


Source: IMF staff calculations.

41. The longer actions towards reducing emissions are delayed, the larger the future actions on emissions reduction might need to be. This is because, in order to achieve the same climate goals, if no action is taken today, it necessarily implies that future actions need to be even larger than otherwise under an early course of action. As such, for example, the impact on the sectoral output by 2030 could be much larger than otherwise.

42. To capture this uncertainty and consequent risks, the analysis explores a new "scenario," i.e., 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 a robust way of modeling uncertainty that necessarily implies multiples states of the world and hence, multiples 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, in 2023, there could be a global action or there may be no such action, i.e., 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 faces the same decision in 2024 -either continue delaying the action or to act and branch out. This sequence continues (theoretically indefinitely) into the future.[10]

Figure 6. Transition Policy Scenarios: Schematic



Source: IMF staff.

43. The various pathways can be effectively viewed as paths of a simple stochastic Monte Carlo simulation. The macro CGE model produce deterministic scenarios generating only one linearized-average path at a time. To capture the notion of uncertainty from delayed transition, requires running the CGE model multiple times under different delayed scenarios and eventually "stitching" them in a binomial tree structure to generate 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 the world could through 2026. Otherwise, in principle the number of paths could

[10] The construction mimics the binomial lattice model used for modelling 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.

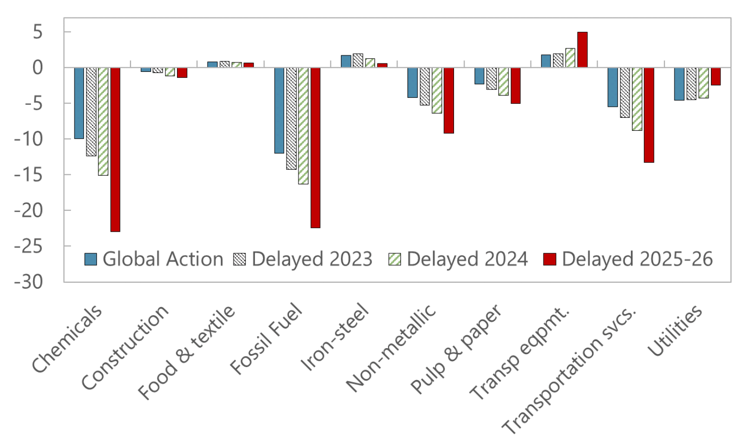
continue as far into the future as required. But the set up considered here that mimic a stochastic Monte Carlo simulation, conveniently allows for analyzing the distribution of outcomes such as PDs and bank capital impact which is not possible with a single/deterministic path by construction. The intuition follows immediately from Figure 6 where under the binomial tree structure, at each point in time (2022, 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 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.[11]

44. The differential impact on sectoral output can be very material the longer the policy actions are delayed into the future. Figure 7 contrasts the sectoral output under various delayed scenarios accounting for all possible paths as deviation from the Business As Usual, i.e., no action pathway (Figure 6) by the end of the 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 in output by 2030, if the global action is delayed to 2025/26. Same thing goes for other vulnerable but economically important sectors like fossil fuel (which includes oil and gas sectors) and transportation services. As evident, the longer the delay, the more severe the negative impact on some sectors, implying 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.

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

Sectoral Output Under Global and Delayed Actions

(In percent deviation from baseline in 2030)



Source: IMF staff calculations.

[11] 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 majority of policy analysis models, especially CGE models that are already quite computationally intensive. As such, the team had to run the model multiple times to mimic Monte Carlo simulation and hence uncertainty set up (with the computational time of almost one week for the CGE model to generate these 5 paths).

45. To consider risks from the financial markets channel, the delayed-uncertain pathways are augmented with an additional layer of jump-diffusion stochastic financial modelling 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 sudden shift in investor risk aversion from lingering global uncertainty and the possibility of having to take increasingly drastic measures in the future with longer delays, there could be sudden and large 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.

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:

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

$\boldsymbol{\kappa > 0}$ is the rate of mean-reversion, $\boldsymbol{\mu > 0}$ is the long-run mean, $\boldsymbol{\sigma > 0}$ 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 $\boldsymbol{2\kappa\mu \geq \sigma^2}$ 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 since 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, i.e., 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 (more details in Appendix I).

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 set 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, wide range of derivatives, among others.

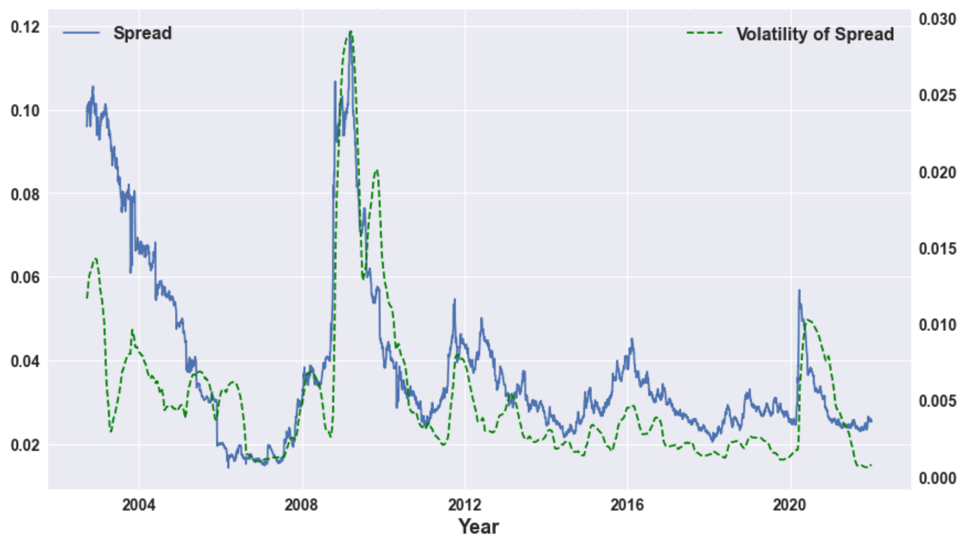
Thus, this model is well suited to analyze impact of large/sudden movements in financial markets (coupled with usual smooth randomness) and consequent rise in heightened volatility/uncertainty. Diffusion term captures continuously changing smooth risks while jump term captures sudden/large and discontinuous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

Note: Given the scope of the FSAP analysis, for more technical details and applications, readers are referred to the literature and related texts on stochastic processes and their applications, e.g., Duffie and others (2000), Lando (2004), Cont and Tankov (2004), Jarrow (2018).

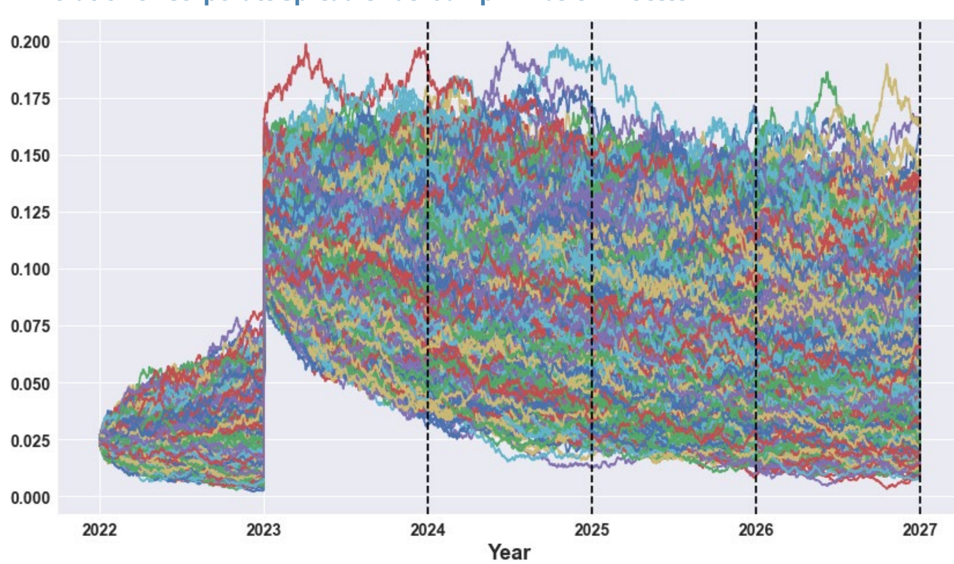
46. The evolution of the corporate spreads is mapped into the micro-simulation of the firms' balance sheet and P&L items as time varying interest rates to capture effects from debt capital markets. Figure 8 (bottom panel) shows the full stochastic Monte Carlo simulation of Mexican corporate spreads consisting of 20,000 paths simulated at daily frequency till end of 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 of 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.

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

Corporate Spread and Its Volatility (2002 - 2021)



Evolution of Corporate Spread Under Jump-Diffusion Process



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

47. While in principle it is possible to model a variety of other market variables (equity, derivatives etc.) 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 since 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 for representing aggregate corporate bond spreads index. This is a widely used index to track performance of corporate debt markets in emerging economies. As such, the model was calibrated to this index.

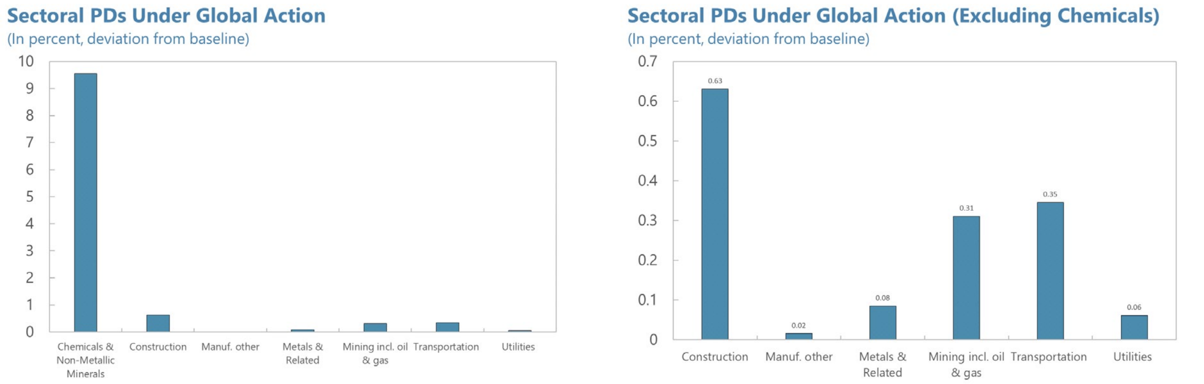
D. Impact on Corporate Sectors and Financial System

48. 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 share in Figure 2. Second, the heterogeneous sectoral impact in Figure 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. Lastly, the credit exposure of the banking system which is directly responsible for the materiality of bank capital impact, is also quite diverse across sectors.

49. 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 and 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 to almost 10 percent. This is largely driven by the negative impact on the sectoral output relative to other sectors under global action scenario. Credit risks in other sectors are also notable even if relatively small compared to that in the chemicals and non-metallic sectors. For example, deviation in PDs in construction sector is around 0.65 percent and that in mining and transportation are also notable. The reason for high risk in construction sector relative to other sectors like mining and transportation with significantly higher emission profile, is due to its initial weak solvency and liquidity metrics, i.e., interest coverage ratio and current ratio (Figure 4). This generates high sensitivity to even small shocks.

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

51. 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 reaches 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. This shows pockets of vulnerabilities in some parts of the system that warrants caution.

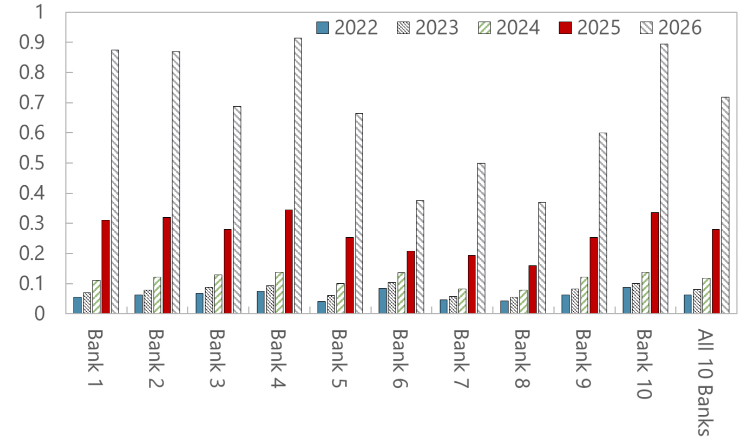
52. The mapping of sectoral PD paths into bank capital under global action generates relatively small effects (Figure 10) which again needs to be interpreted with caution. The cumulative impact on the bank capital due to expected credit losses from exposures to these sectors, under static balance sheet 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 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.

53. 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.[12]

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

Delta PDs by Banks Under Global Action

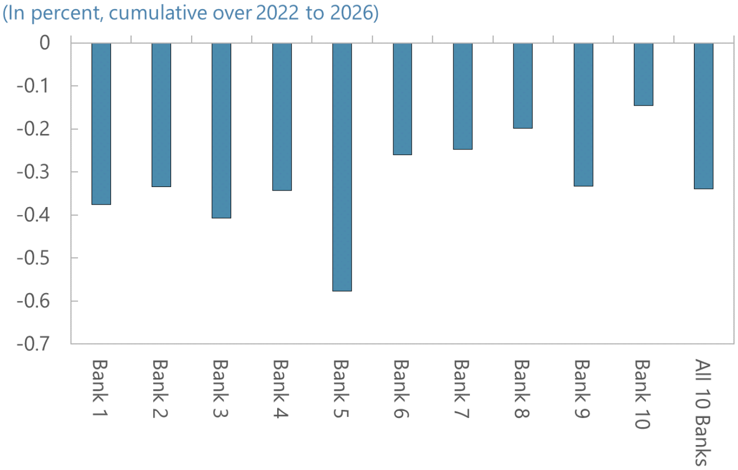
(In percent, weighted by sectoral credit exposures)



Sources: Banxico; and IMF staff calculations.

Bank Capital Impact Under Global Action

(In percent, cumulative over 2022 to 2026)



Sources: Banxico; and IMF staff calculations.

54. **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 towards transition to a low carbon economy. This is also accompanied by

[12] The intuition follows immediately from the 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 illustrated why this is the case.

sharp increase in the mass of the tail of the distribution.[13] 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 represent the corporate credit risk profile (as measured by PDs) increases by more than 4 times under 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.

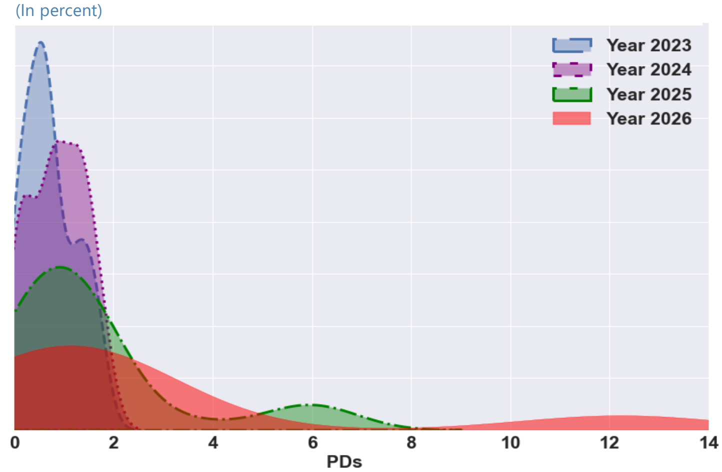
55. The distribution of bank delta PDs shifts significantly to the right where the tail gets increasingly longer and heavier (Figure 11 mid-panel). Under the early action in 2023 (albeit slightly delayed) the maximum delta PD across banks was around 0.2 percent. However, considering the uncertain future pathways coupled with longer delays in global action, the delta PDs in banking system could rise to as high as 1.5 percent if the actions are delayed to 2026. This constitutes more than 7-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.

56. The distribution of bank capital ratios also shifts to the right as tail gets increasingly longer and heavier, but the absolute impact appears modest (Figure 10 (bottom panel). As discussed above, since the impact on capital ratios is determined by expected credit losses from sectoral exposures under static balance sheet assumption, the absolute impact appears modest. However, judging by the relative increase, the maximum range of the distribution increases by almost 5 times under delaying the actions till 2026 versus 2023. The cumulative bank capital impact under delayed-uncertain path could reach as high as 0.8 with non-trivial probability relative to a maximum impact of around 0.3 percent under global action. As such, caution is required in interpreting these relatively benign system wide capital impact. The analysis shows that, once additional sources and channels of risks are allowed, the probability and size of impact to financial system could, in principle, significantly increase with longer delay in the action.

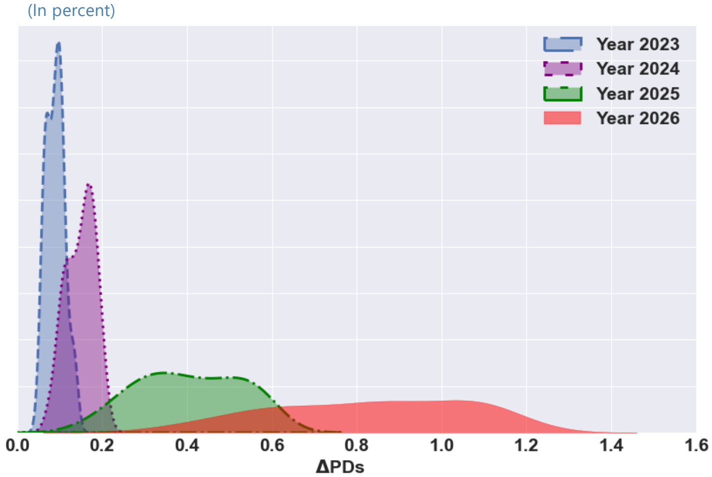
[13] The intuition follows mainly from the jump part of the financial model (Box 1) which generally captures sudden/discontinuous large shocks. This implies that the tails of the distribution are reached more often in presence of jumps than otherwise. For example, let us assume that in absence of jumps we observe a large (tail) shock to the spreads, say 500 bps basis points, just 1 percent of time, i.e., with 1 percent probability. Then, in presence of jumps, we would observe the same shock more often, say 5 percent of time, i.e., with 5 percent probability. Since increasing probability means 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 due to 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.

Figure 11. Significant Tail Risks Under Delayed-Uncertain Pathways

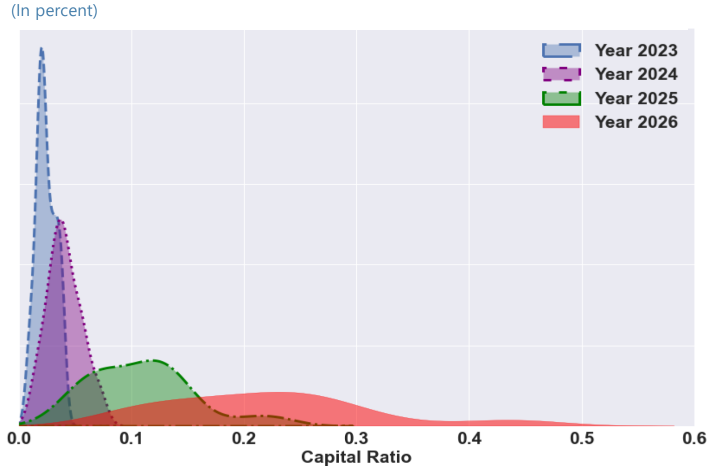
Time Varying Sequence of Distribution: Sectoral Corporate PDs
(In percent)



Time Varying Sequence of Distribution: Bank ΔPDs
(In percent)



Time Varying Sequence of Distribution: Bank Capital Impact
(In percent)



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

PHYSICAL RISK

A. Overview: Physical Risks in Mexico

57. This FSAP focuses on the analysis of acute physical risks, while recognizing that chronic risks may also be substantial for Mexico. Acute risks are associated with increased frequency and severity of hydrometeorological disasters (e.g., tropical cyclones, storms, floods, and droughts). Chronic risks are associated with gradual changes (e.g., sea level rise and gradual increases in temperatures). The focus of this analysis is acute risks. However, it is important to note that Mexico is also exposed to chronic risks, and these are relevant for inclusion in future analysis, given potential impacts of increasing temperatures (e.g., on labor productivity) and sea-level rise (e.g., on the tourism sector).

58. Mexico is highly exposed to hydrometeorological disasters associated with acute risks, **such as tropical cyclones, floods, droughts, and heatwaves.** During the last two decades, floods and tropical cyclones have constituted a substantial hazard burden among hydrometeorological disasters (Figure 12), both in terms of frequency of occurrence and the number of people impacted, with more than 15 million people affected by these hazards over the last two decades. Floods and tropical cyclones are thus the focus of this analysis. However, other acute risks, including drought and heatwaves, as well as chronic risks, may be relevant for future analysis. For example, there is evidence of a relationship between extreme heat and credit performance in Mexico (Aguilar-Gomez and others, 2022). Although direct impacts of droughts on the banking sector may be limited, for example due to low credit exposures to agriculture, they can nonetheless have substantial impacts on communities and the economy. For example, 80 percent of farmers in Mexico are smallholder farmers, with limited access to credit and insurance, and a reliance on rainfed production – hence high vulnerability to drought risk. Recent drought and heatwave conditions in Mexico have highlighted the importance of these risks. It is important to note that Mexico is also subject to substantial risk from other natural disasters that are not climate-related, including earthquakes.

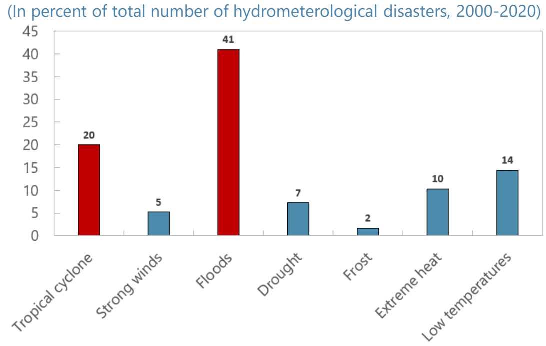
59. Hydrometeorological disasters can have major economic, financial, and fiscal consequences, depending on the geographic distribution of exposures relative to that of physical hazards. In the case of localized extreme events (e.g., floods or tropical cyclones), the concentration and geographic distribution of GDP and credit exposures relative to the geographic distribution of hazards is important for analyzing potential impacts of disasters on the economy and banking sector.

60. Both GDP and credit exposure in Mexico are heavily concentrated in a few states. In 2020, six states contributed collectively to around 50 percent of the national GDP: Mexico City (17.51 percent), Mexico State (9.15 percent), Nuevo León (7.74 percent), Jalisco (6.92 percent), Veracruz (4.53 percent), and Guanajuato (4 percent) (Figure 13). Credit exposure in Mexico is also heavily concentrated geographically in a few states, broadly reflecting the geographic distribution of GDP. More than 44 percent (1,513 billion MXN) of total credit (3,434 billion MXN) is recorded in Mexico City which is aligned with its contribution to GDP. Other federal states that account for a relatively high reported credit exposure are Nuevo Léon, Jalisco, State of Mexico, and Sinaloa which contribute respectively 13 percent, 6.4 percent, 4.9 percent, and 3.2 percent of total credit. The remaining 27 federal states account for only 28 percent of total credit exposure. The low concentration of credit exposure in several federal states known for their active economic activity may in part be due to the recording of credit at the domicile of a firm's headquarters (often in Mexico City), even though the operations financed by the credit may be located elsewhere in the country.

Figure 12. Hydrometeorological Disasters

Floods and tropical cyclones are the most frequent hydrometeorological disasters in Mexico…

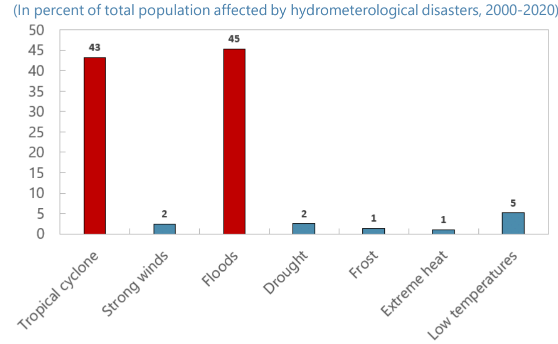
Occurrence of Disasters in Mexico by Disaster Type
(In percent of total number of hydrometerological disasters, 2000-2020)



Source: WB staff calculations based on CENAPRED data.

…and affect the highest number of people.

Population in Mexico Affected by Disaster Type
(In percent of total population affected by hydrometerological disasters, 2000-2020)



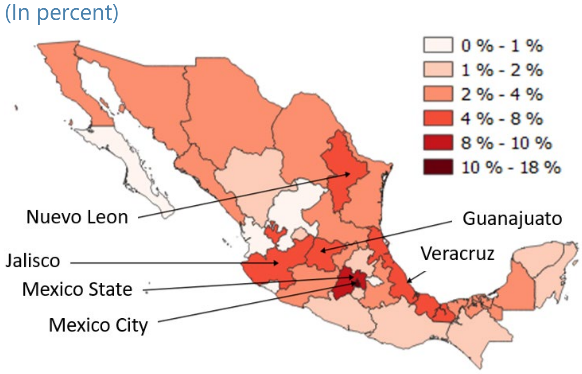
Source: WB staff calculations based on CENAPRED data.

Note: The estimates presented in Figure 12 are based on data from CENAPRED. Different methodologies for defining events and for estimating the affected population may result in different estimates of these variables, potentially resulting in higher estimates for some disaster types. The time period of the analysis (2000-2020) does not include the recent severe drought and heatwave events occurring in 2021 and 2022. Furthermore, Figure 12 does not include an estimate of the direct and indirect damages and economic losses associated with different hazard types and does not consider chronic risk

Figure 13. Geographic Distribution of GDP and Credit Exposure in Mexico

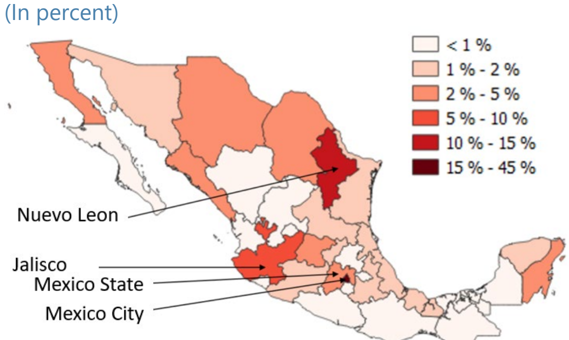
GDP is highly concentrated in a few states…

State Contribution to National GDP
(In percent)



…Credit exposure is too.

State Contribution to National Credit Exposure
(In percent)



Source: WB staff calculation using GDP data from statistica.com and credit data from Banxico (end of 2021).

61. Mexico is subject to a great variety of flood phenomena, including river floods and pluvial floods.[14] Major drivers of rainfall include tropical cyclones and easterly waves during summer, and cold fronts during winter (Magaña and others, 2003), with most rainfall concentrated in the rainy season (generally June to November). Extreme rainfall can result in pluvial floods and river floods. Coastal floods are also common, due to the presence of tropical cyclones that generate storm surges.

62. The most impactful flood events in Mexico over the past two decades occurred in Tabasco, and its surrounding states (Chiapas, Veracruz, Oaxaca and Puebla), generating significant economic losses and impacting millions of people, based on data from the Centro Nacional de Prevención de Desastres (CENAPRED). For example, the October 2007 floods in Tabasco and surrounding states resulted in economic losses of more than 35 billion MXN and affected more than 2 million people.

63. Mexico experiences tropical cyclones from both the Atlantic and Pacific basins. Similar numbers of major hurricane landfalls originate from these two basins (AIR, 2018). These tropical cyclones impact the coastline with strong winds, heavy precipitation, and storm surges. Mexico's mountain ranges along the coast both impact the rate at which landfalling storms dissipate, and result in orographic lifting which increases rainfall, meaning that tropical cyclones in Mexico are often accompanied by heavy rainfall and substantial flooding. Precipitation often extends inland, where it can cause extensive flooding.

64. Eight of the ten topmost impactful tropical cyclone events in Mexico since 2020 impacted states overlooking the Gulf of Mexico, according to data from CENAPRED. There are cases where some federal states were hit twice in a very short period (e.g., Hurricane Karl and Tropical Storm Matthew in Veracruz in 2010, which caused 25 billion MXN of economic losses and affected more than 500,000 people) or the storm had two landfalls (e.g., Hurricane Alex in 2010, which caused 25 billion MXN of economic losses and affected 650,000 people), significantly exacerbating financial losses and the impact on populations.

65. Climate change is expected to affect the frequency and severity of extreme precipitation in Mexico. The historical (1985-2014) 1-in-100-year maximum 5-day cumulative precipitation for Mexico is expected to occur with a return period of less than 50 years by the end of the century under SSP5-8.5 (WB, 2021a).[15] Similarly, the historical 1-in-100-year maximum 1-day cumulative precipitation is expected to occur with a return period of less than 40 years by the end of the century under SSP5-8.5. Such increases in the frequency of extreme rainfall events could in turn lead to increased flood risk.

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[14] River floods occur when water in a river, lake or other waterbody overflows onto adjacent land. Pluvial floods occur when extreme rainfall results in inundation independent of an overflowing waterbody.

[15] SSP5-8.5 represents an extreme climate change scenario, corresponding to Shared Socioeconomic Pathway (SSP) 5 with a total radiative forcing level by 2100 (cumulative measure of greenhouse gas emissions from all sources) of $8.5 W/m^2$.

66. Although increased extreme precipitation may increase flood risk, it is important to note that other factors may influence flood risk too, including changes in antecedent conditions, due to increase temperature resulting in reduced soil moisture. Whilst some studies suggest increased flood risk in Mexico due to climate change, several studies have found that the risk may decrease in some regions, including in Tabasco and other southeastern states (Haer and others, 2018, Hirabayashi and others, 2013, Hirabayashi and others, 2021). There is substantial uncertainty in flood risk projections for Mexico (Alfieri and others, 2017).

67. Climate change is projected to impact tropical cyclone risk in Mexico, with tropical cyclone frequency estimated to decrease in the North Atlantic and increase in the northeast Pacific under Representative Concentration Pathway (RCP) 4.5 (Knutson and others, 2015). Both basins, however, are expected to experience an increase in the frequency of tropical cyclones of at least Saffir-Simpson Category 4 intensity (Knutson and others, 2015). Focusing on landfalling tropical cyclones in the Yucatan Peninsula, it is estimated that intense hurricanes will be more frequent under RCP 8.5 (Appendini and others, 2019). Sea level rise may exacerbate storm surge risk associated with tropical cyclones. The precipitation associated with tropical cyclones is projected to increase, with projected increases ranging from ~5 percent to 40 percent (Knutson and others, 2020), driven by increased tropical water vapor. However, there is substantial uncertainty associated with these projections.

B. Physical Risk Scenarios

68. Five scenarios have been designed to explore the potential impacts of tropical cyclones and floods.[16] Scenarios TC1, TC2 and TC3 are tropical cyclone events, Scenario F1 is a flood event, and Scenario ES1 is an extreme season comprised of a sequence of several extreme events (i.e., TC1, TC2, TC3, and F1 all occurring within a few months of each other during one season) (Figure 14). Each of the scenarios is an extreme (but plausible) event and is estimated to result in direct damages with a return period greater than 50 years at a national scale.

69. To analyze the impacts of climate change on the severity of these scenarios, two versions of each scenario have been defined. The first has been defined based on the estimated distribution of extreme events under historical/current climate conditions ("historical conditions"; Scenarios TC1-hist, TC2-hist, TC3-hist, F1-hist, and ES1-hist). The second has been defined based on the estimated distribution of extreme events under future climate change conditions corresponding to RCP8.5[17] by the middle of the century and the end of the century ("climate change conditions"; Scenarios TC1-cc, TC2-cc, TC3-cc, F1-cc, and ES1-cc).[18] The modelling of these scenarios considers potential future increases in hazard severity associated with climate change (i.e., increased

[16] The team also explored a sixth scenario, corresponding to an urban flood event in Mexico City but it was not included in this report due to the very high uncertainty associated with direct damages estimates for this scenario, given a lack of historical events of a similar severity and modelling limitations.

[17] Representative concentration pathway (RCP) 8.5 represents an extreme climate change scenario, corresponding to 8.5W/m2 of total radiative forcing (a cumulative measure of greenhouse gas emissions from all sources) by 2100.

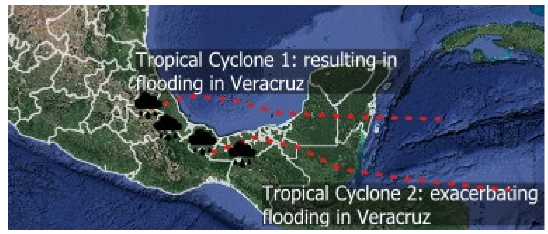
[18] The team also analyzed some scenarios using RCP4.5 but these results are not included in this report.

windspeed and precipitation for tropical cyclone scenarios and increased streamflow for flood scenario), but assumes constant vulnerability and exposure (i.e., potential future growth of capital stock is not considered). Each scenario is intended to have the same frequency of occurrence (return period) for the historical and climate change conditions, with the climate change adjustment applied to the hazard severity only (keeping the frequency fixed).[19]

Figure 14. Tropical Cyclone and Flood Scenarios

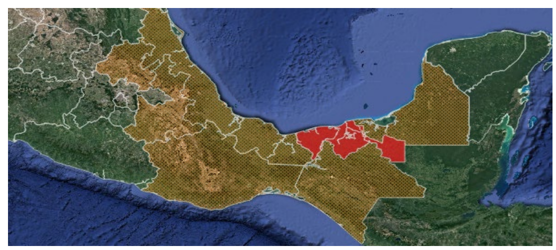
The scenarios analyzed are a tropical cyclone with two landfalls (Yucatan Peninsula as Category 4 hurricane and northeast Mexico with heavy precipitation) (TC1), …

…two tropical cyclones impacting Veracruz within approximately 10 days (TC2), …

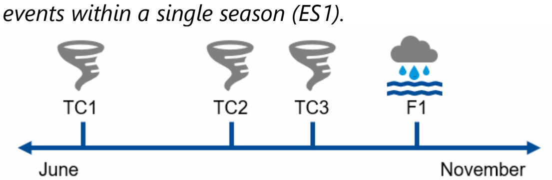


…a tropical cyclone making landfall in Colima impacting Guadalajara with Category 1-2 winds (TC3), …

…a river flood in Tabasco and surrounding states (F1), …



…and an extreme season scenario combining all these events within a single season (ES1).



Source: WB staff.

70. Scenario TC1 is defined as a North Atlantic tropical cyclone event with two landfalls in Mexico. The first landfall is on the Yucatan Peninsula as a Category 4 hurricane. The second landfall is in Tamaulipas in northeast Mexico, with lower wind speeds (Tropical Storm / Category 1 hurricane) but heavy rainfall impacting Nuevo León, including Monterrey. The initial landfall may be compared with other hurricanes impacting the Yucatan Peninsula, including Janet 1955, Gilbert 1988, Wilma

[19] Analyses of climate change impacts can consider the change in frequency for an event (or series of events) of a given magnitude/severity, and/or the change in the magnitude/severity for an event (or series of events) of fixed frequency. The two approaches are related due to the relationship between the frequency and severity of extreme events, and the decision regarding which approach to use should be tailored based on the specific application. For this FSAP analysis, the frequency was kept fixed to explore the potential impacts of climate change on the magnitude/severity of extreme events.

2005, and Dean 2007 (see Appendix II for map showing these events). The second landfall may be compared with other tropical cyclones that made landfall in northeast Mexico that were associated with flooding in Monterrey, including the 1909 Monterrey Hurricane, Hurricane Beulah 1967, Hurricane Gilbert 1988, and Hurricane Alex 2010.

71. Scenario TC2 is defined as two tropical cyclones impacting the state of Veracruz 10 days apart with heavy precipitation. This scenario is based on a similar sequence of tropical cyclones that impacted Veracruz in 2010 (Hurricane Karl and Tropical Storm Matthew), which resulted in substantial damages, mainly due to flooding caused by heavy precipitation.

72. Scenario TC3 is defined as an Eastern Pacific tropical cyclone making landfall at Manzanillo, Colima as a Category 4 hurricane and impacting Guadalajara, Jalisco as a Category 1-2 hurricane.[20] The event may be compared with other Category 4+ hurricanes impacting the Jalisco/Colima region of Mexico, including Hurricane Patricia 2015. However, the estimated losses from this event are higher than those of Hurricane Patricia, since Hurricane Patricia did not make a direct hit on the exposure concentrations of Manzanillo and Guadalajara (AIR, 2015).

73. Scenario F1 is defined as a river flood event in Tabasco and surrounding states. This scenario is based on several historical floods that have impacted the region, including the 2007 Tabasco floods. Key factors that contributed to this flood event include heavy rains associated with the combination of a cold front and tropical storm Noel and the release of water from the Peñitas dam. This event was estimated to have a 1-in-100-year return period in the region (Ramos and others, 2009). Tabasco is an area of concern for flooding, having experienced frequent flood events over the past decades (Haer and others, 2017), including floods in 1993, 1999, 2007, 2008, 2009, 2010, 2011 and 2020.

74. Scenario ES1 is defined as an extreme season comprised of a sequence of several extreme tropical cyclone and flood events, namely TC1, TC2, TC3 and F1, all occurring within a few months of each other during one season. This scenario was included to analyze the potential for substantial economic and financial impacts if Mexico is impacted by a series of extreme events affecting different parts of the country in close succession. Such seasons with a series of extreme events have occurred historically, as illustrated by an analysis of EMDAT event frequency (Table 2). A recent example of a year with multiple severe events is 2010, when Hurricane Alex (one of the similar events for the second landfall of Scenario TC1), Hurricane Karl and Tropical Storm Matthew (similar events for Scenario TC2), and flooding in Tabasco (albeit much less severe than in 2007, a similar event for Scenario F1) occurred.

[20] This event was selected from the STORM global synthetic tropical cyclone hazard dataset (Bloemendaal and others, 2020), which consists of 10,000 years of synthetic tropical cyclone tracks, generated using historical data from IBTrACS.

Table 2. Mexico: Historical Frequency of Tropical Cyclone and Flood Events[1/]

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean
Flash flood	1	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	3	0	1	0	0	2	0.55
Riverine flood	0	0	1	1	1	2	1	1	0	5	2	3	0	1	0	1	0	1	0	0	0	0	0.91
Tropical cyclone	1	5	3	2	0	4	3	4	1	2	4	5	2	4	6	1	2	4	2	3	5	5	3.09
Total	2	6	5	4	2	6	4	5	2	7	6	8	2	5	6	2	5	5	3	3	5	7	4.55

1/ Number of events meeting EMDAT event criteria 2000-2021. At least one of the following criteria must be met for an event to be included in the EMDAT database: (i) 10 or more deaths; (ii) 100 or more people affected; or (iii) declaration of state of emergency or appeal for international assistance.
Source: WB analysis of EMDAT data (CRED, 2022).

C. Direct Damages

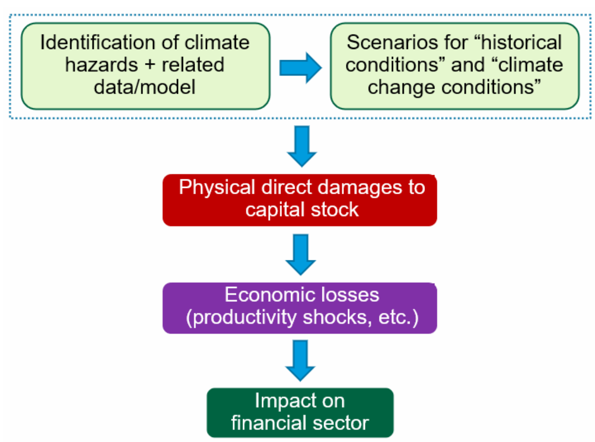
75. To estimate the financial sector impacts for each of the defined scenarios, the direct damages and economic losses are first estimated (Figure 15). The direct damage estimates, expressed as the percentage of physical capital stock that is damaged for a given scenario, are used as an input to the economic and financial sector impact modelling described in Sections D and E.

Figure 15. Method for Direct Damages and Financial Sector Impact Modelling

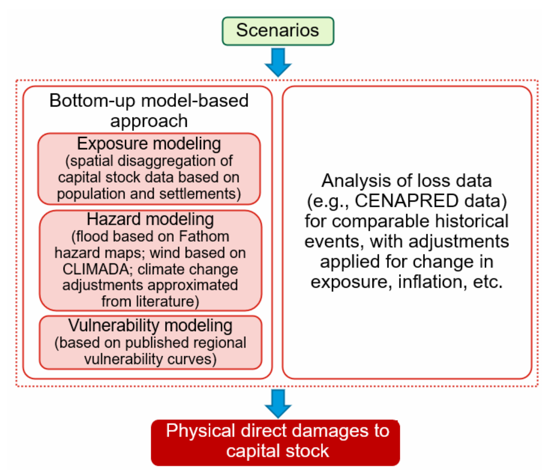
To estimate the financial sector impacts for each scenario, the direct damages and economic losses are first estimated.

Specifically, the direct damage estimation combines an analysis of historical data with a model-based approach.

Method for Direct Damages



Method for Financial Sector Impact Modelling



Source: WB and IMF staff.

76. The methodology used to estimate direct damages[21] for each scenario combines: (i) an analysis of historical loss data for comparable events; and (ii) a model-based approach using exposure, hazard, and vulnerability data (Figure 15). For the analysis of historical CENAPRED loss data, historical losses for events comparable to each scenario (where available) are scaled to a 2020 loss estimate based on exposure growth and inflation assumptions. The model-based approach combines three modules: (i) an exposure module, which characterizes the spatial distribution of capital stock;[22] (ii) a hazard module, which characterizes the flood depths and/or windspeeds associated with a scenario;[23] and (iii) a vulnerability module, which estimates the damage for a given flood depth and/or windspeed for the exposure at risk.[24] Additional details regarding the methodology for direct damage estimation are provided in Appendix II.

77. The modelling of the "climate change conditions" scenarios considers potential future increases in hazard severity associated with climate change by adjusting the flood depths and/or windspeeds. In the case of tropical cyclone scenarios, windspeeds and precipitation increase assumptions were based on the methodology used in CLIMADA (CLIMateADAptation; Aznar-Siguan and Bresch, 2019),[25] applied to estimates from Knutson and others (2015). The changes in tropical cyclone precipitation were subsequently translated to changes in flood depth.[26] In the case of the flood scenario, estimated changes in streamflow available from literature (Raffaele and Di Sante, 2020) were converted to changes in flood return period and finally flood depth.

78. Direct damages for the most severe scenario, namely the extreme season scenario, are estimated to be approximately 0.9 percent of the total national capital stock for "historical conditions" (ES1-hist) and 1.9 percent for "climate change conditions" (ES1-cc end-of-century) (Table 3).[27] Direct damages for individual scenarios vary from 30 billion MXN

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[21] Direct damages (first-round effect) refer to the physical damage to assets caused directly by an event, with the losses occurring at the time of the disaster or shortly thereafter. Examples of direct physical damages include the destruction of residences, productive capital, infrastructure, and crops.

[22] 2013 total physical capital stock data from Instituto Nacional de Estadística y Geografía (INEGI, 2013) was scaled to an estimate of 2020 exposure, then spatially disaggregated using population and settlement data from the Global Human Settlement Layer.

[23] The approach used to model hazard is based on the perils considered in each scenario, namely wind and/or flood. Note that storm surge is not modelled. The wind component of hazard was modelled based on CLIMADA's implementation of Holland's (2008) method to calculate a wind field of each scenario track. The flood component of hazard was modelled using Fathom riverine (defended) hazard maps (Sampson and others, 2015), with the selection of return period for each basin based on a combination of historical flood footprints for similar events, event descriptions, precipitation maps, and available precipitation and streamflow return period analyses.

[24] The European Commission Joint Research Centre vulnerability curves (Huizinga and others, 2017) were used for flood damage estimates, and the Eberenz and others (2021) regional tropical cyclone impact functions were used for wind damage estimates. The flood vulnerability curves relate flood depth to damage. The tropical cyclone vulnerability curves relate wind speed to damage.

[25] CLIMADA is an open-source natural catastrophe damage model.

[26] To translate precipitation changes to changes in flood depth, it was assumed that precipitation-streamflow elasticity for extreme events approaches unity, and published streamflow return period relationships were applied.

[27] These estimates are for an extreme season scenario with a high return period (i.e., they are not expected to occur at this level of severity every year). The estimated damages are the total damages for the entire season.

(approximately <0.1 percent of capital stock) to 600 billion MXN (approximately 0.7 percent of capital stock) under "historical conditions". The return period of the direct damages at a national scale is estimated as 50 years for TC1-hist, 50-100 years for TC2-hist, 500 years for TC3-hist, and 50-100 years for F1-hist, with details of the methodology used to estimate return periods is available in Appendix II. However, there is substantial uncertainty associated with these estimates due to the lack of access to a full catastrophe model. A comparison with the "climate change conditions" scenarios indicates that damages may increase by 40-50 percent by mid-century under RCP8.5, and by more than 100 percent by end-of-century.

Table 3. Mexico: Direct Damage Estimates for Physical Risk Scenarios

Scenario	Climate conditions[1/]	Direct damage rate (percent of capital stock)	Climate change impact (relative to "historical conditions" scenario)
TC1	historical conditions	0.14 percent	
	climate change conditions mid-century	0.21 percent	43 percent
	climate change conditions end-century	0.23 percent	59 percent
TC2	historical conditions	0.03 percent	
	climate change conditions mid-century	0.05 percent	54 percent
	climate change conditions end-century	0.08 percent	124 percent
TC3	historical conditions	0.67 percent	
	climate change conditions mid-century	1.01 percent	51 percent
	climate change conditions end-century	1.45 percent	118 percent
F1	historical conditions	0.05 percent	
	climate change conditions mid-century	0.08 percent	54 percent
	climate change conditions end-century	0.13 percent	145 percent
ES1	historical conditions	0.90 percent	
	climate change conditions mid-century	1.35 percent	50 percent
	climate change conditions end-century	1.89 percent	110 percent

1/ "Climate change conditions" are based on RCP8.5.

79. These direct damage estimates are subject to a range of assumptions and limitations. Several catastrophe models are available for Mexico (e.g., those developed by Universidad Nacional Autónoma de México, Evaluación de Riesgos Naturales, Verisk, RMS and other commercial vendors), and are widely used in the insurance industry and for regulatory purposes. It is important to note that the FSAP team did not have access to these models for this analysis, and that the loss estimates could potentially be substantially improved using such a model. For the exposure module of the model, the approach for spatially disaggregating capital stock data assumes that capital stock distribution is reflective of the spatial distribution of population, which may not be accurate due to inequalities and the non-homogenous distribution of wealth and poverty. There is also substantial uncertainty associated with the hazard module, particularly when modelling the "climate change conditions" scenarios. For example, there is uncertainty associated with projected changes in windspeed and precipitation, and the relationships used to translate precipitation changes to changes in flood depths rely on several simplifying assumptions, some of which have not been validated locally. The vulnerability module relies on regionally calibrated curves that have not been locally validated for Mexico. The model results are sensitive to each of these model components and should thus be interpreted with full recognition of the limitations of the analysis. Further analysis based on more granular exposure information and leveraging latest climate science and catastrophe modelling expertise in Mexico would allow damage estimates to be refined.

D. Macro-Financial Impact

80. The estimates of direct damages and destruction to the physical capital from physical hazards constitutes the key link between climate driven risks and macro-financial outcomes that can be further translated into impact on the financial sector. The key outcome from the above analysis on climate scenarios that connects the impact of climate related physical hazards to the economic and financial system is the estimate of damages. These damages are first approximated at regional level and then aggregated up to generate the damage at the national level. As such, the estimated direct damage rates to the physical capital stock can be interpreted as an immediate direct shock (equivalently, a depreciation shock) to the capital stock in an aggregated macroeconomic model. However, it is important to contextualize the macro-financial impact of climate risk driven estimated damages in terms of a country's specific physical risk characteristics. In this regard, the overall size, geographical location of the country, and exposure of various locations of the country to a variety of physical hazards, play a fundamental role in driving the aggregate damage estimates as reported above. Additionally, the limitations of the methodologies and models as discussed above also apply.

81. The team used the damage estimates from the extreme season scenarios as the key input in generating scenario dependent macro-financial paths. One of the key objectives of the FSAP risk analysis is to use extreme but plausible risk scenarios. This is because the analysis is largely attempts to quantify channels and mechanisms of risk propagation and their implications due to potential materialization of tail risk events. Given these broad objectives and considering the materiality of the estimated damage rates as reported in in Table 3 above, the natural choice is to explore macroeconomic impact of the extreme season scenarios (ES1). To point out for clarity, the direct damages to aggregate capital stock used in the macro model is 0.9 percent under the ES1-hist, i.e., under historical conditions, and 1.9 percent under the ES1-climate change conditions. Thus, the results discussed below will correspond to these set of scenarios and corresponding damages. The horizon of the analysis is three years till 2024.[28]

[28] The years 2022-2024 are consistent with the analysis used in the FSAP stress testing exercise (which was calibrated using recent data), with the historical and future climate change conditions modeled as added risks to this underlying

(continued)

82. It is well known that the direct effects of physical hazards are also generally accompanied by indirect effects via other channels that could potentially amplify the initial direct effects resulting from physical hazards. In this regard, the team considered three additional channels and amplifiers to account for impact that is not captured by immediate direct damages (break into three bullet points). Note that there could be multiple other channels in addition to these. However, given the data and model limitations, these shocks lend themselves to easy integration into the existing macro model (GFM), while also capturing relevant economic dynamics one would likely observe in the immediate aftermath of extreme events.[29]

- **Direct destruction of physical capital:** The direct damages to the existing physical capital were estimated at the regional state level and aggregated to arrive at the damages to the national capital level (Table 3). This constitutes the direct channel of risk transmission from climate events, leading to an immediate impact or shocks to the physical capital in a macro model.
- **Impact on total factor productivity (TFP):** The team considered shocks to the TFP arising from the direct damages to the capital stock. Disasters reduce the productivity since it may not be possible to rebuild the capital quickly in order for the output to recover. One of the drivers of TFP reduction after a disaster could come from the complementarity of infrastructure and non-infrastructure capital, meaning that if infrastructure capital is damaged by a disaster, then non-infrastructure capital also becomes unproductive, which can magnify the impact of the disaster (Hallegatte and others, 2022). The shock was calibrated to be twice as much as the damage rate and assumed to be highly persistent. This is consistent with a general finding in the literature that overall productivity tends to be significantly lower after the disaster events (e.g., Dieppe and others (2020)).
- **Impact on unemployment:** Since capital stock and labor also complement each other during production, it is economically intuitive to consider a concurrent shock to unemployment in the event of large/immediate destruction to capital stock. For example, as factories and other productive infrastructures are damaged, the workers that complement the uses of these capital stocks are likely to be displaced as well. The shock is informed by the elasticity of unemployment to changes in capital stock in Mexico.
- **Effects from financial markets:** Given the sequence of climate events considered in the extreme season scenario, it is highly plausible that equity markets might also experience negative shocks. Since markets are forward looking, such disaster events could imply potential

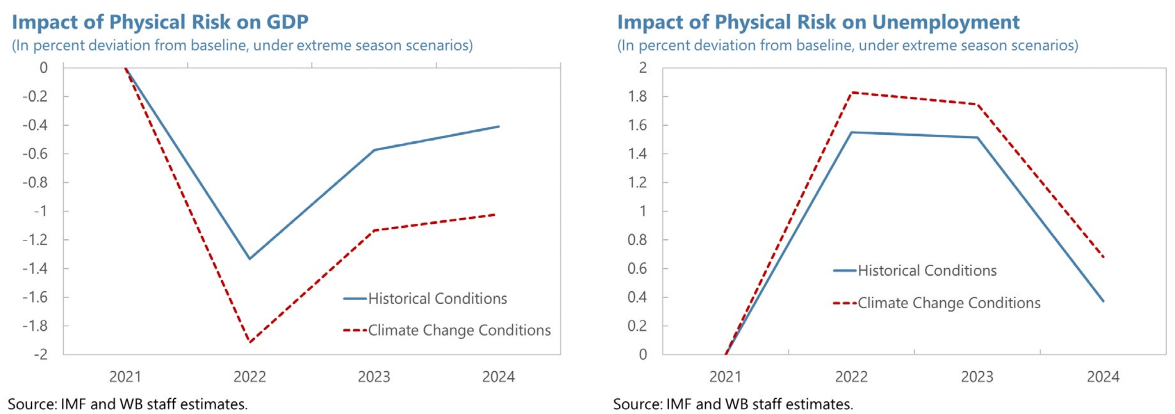
framework. Although the damage estimates from future climate change scenarios explore mid-century and end-of-century physical risk (from tropical cyclones and floods), it is possible that the damages from these risks could materialize within the FSAP analysis horizon, albeit with a substantially lower probability. The macroeconomic impacts conditioned on these damages are modeled using the same underlying macro model as in the FSAP stress test (2022-2024) to enable comparability of the results relative to baseline without climate risk (i.e., isolating the impacts of the potential changes to tropical cyclone and flood hazard due to climate change from other potential future macroeconomic changes).

[29] The GFM model is a standard global macro-financial model is regularly used to generate scenarios for FSAP risk analysis such as solvency stress test. The model allows for generating general equilibrium paths of macro-financial variables given various shocks, such as those arising from labor market frictions, productivity etc. Some of these shocks, the primary one being the immediate destruction of physical capital stock (analogous to shocks to capital depreciation), were applied in this analysis as discussed above. Details of the model are contained in Vitek (2018).

negative impact on the cash flow generating capacity of the firms, thereby lowering the market value of the equity of the firms. The shock is informed based on the elasticity of changes in overall equity market returns to changes in capital stock in Mexico. It is possible to calibrate shocks to other market variables as well, but the team picked equity markets given its importance in satellite model calibrations of the standard solvency exercise.[30]

83. The impact of physical hazards from floods and tropical cyclones on the overall macroeconomy could be significant as observed from the impact on GDP. Under the extreme season scenario, the impact on GDP in growth terms (in deviation from the baseline) under the "historical conditions" (ES1-hist) is about 1.4 percent in 2022. However, considering the impact of climate change (ES1-cc end-of-century), the effect on GDP rises to as much as 2 percent in 2022 (Figure 16). These results confirm that increased climate risks could have significant impacts going forward and the economic costs of climate driven risks are non-trivial. Additionally, the initial impact of the risk could persist well into the future from additional indirect channels as discussed above.

Figure 16. Impact of Extreme Season Scenarios on Macroeconomic Variables



Note: The extreme season scenarios shown are ES1-hist (historical conditions) and ES1-cc end-of-century (climate change conditions based on RCP8.5).

E. Impact on the Financial System

84. The approach follows standard FSAP stress testing methodology where the capital adequacy ratio (CAR) of the entire financial system was projected, although this is not a standard stress testing exercise. Standard stress testing practice is generally designed to assess the resilience of banks and the financial system as a whole against pass-fail criteria, based on the impact on capital ratios relative to the regulatory requirements. Importantly, the standard stress tests, as used in other workstreams of this FSAP rely on historical relationships between macro-financial tail risks and the consequent impacts on banks and the financial sector. The corresponding risk scenarios are extreme but plausible based on historical episodes. In the case of climate risks, the scenarios are similarly defined to be extreme but plausible, considering potential future changes in

[30] While other macroeconomic and financial variables (including interest rates, PDs of loans/debt) could also be impacted after materialization of climate events, their impact (other than the endogenous impact already captured by the scenario model) is not considered in this analysis.

the likely severity of extreme events due to climate change. The analysis of physical climate risks in FSAPs is still at an early stage, with a focus on raising awareness of these risks, and exploring new methodologies to analyze them.

85. The impact on CAR is also represented as deviation from baseline CAR projections for the baseline plus current/historical condition scenario and baseline plus climate change conditions scenario. The baseline of the exercise is the same one used in the risk analysis of this FSAP and based on the most recent (prior to the exercise) June 15, 2022 World Economic Outlook projections. Given that the two climate related scenarios are considered as additional risks on top of the baseline, the impact on capital adequacy ratios can also be interpreted analogous to that in the standard baseline versus adverse scenario(s) setting of the standard stress test exercise.[31]

86. The current physical risk analysis suggests that impacts on the banking system might occur in the near term, but not at a scale to generate a systemic stress event. Figure 17 shows that under the extreme season scenario under historical conditions (ES1-hist), the aggregate capital adequacy ratio of the Mexican banking system would decline by about 1 percentage point versus the baseline. Considering risk under climate change conditions (ES1-cc end-of-century), the capital ratio depletion is approximately 1.2 percentage points. While these are relatively modest effects, they nevertheless suggest non-trivial effects that increasingly severe climate events could generate in the future. Furthermore, there is also significant heterogeneity of capital impact across banks. For example, at some banks the CAR could decline by almost 4 percent under historical conditions and over 4 percent under climate change conditions, relative to the baseline. These estimates show that significant vulnerabilities do exists among some individual banks, even if the system-wide aggregate impact is relatively modest.

87. It is important to interpret the results with caution given a range of scenario and model limitations. For example, the FSAP team did not have access to granular exposure data and a full catastrophe model, and there are substantial uncertainties associated with quantifying effects of complex risks associated with climate change. The analysis only considered a set of tropical cyclone and flood scenarios, thereby not accounting for the potential for other climate-related disasters to occur simultaneously, resulting in non-linear compounding or amplification of impacts.[32] The materiality of the physical risks associated with climate change could be much larger if other risks (e.g., droughts, heatwaves, and chronic risks) are also considered. Furthermore, whilst the

[31] A fully-fledged solvency ST exercise is assumed under the physical risk scenario where shocks from economic losses is fed into the same scenario generation framework (as discussed earlier). This allows us to perform a full top-down exercise that includes all components (credit, market, NII, RWAs etc.) as described and documented in the separate Mexico FSAP TN on Systemic Risk Analysis and Stress Testing (July 2022).

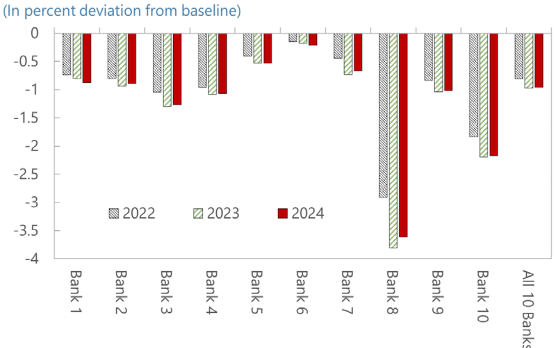
[32] It is possible for some events associated with substantial precipitation to have a positive effect in relieving drought conditions, and other physical risks (e.g., heatwave conditions). Such effects have not been considered by the FSAP team for this analysis but are nonetheless relevant to note. The Monterrey region is currently experiencing a severe drought, with water rationing potentially affecting productivity in this important industrial region. The rainfall associated with an event such as Scenario TC1 could potentially help to alleviate the drought conditions, highlighting the potential interactions between different types of physical risks. Similarly, Lake Chapala, located on the situated on the border of the states of Jalisco and Michoacán, currently has a relatively low water level, contributing to potential water scarcity issues. Although Scenario TC3 is defined as mainly a wind-driven event (rather than an event causing widespread flooding), it is possible that any precipitation associated with the event could help to partially replenish the lake. However, such effects are complex and not modelled in this analysis.

modelling of direct damages captured impacts to physical capital stock by taking into account the geographical distribution of hazard and exposure, this geospatially explicit modelling did not model potential indirect effects, including those associated with business interruption and large-scale disruptions in supply chains.

88. While the macroeconomic model attempted to capture some of these indirect effects, important limitations exist. Given the aggregated national-scale macro model used to arrive at impact on GDP and other macro relevant variables, the regional variations, and interconnected dynamics across different parts of the country, could not be captured in a sufficiently granular way. Additionally, given the linearized dynamics of the model, the significant non-linearity that could potentially be associated with amplifications effects even in an aggregated model, are not captured.[33] Nevertheless, despite the limitations, the non-negligible impact on the CAR, coupled with potential for significant future risks, highlight the need for vigilance regarding physical risks to the financial system, and suggest that further analysis and monitoring of these risks should be developed.

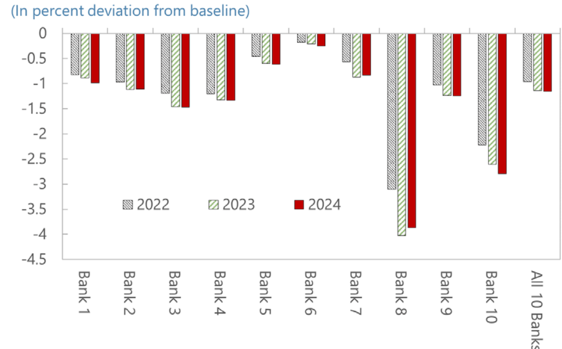
Figure 17. Impact of Extreme Season Scenarios on Capital Adequacy Ratio

CAR of Banks Under Historical Conditions
(In percent deviation from baseline)



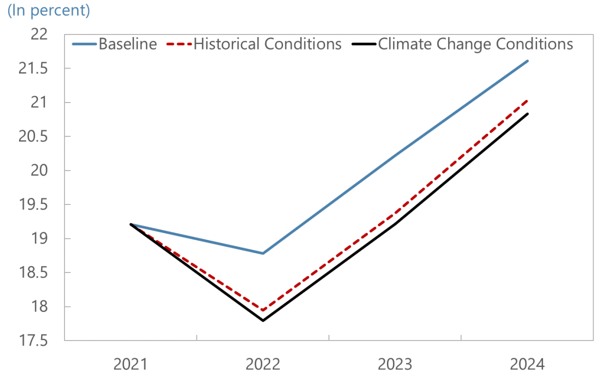
Source: IMF and WB estimates.

CAR of Banks Under Climate Change Conditions
(In percent deviation from baseline)



Source: IMF and WB estimates.

Aggregate CAR in Baseline vs. Extreme Season Scenarios
(In percent)



Source: IMF and WB estimates.

Note: The extreme season scenarios shown are ES1-hist (historical conditions) and ES1-cc end-of-century (climate change conditions based on RCP8.5).

[33] Further, the analysis also does not account for potential adaptation policies in the future that could mitigate the impact of extreme climate events and thereby lessen the severity of impact on the banking sector.

CONCLUSIONS AND RECOMMENDATIONS

89. The transition risk analysis revealed heterogeneous impacts across different corporate sectors. 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 significantly get 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. However, it must be emphasized that even though some sectors are not as emission intensive in their production, like the construction sector, they could still be negatively affected depending on their initial financial conditions.

90. The results, while not finding evidence of imminent systemic risk at this early stage of modeling, point to the need for more work and continued vigilance. The analysis only covered the corporate loan portfolio of the commercial banking sector where the data limitations precluded a more granular analysis. Further, multiple layers of complexities, uncertainties, and simplifying assumptions warrant caution in interpreting the results. Nevertheless, the analysis discovered pockets of vulnerabilities in the corporate sector, suggesting that there could be other risks that still need to be fully explored. Further, whereas the bank capital impact appeared somewhat modest under the global action, delayed-uncertain analysis also revealed significant increases in the tail of the capital impact distribution, suggesting potential for material impact. Since tail risks get larger the longer the delay, continued vigilance is required with respect to other channels of risks that the analysis did not cover as discussed before. 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.

91. The results of the physical risk analysis (focused on acute risks associated with tropical cyclones and floods) highlight the potential for non-trivial impacts of these hazards on the financial system in Mexico. Material impacts due to hydrometeorological disasters may be realized both under historical/current climate conditions and considering the impacts of climate change, albeit with greater severity. It is important to recognize that the analysis is only limited to tropical cyclones and floods, and that the materiality of the physical risks associated with climate change could be much larger if other risks (e.g., droughts, heatwaves, and chronic risks) are also considered. In this context, it is important to ensure that mechanisms are in place to improve financial resilience to such disasters.

92. The analysis is subject to uncertainty at multiple levels, and the results should thus be regarded as a preliminary "first estimate" using the data and tools available. Uncertainties exist in all layers of the physical risk analysis, including the definition of climate and disaster scenarios, the model used to estimate direct damages, the transmission channels in the macro-financial model, and the financial sector impact model. Hence, using the results of the analysis to draw precise prudential policy implications is likely to be premature at this stage. However, it is important to note that although there is substantial uncertainty on the quantitative side (i.e., strength of climate change risks), the qualitative effects (i.e., the sign of risk materialization) are increasingly well understood. Further analysis of the potential impacts of climate change on financial stability should be a priority, and the sensitivity of results to key modelling assumptions should be explored.

93. The authorities should improve data collection and modelling to enable more comprehensive and granular analysis of transition and physical risks. To improve confidence in the results of the analysis of physical and transition risks, improved data and further modelling are essential. Given sizable concentration of corporates in the banking sector portfolio, disclosure should be enhanced to collect granular data for understanding the carbon footprint of the entire spectrum of firms, not just the larger and listed ones. Further climate-related financial risk management and disclosure is discussed further in the FSAP Policies and Regulations to Manage Climate Risks and Stimulate Green Finance Technical Note.

94. Additionally, authorities are encouraged to partner further with other government entities, the private sector, and research institutions to leverage their expertise in climate and catastrophe modelling to assess the impact of physical risk in a highly granular and data-driven way, and to incorporate that into analysis of banking sector resilience to climate-related hazards. This analysis should cover a broad range of physical risks, including both acute and chronic risks. In this regard, the enhanced analysis in the latest Financial Stability Report, studying exposures of corporate and consumer credit portfolios to physical and transition risks, is a welcome development. Authorities are encouraged to strengthen, expand, and accelerate such efforts on incorporating climate related risk analysis in the financial system analysis.

95. Given the potential for substantial risks associated with climate-related disasters, the authorities should further strengthen their climate and disaster risk finance strategy and explore opportunities to expand insurance for climate-related risks. Disaster risk finance and insurance, including both public and private instruments, are an important tool for improving resilience to climate-related disasters. Despite the dismantling of FONDEN[34] in 2021, the Mexican government continues to allocate budgetary resources for emergency response and reconstruction. Going forward, Mexico's climate and disaster risk finance strategy should prioritize key principles of integrated financial and operational preparedness at local, state, and national levels, and continue to leverage private risk capital (e.g., insurance and catastrophe bonds). In addition, given current low levels of insurance penetration in Mexico, there is a need to further develop catastrophe risk insurance markets in Mexico to help improve financial resilience. This is explored further in the FSAP Policies and Regulations to Manage Climate Risks and Stimulate Green Finance Technical Note.

[34] FONDEN was a natural disaster fund established by the government in 1996 to support disaster relief and reconstruction using ex-ante federal government budget allocations. FONDEN's resources were leveraged using market-based risk transfer instruments, including catastrophe insurance and catastrophe bonds.

Appendix I. Transition Risk

1. 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 common for reporting corporate data by many commercial data vendors, but it is very close to NAICS classification, but some minor differences exist between the two- systems. As such, first the firms were grouped into sectors based on their SIC codes that 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 manufacturing sector in the CGE model to match the sectoral affiliations of the firms based on 4 digit SIC codes. As such, not all sectors of highly granular CGE model could be used. Then these aggregated sectors, were mapped into corresponding 2-digit NAICS sectors. Despite the limitations, finally a coherent set of aggregated sectors of corporate data were created to broadly correspond to 2-digit NAICS sector, with minimal discrepancy. The main reason for this exercise was to allow for consistently translating the sectoral PD paths into corresponding impact on bank credit exposures based on 2-digit NAICS codes.

Appendix Table 1. Mexico: Mapping of Sectors From CGE Model to 2-Digit NAICS Sector

CGE Sector Names	Aggregated sector names in the analysis	Approx. NAICS sector and 2-digit code equivalent
Fossil Fuel	Mining incl. oil & gas	Mining, 21
Utilities	Utilities	Utilities, 22
Construction	Construction	Construction, 23
Food & Textile 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

Appendix Table 2. Mexico: Projection of Corporate Variables and Vulnerability Indicators

Interest Coverage Ratio (ICR):

$$ICR_t = \frac{EBIT_t}{Interest\ Expense_t}$$

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

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

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):

$$CR_t = \frac{Current\ Assets_t}{Current\ Liabilities_t}$$

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

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

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

Appendix Table 3. Mexico: 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

Note: t-values are reported in parenthesis. Intercept is set to equal to the average of fixed effects across firms since firm that are used in the projections are subset of the firms used I the panel regression.

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

Mapping Stochastic Model Outputs to the Micro-Macro Framework

2. A key assumption in the delayed-uncertain analysis is that since no action takes place by end of 2022, corporate bond markets sharply react anticipating heightened uncertainty into the future. To simplify the analysis, only one jump is considered at year 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 2-year changes in the corporate spread. Such large shocks have been seen during the 2007–2009 GFC periods where the spreads increased from around 2 percent to almost 12 percent in the height of GFC.

3. 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 to those in other market segments, such as equity. It is also unnecessary for this analysis since the large jump increases the uncertainty significantly due to the square root process that renders the effective volatility higher as evident from equation in Box 1 and from the historical time varying volatility (rolling 6 month) in Figure 8 top panel.

4. Thus, the following scheme is followed to arrive at increasingly higher funding costs in the debt markets. For delayed-2023 path, the average across all the possible paths between each time slices (the vertical lines between years in Figure 7 in the simulation) are computed. This gives dynamic path of interest rate shocks. For delayed-2024 path, the 75th percentile is used instead of average. Similarly, for delayed-2025 and delayed-2026 paths, 90th and 95th percentiles 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, this 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.

5. 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 modelling into a manually constructed simplified delayed-uncertain pathways to mimic impact of uncertainty. Nevertheless, since financial markets are assumed to be embedded into the broader macro uncertain environment (Figure 6), this approach is conceptually consistent, while at the same time sufficiently flexible. For example, since the financial model delivers a full set of distributions at each day into the future five-year horizon (Figure 7), 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.

6. Lastly, the scaling factor in Box 1 is a random variable that is constructed to link the sectoral outputs to corresponding impact 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 baseline by 2030 (as in Figure 5) is constructed. In principle, other distributions could also be fitted. However, since 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 one-time large shock due to sudden rise of macro policy uncertainty. Thus, this scaling factor links the climate policy scenarios to evolution of corporate spreads, in a very simple, but internally consistent and coherent manner.

Appendix II. Physical Risk Direct Damages Estimation

1. **The methodology used to estimate direct damages for each scenario combines: (i) an analysis of historical loss data for comparable events; and (ii) a model-based approach using exposure, hazard, and vulnerability data**. The results of the analysis of historical loss data are used to inform and validate the model-based approach, with the final direct damage estimates for each scenario based on a combination of the results of these two approaches.

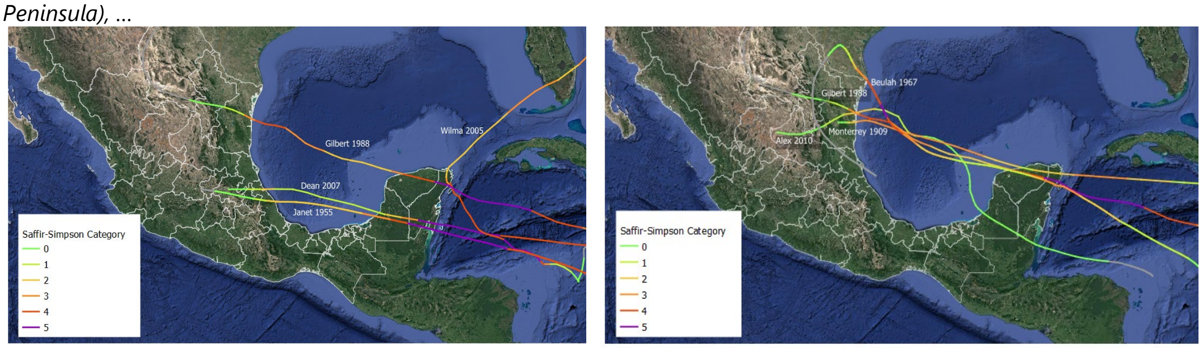
2. **To estimate the direct damages for the extreme season scenario (Scenario ES1), the results of the direct damage estimation methodology for individual events are summed.** Note that a simple addition is plausible in the case of the direct damages for ES1 since the spatial extents of the direct damages of the constituent scenarios (Scenarios TC1, TC2, TC3 and F1) do not overlap (though for indirect economic impacts, compounding effects may occur due to transmission channels that can result in impacts beyond the original spatial extent of the area directly affected by an event).

3. **For the analysis of historical CENAPRED loss data, historical losses for events comparable to each scenario (where available) are scaled to a 2020 loss estimate based on exposure growth and inflation assumptions.** Historical loss data were extracted from detailed CENAPRED reports for events similar to the defined scenarios (see Figure A1 for examples of comparable historical events identified for Scenario TC1). CENAPRED provides economic loss data divided into direct damages ("daños directos"/"daños") and indirect losses ("daños indirectos"/ "pérdidas") by state. In cases where the split between direct and indirect impacts is unavailable, this is estimated using the average ratio for other events of the same peril type (flood or tropical cyclone). These data were then scaled to estimated "as-if" 2020 losses, using estimates of exposure growth and inflation. These government data are considered a reliable historical loss dataset, and were also compared with other historical loss databases, including EMDAT.

Appendix Figure 1. Comparable Historical Events for Scenario TC1

Several comparable historical events were identified for Scenario TC1's first landfall (impacting the Yucatan Peninsula), …

…and Scenario TC1's second landfall in northeast Mexico.



Source: WB illustration using IBTRACs data.

4. The model-based approach combines three modules: (i) an exposure module; (ii) a hazard module; and (iii) a vulnerability module. A comparison of the results from the approach based on historical loss data and the model-based approach was conducted, to further tune the parameters of the model-based approach, and to determine the final loss estimates.

A. Exposure Module

5. The exposure module involves two steps: (i) the scaling of total physical capital stock data by state to an estimate of 2020 exposure; and (ii) the spatial disaggregation of this data. This process was used to generate a map of exposures that can subsequently be overlaid with hazard maps.

6. The scaling of physical capital stock data utilized variables from the World Development Indicators database to adjust the 2013 capital stock data from the Instituto Nacional de Estadística y Geografía (INEGI) to estimates for 2020. INEGI capital stock dataset for 2013 (INEGI, 2013) includes both public and private capital stock, including fixed assets (e.g., real estate, infrastructure), and movable assets (e.g., machinery and equipment), reported at a state level. From the dataset, the ratio between total capital at stock and annual GDP was extracted. Data from the World Development Indicators database (WB, 2022), including data regarding inflation in Mexico between 2000–2020, as well as the nominal GDP values for the period 2000–2020 and the gross fixed capital formation, was then used to estimate the value of the capital stock in 2020.

7. State-level exposure estimates for 2020 were spatially disaggregated to a resolution of approximately 100m, and split into agricultural and built-up (industrial, commercial and residential) classes. The spatial disaggregation utilizes the Global Human Settlement Layer – Population (GHS_POP; Schiavina and others, 2019) and the Settlement Model Grid (GHS_SMOD; Pesaresi and others, 2019), which provide population and built-up area densities. The rationale is that capital stock (e.g., machinery and equipment) is more likely to be in populated or built-up areas. The maximum of the two normalized GHS_POP and GHS_SMOD densities per pixel is used to estimate capital stock density. The capital stock density map is then classified into two sectors using agriculture and built-up land cover classes identified from the Copernicus Global Land Service Land Cover data set (Buchhorn and others, 2020). Finally, the capital stock data is distributed by means of its density. Whilst this methodology provides a useful method for disaggregating the available capital stock data to a more granular geographic dataset, it is important to note the limitations of this approach. For example, the spatial population distribution in Mexico City may not be reflective of the spatial distribution of capital stock (e.g., due to inequalities and the non-homogenous spatial distribution of wealth and poverty).

B. Hazard Module

8. The approach used to model hazard is based on the perils considered in each scenario, namely wind and/or flood. For some tropical cyclone scenarios, wind is considered to be the main driver of losses, whereas for others, the wind hazard is considered negligible, with most of the losses driven by flooding caused by heavy precipitation associated with the tropical cyclone. Depending on the nature of the scenario, the modelling approach was adjusted accordingly (i.e., for some tropical cyclones, wind was modelled, whilst for others, only flood was modelled). Note that storm surge is not modelled.

9. For the "historical conditions" tropical cyclone scenarios, the approach used to generate a windspeed map to model the wind hazard differed between scenarios:

- For Scenario TC1-hist, the wind component of tropical cyclone scenarios was modelled based on historical IBTrACS track data for similar historical events, with wind fields calculated from the track data using CLIMADA's implementation of Holland's (2008) method. Whilst several historical wind fields were modelled, it was decided to use the Hurricane Wilma 2005 track as a reference event for Scenario TC1-hist, since its landfall path and intensity is considered representative of the scenario's first landfall, which is associated with the wind-driven loss component of the scenario.
- The wind component of Scenario TC2-hist is negligible, with most damages driven by flooding caused by precipitation associated with the tropical cyclone. Hence, the wind hazard was not modelled in detail for this scenario.
- For Scenario TC3-hist, for which there is no similar historical event, a similar track was selected from the STORM stochastic track dataset (Bloemendaal and others, 2020), with wind fields subsequently simulated using the CLIMADA implementation of Holland's (2008) method.

10. In the case of the "climate change conditions" scenarios, for the wind hazard, an intensity adjustment is applied using CLIMADA, based on the Knutson and others (2015) intensity adjustments. Since the intensity adjustment factor from Knutson and others (4.5 percent increase in intensity for North Atlantic basin) is only available for one RCP and time horizon (RCP4.5 late 21st Century), the CLIMADA implementation scales this adjustment factor for RCP8.5 and other time horizons by interpolating them according to their relative radiative forcing.

11. For flood, the hazard module is based on the Fathom hazard maps (Sampson and others, 2015), available for a range of return periods. The riverine (defended) hazard maps are used to model flood risk in Scenarios TC1, TC2 and F1, based on a literature review highlighting that riverine flooding was the main driver of flood-related losses for similar historical events. It is important to note that the hazard maps are a global product and may not have been locally calibrated for Mexico. The use of different flood hazard maps can result in large differences in risk estimates.

12. To define the flood hazard for a given scenario event, it was necessary to select a hazard map with an appropriate return period, and to delineate the area in which this hazard map is to be applied. Here, return periods for spatial units were defined as river catchments within a state. The approach to define the appropriate return period for each state/river basin varies between the scenarios, based on a combination of historical flood footprints for similar historical events, event descriptions, precipitation maps for similar historical events, precipitation and streamflow return period analyses available in the literature, and a calibration based on the comparative analysis outlined below.

13. In the case of "climate change conditions" scenarios for tropical cyclone-driven flooding, a change in rainfall is estimated from Knutson and others (2015). The estimate from Knutson and others (17.3 percent increase in rainfall rate) is only available for one RCP and time horizon (RCP4.5 late 21st Century). To derive factors for RCP8.5 and other time horizons, the adjustment factor is scaled according to relative radiative forcing estimates, based on the methodology implemented in CLIMADA for wind adjustment factors. The rainfall adjustments are then translated to an estimated change in streamflow, based on an assumption that the precipitation-streamflow elasticity for extreme events approaches unity (Breinl and others, 2021). Finally, the change in streamflow is converted to an estimate of the change in return period based on published streamflow return period estimates for rivers in Mexico (Isela and Zarco, 2014, Neri-Flores and others, 2019). This approach uses several simplifying assumptions, and the results should be interpreted recognizing the limitations. For example, the results are highly dependent on the elasticity assumption, which has not been locally proven for Mexican rivers. In addition, published streamflow return periods are only available for some gauges along the rivers and may not be representative of the flood frequency relationships elsewhere in a catchment.

14. In the case of "climate change conditions" scenarios for non-tropical cyclone-driven flooding, a change in streamflow for a 1-in-100-year is estimated using Di Sante and others (2020). The change in streamflow is converted to an estimate of the change in return period based on published streamflow return period estimates (Mora and others, 2008). This approach is subject to similar limitations to those outlined above for the tropical cyclone-relating flooding climate change adjustments.

15. Whilst the approaches for climate change adjustments outlined above result in increases in flood risk, it is important to note that several papers indicate that the risk may decrease for some rivers in Mexico (see, for example, Haer and others, 2018, Hirabayashi and others, 2013, Hirabayashi and others, 2021). This may be a result of potentially drier antecedent conditions in the river catchments due to the influence of climate change on other hydrologically important climate variables (e.g., increased temperature and evaporation). Thus, the climate change scenario damage estimates presented in this analysis may be more representative of a "bad case" change in flood risk, yet potentially not the "worst case" given that some model projections show even more severe increases in rainfall and/or streamflow with climate change than the increases assumed in this analysis.

C. Vulnerability Module

16. To calculate the damage for a given hazard severity for the modelled exposures, published vulnerability curves were used. The European Commission Joint Research Centre vulnerability curves (Huizinga and others, 2017) were used for flood damage estimates, and the Eberenz and others (2021) regional tropical cyclone impact functions were used for wind damage estimates. The flood vulnerability curves relate flood depth to damage. The tropical cyclone vulnerability curves relate wind speed to damage. Where available, separate curves were used for agriculture and built-up (combination of residential, commercial and industrial) exposures. It is important to note that there are other vulnerability curves available for Mexico (e.g., CENAPRED, 2006), and that model results are sensitive to selection of vulnerability curve.

17. There is substantial uncertainty associated with modelling vulnerability (Kaczmarska and others, 2018). This includes uncertainty in both: (i) the development of the vulnerability model, including aleatory uncertainty (due to randomness of the processes governing the relationships between hazard severity and damage) and epistemic uncertainty (due to a lack of knowledge or data); and (ii) the use of the vulnerability model when modelling a given scenario (Trendafiloski and others, 2017). In this analysis, vulnerability has been modeled as a deterministic function of wind speed or flood depth. However, it is important to note that other methods may be better able to capture uncertainty. For example, vulnerability may be modelled by sampling the damage ratio for each asset from a statistical distribution. Due to an inability to differentiate between exposure data, the same vulnerability curves have been used for all exposures within a given class (built-up or agriculture), rather than differentiating between individual assets based on factors such as their construction type, age, number of stories, and occupancy. The use of a different vulnerability curve, adjustments based on modifiers related to detailed characteristics of the exposed assets, or a probabilistic sampling method for modelling vulnerability may substantially impact the results of the analysis.

D. Estimation of Return Periods

18. Return periods have been estimated for the "historical conditions" scenarios based on the magnitude of estimated direct damages. Without access to a full catastrophe model for Mexico, it is difficult to accurately determine the return periods associated with the damages estimated for each of the scenarios in this assessment. However, to estimate the approximate return periods, for wind-driven loss scenarios (i.e., Scenarios TC1 and TC3) the estimated damages were compared with the probable maximum loss curve for wind events in Mexico from the Global Assessment Report 2015 analysis (UNISDR, 2015), and for flood-driven loss scenarios (i.e., Scenarios TC2 and F1) the estimated damages were compared with a statistical analysis of historical flood event data from EMDAT using the World Bank Financial Risk Assessment Tool (WB, 2021b). It is important to note that there is substantial uncertainty associated with the analysis of flood return periods using the World Bank Financial Risk Assessment Tool, due to difficulties fitting a distribution that adequately captures the historical data, and due to the limitations associated with using a relatively short record of analysis to define return periods of very infrequent extreme events. These resources are used to estimate the return period of direct damages at a national scale by peril. The return period for a given scenario may be substantially higher if quantified as the return period of direct damages at a state scale or as the return period of a given physical hazard level for a given region (e.g., a 1-in-100-year flood event for a given river).

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