



Central Bank
of Armenia



WORLD BANK GROUP

Climate Transition Risk Stress Testing of the Armenian Banking Sector

Macro-Financial and Sectoral Insights

APRIL 2026

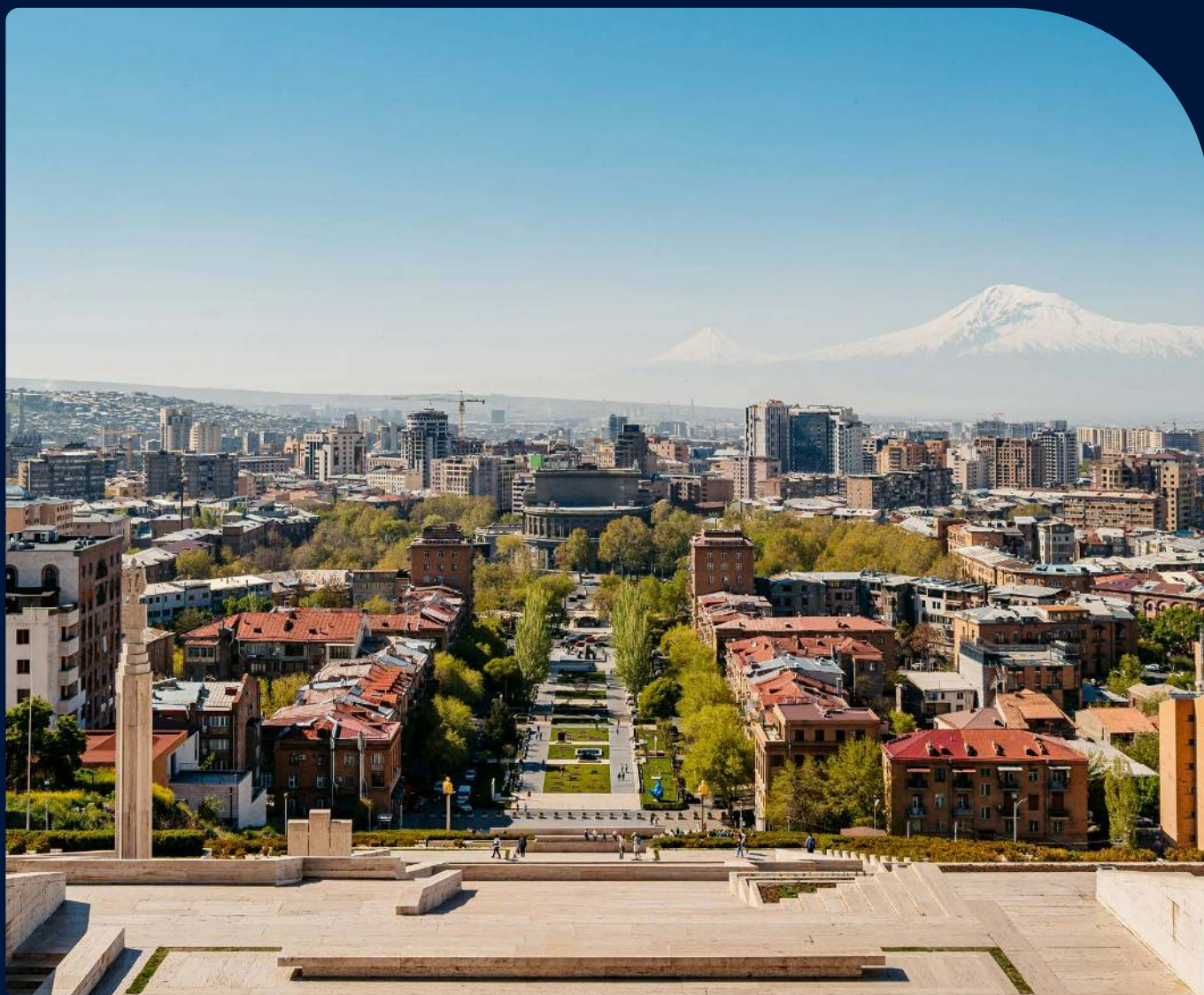




Table of Contents

Acknowledgements.....	4
Abbreviations.....	5
List of Figures.....	6
List of Boxes.....	6
List of Tables.....	6
Executive summary.....	7
1. Introduction.....	10
2. Climate and financial sector context.....	12
2.1 Climate context relevant for the climate transition risk stress test.....	12
2.2 Banking sector characteristics informing the climate transition risk stress test.....	15
3. CTRST methodology and approach.....	18
3.1 The CTRST framework.....	18
3.2 Climate transition scenarios.....	19
3.3 Macroeconomic model for assessing climate transition impact.....	21
3.4 Credit risk transmission satellite model.....	23
3.5 Stress test model.....	24
4. Macroeconomic and sectoral impacts of low-carbon transition scenarios.....	26
4.1 Modelling findings under different scenarios.....	26
4.2 Macroeconomic impact of transition scenarios.....	27
4.3 Sectoral impacts of transition scenarios.....	29
5. The impact of transition scenarios on the banking sector.....	31
5.1 Mapping macro paths and sectoral shifts into credit outcomes.....	31
5.2 Factors which may impact modelling findings.....	35
6. Conclusions and policy implications.....	36
Appendix A: Use of MFMod to capture energy transition dynamics.....	39
Appendix B: GTAP-based disaggregation of aggregate MFMod outputs.....	40
Appendix C: Stress test framework.....	41
Appendix D: Robustness check and dynamic balance sheet assumption consideration.....	45
Appendix E: Applied loan classification against NACE 2 Level.....	47

Acknowledgements

The report was developed jointly by the Central Bank of Armenia (CBA) and the World Bank (WB).

The CBA team included Gayane Vardanyan, Henrik Manukyan, Arthur Grigoryan, Viktoria Alaverdyan, and Susanna Saroyan (Research Fellow, Oxford Martin School). The WB team included Milica Nikolic (team lead), Unnada Chewpreecha, Martin Hafner-Guth, and Mansi Panchamia.

The WB team was supervised by Martha Martinez Licetti and Cecile Thioro Niang (Practice Managers, Finance, Competitiveness, and Innovation, Europe and Central Asia) and received strategic guidance and support from Vahe Vardanyan (Lead Financial Sector Specialist and FinSAC Coordinator). The report was designed by Kane Chong.

The team would like to thank the following WB staff for their invaluable feedback as peer reviewers: Patricia Caraballo (Senior Financial Sector Economist), Sharon Kirenga Lwamafa (Financial Sector Specialist), Irina Ghaplanyan (Senior Climate Change Specialist) and Ou Nie (Senior Financial Sector Economist).

This work is a product of the staff of the CBA and the WB. The findings, interpretations, and conclusions expressed in this assessment do not necessarily reflect the views of the CBA and the WB.

Abbreviations

AMD	Armenian dram
BART	Bayesian Additive Regression Trees
CAR	Capital Adequacy Ratio
CBA	Central Bank of Armenia
CCDR	Country Climate and Development Report
CES	Constant Elasticity of Substitution
CO₂	Carbon Dioxide
CTRST	Climate Transition Risk Stress Test
DSIK	German Sparkassenstiftung for International Cooperation
EAD	Exposure at Default
EL	Expected Losses
GDP	Gross Domestic Product
GHG	Greenhouse gas
GTAP	Global Trade Analysis Project
GVA	Gross Value Added
IO	Input–Output
LCR	Liquidity Coverage Ratio
LGD	Loss Given Default
LLP	Loan Loss Provision
MFM_{Mod}	Climate-enhanced Macro-Fiscal Model
NACE	Nomenclature of Economic Activities
NDC	Nationally Determined Contributions
NGFS	Network for Greening the Financial System
NII	Net Interest Income
P&L	Profit and Loss
PD	Probability of Default
RWA	Risk Weighted Assets
TCO₂	Tons of Carbon Dioxide
USD	US dollar
WB	World Bank

List of Figures

Figure ES1	CTRST Approach	8
Figure 1	Evolution of CO ₂ emissions in Armenia since 2000	13
Figure 2	Electricity generation mix in Armenia	13
Figure 3	Potential transmission channels of carbon tax impacts on the electricity sector	14
Figure 4	Composition of the Armenian banking system's loan portfolio	16
Figure 5	Overview of financial resource flows among households, firms, and the government in the MFMod	21
Figure 6	Disaggregation of MFMod sectors using the GTAP input-output framework	22
Figure 7	Carbon price to achieve NDC target under different scenarios	26
Figure 8	Decline in CO ₂ levels under various scenarios	27
Figure 9	Macroeconomic impacts of carbon pricing under various scenarios	28
Figure 10	Aggregate Sector GVA under various carbon pricing scenarios	29
Figure 11	Impact on CAR per financial item	31
Figure 12	Banking sector's additional credit losses per economic sector	32
Figure 13	The distributions of Armenian banks' CAR impacts per scenario	33
Figure 14	Bank-level expected losses (normalized) versus initial PD under the Perverse Disorderly scenario	34
Figure A1	Structure of consumption choices in MFMod	39
Figure C2	PD-LGD relationship for raw and logit-transformed values	43
Figure D1	Resulting CAR reduction per forecasted drivers (OLS specification)	45
Figure D2	Banking sector's additional credit losses per economic sector relative to baseline	45

List of Boxes

Box 1	Carbon Tax Impacts on the Electricity Sector in MFMod	14
Box 2	How losses feed through to the bank capital	25

List of Tables

Table 1	Transition risk scores of Armenia's banking sector	17
Table 2	Differences in value added in the worst affected sectors between 2024 and 2029	30
Table B1	Mapping of sectors used in the stress testing	40
Table C1	Sample of risk migration matrix	42

Executive summary

This first-of-its-kind climate transition risk stress test (CTRST) in Armenia conducted jointly by the Central Bank of Armenia (CBA) and the World Bank (WB) assesses the impact of climate transition policies on the country's sectoral outputs and the financial sector.

Growing global interest in the financial stability implications of climate change has led many authorities to integrate climate-related risks into their traditional stress-testing frameworks. Beyond physical risks stemming from extreme weather events, such as floods and droughts, climate-related risks also arise from transition risks which are associated with the shift toward a low-carbon economy. Despite being a small emitter with less than 0.02 percent of the global emissions, Armenia remains exposed to transition risk due to its economic structure, sectoral composition, and the potential challenges associated with shifting to a low-carbon economy.¹ The CTRST aims to support the CBA build a stress testing framework to assess and manage climate transition risks for Armenia's banking sector.

Sectoral transition risks highlight the need for stress testing the country's banking portfolio. In November 2024, the CBA along with the German Sparkassenstiftung for International Cooperation (DSIK), assessed sectoral climate and ESG risks, including transition risk. The analysis shows that electricity, agriculture, transport, water, and construction face the highest transition risk; this becomes especially salient as these sectors also represent an important share of the banking sector portfolio. High emissions, regulatory pressures, and technological shifts make these sectors highly vulnerable. These findings underscore the need for a CTRST to understand potential losses and guide strategic risk management of the banking sector portfolio.

Beyond physical risks stemming from extreme weather events, such as floods and droughts, climate-related risks also arise from transition risks which are associated with the shift toward a low-carbon economy.

The CTRST examines transition risk only, tracing how 3 NDC-aligned scenarios (including tail risk pathway) describing a move to a low-carbon economy could affect Armenian banking sector via credit risk. It models three climate transition pathways aiming to reach Armenia's Nationally Determined Contribution (NDC) by 2030, which are compared against the baseline scenario that assumes no policy change: Orderly (gradual, predictable carbon pricing), Disorderly (delayed action followed by a steeper tax), and Perverse Disorderly (delayed action and steep carbon pricing policy combined with weak interagency coordination that captures tail risk events), each assuming a carbon tax on the power sector.² The carbon tax alters sectoral output via Gross Value Added (GVA); those sectoral changes translate into higher borrower default risk, which raises banks' expected credit losses and, in turn, compresses capital adequacy ratios (CAR). Results are reported against a baseline that assumes that carbon tax is not introduced.

¹ World Bank Group (2024). [Armenia Country Climate and Development Report](#).

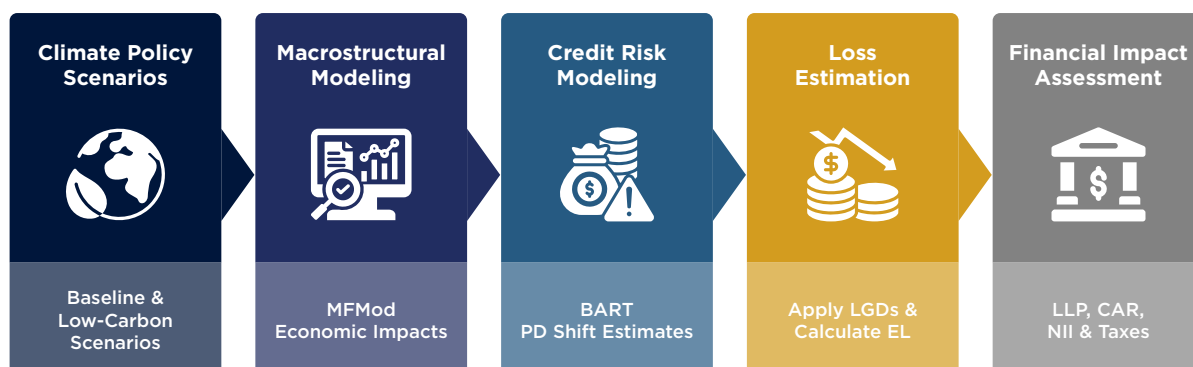
² "Power sector" and "electricity sector" are generally used interchangeably in industry and policy contexts. Both terms refer to the specific sub-segment of the broader energy industry involved in the generation, transmission, distribution, and sale of electrical energy.

The pathways modelled by the CTRST focus on the (most polluting) electricity sector, using relatively short, five-year 2025-2029 horizon scenarios that differ in the timing and stringency of carbon tax implementation. Using December 2024 data as the reference date, the exercise begins from a position of strength with a sound and well-capitalized system with a CAR of 20.2 percent, above the 15 (16.5 for systemic banks) percent overall capital requirement. Although easiest from the modeling perspective, the carbon tax used in this exercise is a proxy for any other policy measure that can be taken by the government to decrease greenhouse gas emissions in the country. Differences in the policy-support environment of the Perverse Disorderly scenario are introduced through production function parameters such as the level of the elasticity of substitution between different energy sources.

The CTRST uses the following approach (Figure ES1) (see Section 3 for more detail):

- The designed scenarios and the World Bank climate-enhanced macrostructural model (MFMod) are used to assess both aggregate and sectoral economic impacts under each scenario. The three low-carbon climate policy-determined macroeconomic scenarios are compared against a counterfactual baseline scenario with no additional policy measures to enhance low carbon transition and mitigate climate risk.
- A Bayesian Additive Regression Trees (BART) model is employed as a satellite credit risk model to assess how the aggregate and sectoral outputs of the scenario-based macroeconomic models affect Armenian banks' credit risk by estimating shifts in probability of default (PD) across loan portfolios, both by sector and in aggregate.
- The framework uses estimated PDs to provide Expected Losses (EL) by varying the severity of loss given default (LGD) across scenarios and based on the LGDs' historical distribution. Banks' balance sheets and sectoral exposures are treated as static.
- The resulting EL are treated as Loan Loss Provisions (LLP) to assess the impact on banks' credit risk and financial performance indicators, including CAR, Net Interest Income (NII) and Taxes.

FIGURE ES1
CTRST Approach



The results of the CTRST indicate that transition risk, in isolation, is manageable for the Armenian banking sector under all three scenarios. Credit losses, however, are more prominent under an abrupt and weakly coordinated transition. Cumulative EL increase by 1.2, 1.3, and 1.7 times under the Orderly, Disorderly, and Perverse Disorderly scenarios, respectively, relative to the baseline, translating into reductions in the banking sector's CAR of 0.5, 0.8, and 1.9 percentage points by the end of the five-year horizon. Heterogeneity of impacts within the banking sector is observed, reflecting the differences in banks' portfolio composition and their asset quality. The most affected loan segments are Mortgage, Consumer, Trade, Construction, Manufacturing, and Agriculture, which is broadly in line with their share in the total loan portfolio (almost 80 percent). Sectors such as Water and Mining, albeit highly sensitive to transition risk, have limited impact on overall expected losses due to their small share of bank portfolios and low initial PDs.

These results should be interpreted with caution. The assessment uses the available data but the absence of historical Armenian data on the interlinkages between carbon prices, greenhouse gas emissions and firms' financial health constrains the calibration of PD and LGD stemming from transition risk. Reasonably appropriate sectoral breakdown and integration of firm-level assessments (micro-approach) would enhance the robustness of the results. It should also be noted that the macroeconomic projections suggest that the adverse effects of transition may extend beyond the five-year stress-test horizon assumed under the static balance sheet assumption.

Despite the limitations, the CTRST is an important initial step in quantifying transition risk in Armenia and provides the groundwork for future assessments. Although it is challenged by data and modeling limitations, the assessment aims to act as a first stress testing analysis of the banking sector's vulnerability to climate transition risks. In this way, the analysis is designed to identify policy priorities for assessing and managing transition risks for Armenia's banking sector.

The analysis is designed to identify policy priorities for assessing and managing transition risks for Armenia's banking sector.

From a policy perspective, the stress test underscores the importance of a timely, predictable, and well-coordinated transition policy to limit financial stability risks in line with existing literature. It also highlights opportunities for banks and financial institutions to support and finance the greening of transition sensitive sectors. Key follow-up priorities include: (i) addressing identified data gaps and quality issues; (ii) conducting physical climate risk stress testing, (iii) developing supervisory guidance on climate risk management, (iv) embedding transition planning for financial institutions, and (v) enhancing interagency coordination in Armenia on transition policies. The current exercise can also serve as a foundation for future stress tests that incorporate physical climate risks, such as heatwaves, floods, droughts, and others, alongside transition risks. Such comprehensive and quantitative assessments will offer a more robust basis for drawing financial stability conclusions and designing supervisory responses in Armenia.

1 Introduction

Climate change poses growing risks for Armenia across two distinct but interconnected dimensions. Physical risks including rising temperatures, increased drought frequency, and more intense extreme weather events, are already materializing: temperatures have increased by 1.2°C since the 1990s and, in an unmitigated emissions scenario, are projected to rise by 5.6 degrees by 2100, placing Armenia in the third quartile of global temperature rises by country.³ At the same time, as Armenia accelerates its decarbonization agenda, transition risks are becoming an increasingly important area of attention for the financial sector. Armenia ranks 83rd worldwide on transition risk exposure, with per capita emissions of 2.535 tCO₂.⁴ This assessment focuses on transition risk as a first step toward building a comprehensive climate risk framework for the Armenian banking sector, with physical risk dimensions to be incorporated in future iterations.

Emissions in Armenia are currently rising, out of line with both global pathways and domestic commitments, affirming the need to decarbonize.⁵ While global benchmarks assume immediate emissions declines, Armenia's trajectory reflects its status as a low-emitting developing economy, with potential near-term growth in emissions before peaking and declining. Emissions have been increasing by roughly 3.2 percent annually since 2000, and the decline in emissions intensity has slowed. At the same time, Armenia has committed to reducing its greenhouse gas emissions by 40 percent below 1990 levels by 2030 and to reaching 2.07 tCO₂ equivalents per capita by 2050, according to the NDC established in 2021.⁶ With the updated NDC, for 2026-2035, established in 2026, the government sets an economy-wide GHG emission reduction target for 2035 of 44 percent unconditionally and up to 52 percent with international support. This in turn, is planned to be implemented by a set of measures, comprising 35 mitigation (22 unconditional, 13 conditional) and 41 adaptation measures across key sectors including energy, transport, agriculture, forestry, water, health, and tourism.

Despite these, current policies are insufficient to meet the long-term goal. As a result, although Armenia remains on track to fulfill its current NDC targets, which are benchmarked against 1990 emissions, existing trends are inconsistent with deeper, long-term decarbonization goals. Achieving the 2050 target would require a stronger 2030 goal of at least a 65 percent reduction and significantly more ambitious near-term climate policies.

Armenia has strong potential to transition to renewable energy sources, improving energy security and reducing emissions. Armenia's energy system underscores the need and the opportunity for a low-carbon transition. The main sources of emissions in 2023 were electricity and heat production (about 22 percent), transport (about 35 percent), and the residential sector (about 24 percent).⁷ These sectors rely heavily on imported natural gas,⁸ which accounted for 57 percent of the energy mix in 2023, followed by domestically produced nuclear energy (18 percent),

³ International Monetary Fund (2022). [Armenia: Technical Report – Quantifying Fiscal Risks From Climate Change](#).

⁴ International Energy Agency. [Armenia](#). Data for 2022, accessed in 2025.

⁵ World Bank (2024). [Country Climate and Development Report: Armenia](#).

⁶ This assessment references Armenia's NDC (2021), which was in force at the time of the analysis. Armenia's latest NDC may be integrated in future iterations.

⁷ International Energy Agency. [Armenia](#). Data for 2023, accessed in 2025.

⁸ Imported gas is traditionally supplied at prices below international market levels.

and hydropower (about 4 percent).⁹ The country's additional domestic production capacity across nuclear (69.1 percent), hydropower (13.8 percent), biofuels and waste (9.3 percent), and solar, wind, and other renewables (7.8 percent) demonstrates Armenia's strong potential to transition toward renewable energy sources.¹⁰ This would help achieve Armenia's NDC target and improve energy security by reducing dependence on imported gas.¹¹

The CBA, in line with its mandate to maintain financial stability, recognizes the potential implications of climate-related risks for the financial sector due to its exposure to the real economy. According to the World Bank's Country Climate and Development Report (CCDR) for Armenia, a scenario in which Armenia pays international natural gas prices would lead to higher power system costs than a decarbonization scenario in which the country transitions from a gas-based system toward a solar-dominated power sector, achieving an emissions target of 2.07 tCO₂ per capita by 2050.¹² The CCDR estimates that investment of USD 3 billion in the electricity sector would facilitate this transition. These low-carbon transition costs would emerge through evolving climate policies, market dynamics, and technological shifts which are subsequently expected to affect economic performance, particularly in carbon-intensive sectors.

The Climate Transition Risk Stress Test (CTRST) 2025 is a pilot exercise aimed to assess the Armenian banking sector's exposure to and preparedness for climate transition-related solvency risks. It defines climate transition scenarios that are aligned with Armenia's NDC and uses the WB's climate-enhanced macrostructural model (MFMod) to assess possible macroeconomic and sectoral economic impacts. Modeling is used to evaluate how this could affect credit risk and the potential impact on banks' CAR. The CTRST seeks to raise awareness and support the CBA in establishing a framework to quantify climate transition-related financial risks, and identify obstacles to accurate quantification.

The CTRST framework is designed to evaluate the resilience of all 17 banks operating in Armenia to three climate transition risk scenarios over a five-year horizon. It is aligned with the scenario design of the Network for Greening of Financial System (NGFS) and with the global trend among central banks to adopt shorter climate stress scenario horizons. For example, the European Central Bank's first climate stress test in 2022 employed long-term horizons to assess both transition and physical risks, typically extending beyond 20 years for transition pathways and several decades for chronic physical hazards. By 2024, the Fit-for-55 scenario analysis significantly shortened its time frame to 2023–2030. This temporal contraction also mirrors the approach of the latest NGFS short-term scenarios (2025), which focus on five-year horizons to evaluate the immediate financial stability impacts of extreme events or delayed policy action.

This report outlines the procedure and findings of the CTRST and offers policy recommendations. It is structured as follows. Chapter 1 introduces the study, Chapter 2 outlines the country's transition and banking sector context, including elaborating the banking sector characteristics that inform the CTRST. Chapter 3 presents the methodological approach, covering the macroeconomic model, credit risk satellite model, and the climate risk stress test tool, and the low-carbon transition scenarios used in the exercise. Chapter 4 analyzes the resulting macroeconomic and sectoral impacts. Chapter 5 considers the potential impact of the transition scenarios on the financial sector, and Chapter 6 presents lessons learned and next steps.

⁹ International Energy Agency. [Armenia](#). Data for 2023, accessed in 2025.

¹⁰ IBID.

¹¹ [UNFCCC NDCs for Armenia](#).

¹² World Bank (2024). [Country Climate and Development Report: Armenia](#).

2 Climate and financial sector context

This chapter provides an overview of the climate and financial sector context, setting the foundation for the analysis that follows. It further outlines key climate-related trends and vulnerabilities relevant to Armenia and examines their interaction with the structure and performance of the financial sector. By framing the broader macro-financial and climate environment, the chapter highlights why climate-related risks and opportunities are increasingly relevant for financial institutions and financial stability.

2.1 Climate context relevant for the climate transition risk stress test

Armenia ratified the Paris Agreement in February 2017 and has articulated its climate ambitions through its NDC. Under its updated NDC for the 2021–2030 period, approved in April 2021, Armenia has committed to reducing economy-wide greenhouse gas emissions by 40 percent below 1990 levels by 2030. The NDC prioritizes mitigation efforts across key sectors, including energy, transport, industry, and agriculture, with a strong emphasis on expanding renewable energy and improving energy efficiency. It is complemented by adaptation objectives aimed at strengthening resilience to physical climate risks such as water scarcity, extreme weather events, and climate impacts on agriculture. Together, these commitments provide the strategic framework for aligning national policies, investment priorities, and financial sector actions with Armenia’s Paris Agreement objectives.¹³

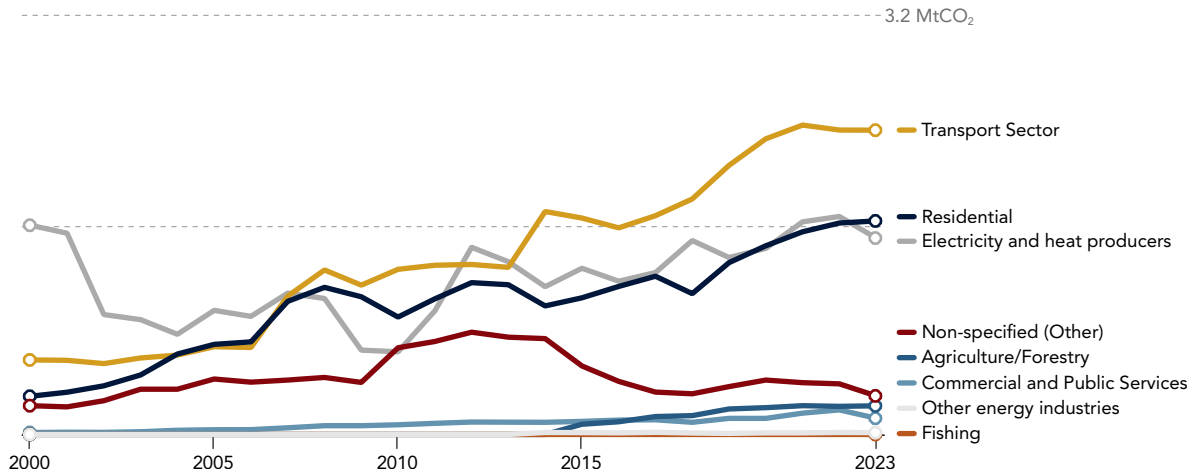
To effectively decrease greenhouse gas emissions, Armenia will need to focus on the highest emitting sectors. Armenia’s electricity sector has historically been the largest source of greenhouse gas emissions, though emissions from the transport and residential sectors have become increasingly significant over the past decade (Figure 1).¹⁴



¹³ UNDP (2021). [The Government of Armenia approved Armenia’s updated 2021-2030 Nationally Determined Contributions, supported under EU4Climate project.](#)

¹⁴ International Energy Agency. [Armenia](#). Data for 2023, accessed in 2025.

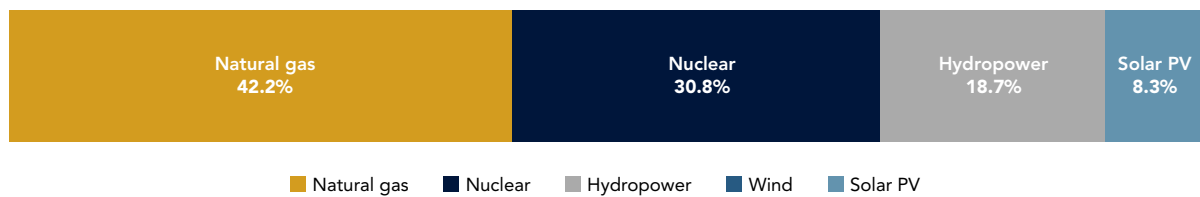
FIGURE 1
Evolution of CO₂ emissions in Armenia since 2000



Source: International Energy Agency.

Decarbonizing the electricity sector will be pivotal to achieving sustained emissions reductions across the economy. Analysis of electricity generation by fuel type shows that over 40 percent of the generation comes from natural gas, followed by nuclear and hydropower (Figure 2).¹⁵ This structure has two implications; 1) given this fuel mix, the electricity sector represents a critical entry point for decarbonization and 2) decarbonizing other sectors, such as transport and residential heating, will increasingly depend on electrification, through measures like electric vehicles and heat pumps. To ensure that this shift results in a net reduction of emissions rather than merely transferring emissions, it is essential that electricity generation comes from low-carbon sources.

FIGURE 2
Electricity generation mix in Armenia (2023)



Source: International Energy Agency.

A carbon tax on the electricity sector is an efficient policy instrument to drive decarbonization of power generation. By targeting the sector that underpins emissions across the economy, this policy lever has the potential to deliver meaningful, economy-wide emission reductions. To effectively assess the broader macro-financial implications of climate mitigation efforts, it is crucial to understand the linkages between energy, the economy, and different sectors, as well as the levels and intensities of emissions (see Box 1 for key impact channels). These elements of Armenia's economic structure and emissions profile are integrated into the country's MFM modeling framework.

¹⁵ International Energy Agency. [Armenia: Electricity](#).

BOX 1

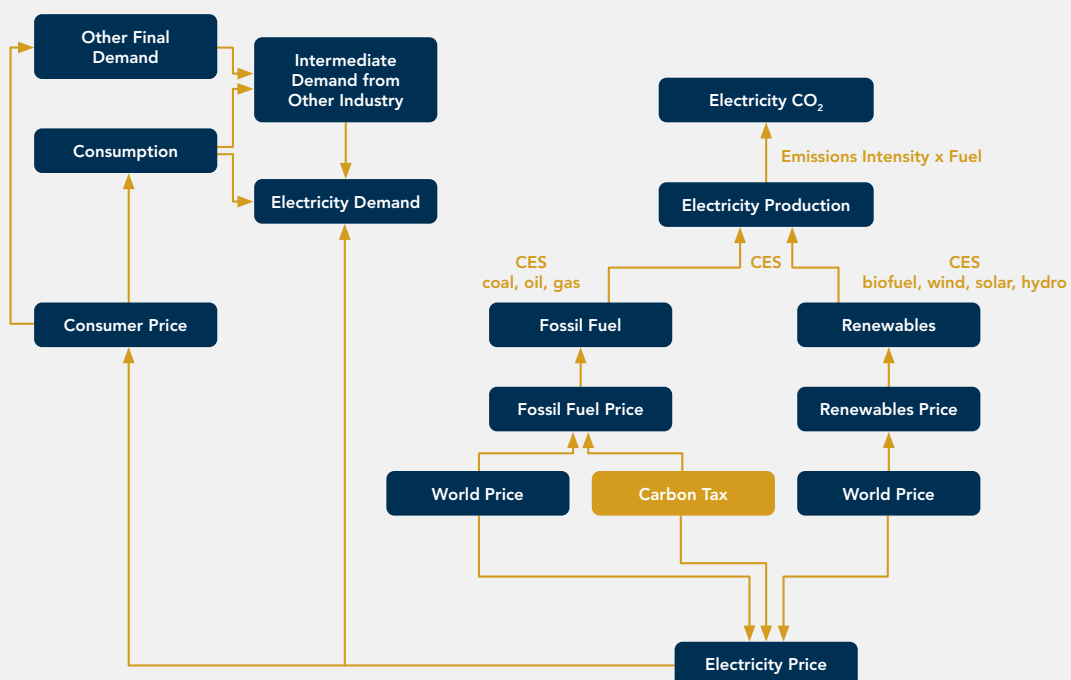
Carbon Tax Impacts on the Electricity Sector in MFMod

The MFMod framework demonstrates the main transmission channels of prices, production, and household consumption through which a carbon tax in the electricity sector affects outcomes (see also Figure 3 below):

- Electricity demand, driven by household and industrial consumption, acts as a primary transmission mechanism, influencing economic activity.
- Electricity production is determined by the mix of fossil and renewable energy sources, with the choice governed by relative prices and substitution elasticities.
- Energy prices, shaped by global market conditions and policy interventions such as carbon taxes, directly affect the cost of electricity, which in turn impacts consumer prices and overall demand.
- A feedback loop where changes in electricity prices influence consumption patterns, affects output and fiscal variables.
- CO₂ emissions from electricity generation serve as an environmental impact channel, linking energy choices and production methods to climate outcomes and potential policy responses.

FIGURE 3

Potential transmission channels of carbon tax impacts on the electricity sector



Source: Authors' presentation.

2.2 Banking sector characteristics informing the climate transition risk stress test

At the end of 2024, total financial sector assets stood at 131.8 percent of gross domestic product (GDP). Armenia's financial system is dominated by banks, with assets equivalent to 82.7 percent of financial sector assets; credit institutions account for about 8 percent; insurance companies account for nearly 6 percent.¹⁶

Armenia's banking system has rapidly expanded over the past two decades. The credit-to-GDP ratio rose from just 6.6 percent in 2003 to nearly 60 percent by 2024. Armenia's banking system is robust and well-capitalized, with total assets of the banking sector amounting to AMD 10.7 trillion (approximately USD 27 million) at the end of 2024, representing almost 25 percent annual growth, supported by a 25 percent expansion in lending and a 14 percent rise in deposits. Liquidity coverage ratio (LCR) reached 230 percent in 2024, underscoring substantial short-term buffers. Profitability indicators were solid, with a return on equity of 22 percent, return on assets of 3.5 percent, and a net interest margin of 4.8 percent. The CAR of 20.2 percent is well above the regulatory thresholds.¹⁷

The Armenian banking sector is moderately concentrated. There are 17 banks. As of December 2024, the four largest banks account for about 55 percent of the total loan portfolio. Within high-risk sectors, exposure is even more concentrated; for example, two banks account for nearly 70 percent of agriculture loans and 78 percent of mining loans, while three banks account for roughly 64 percent of electricity loans and 68 percent of transport loans.

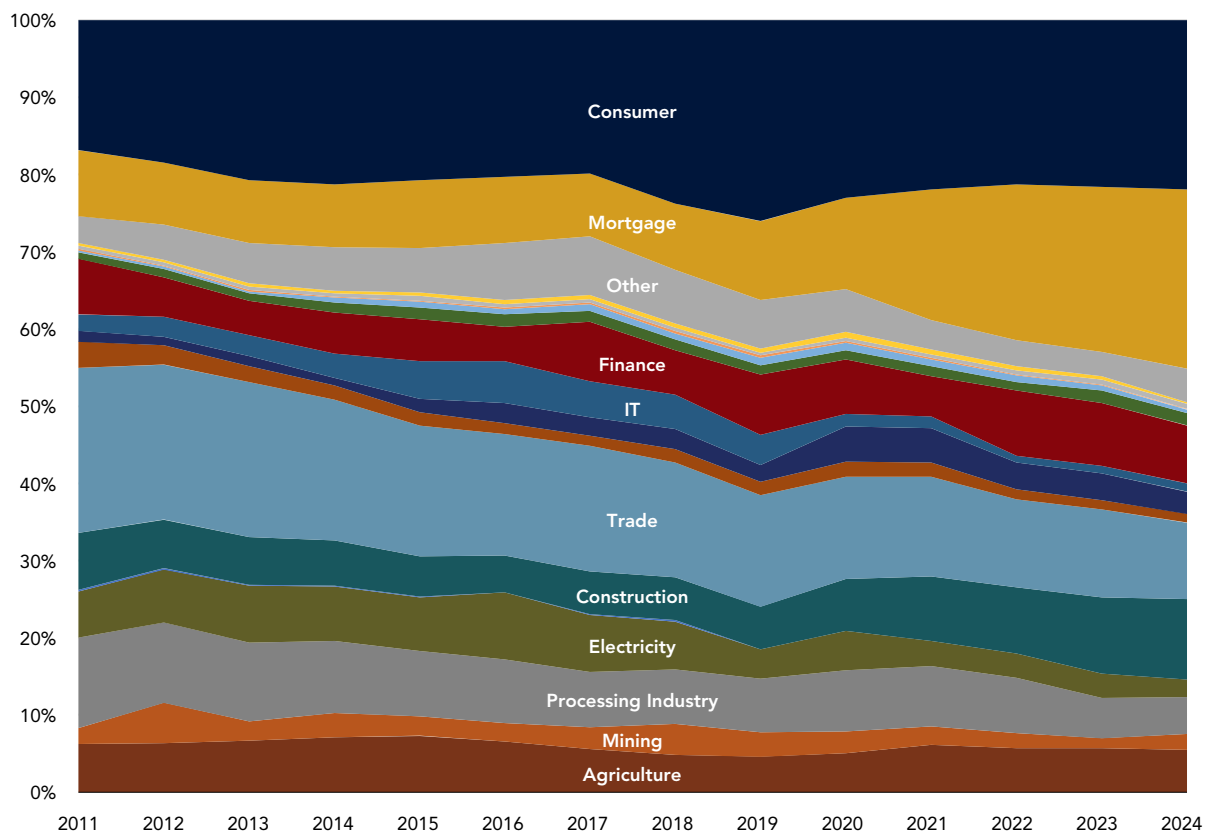


¹⁶ CBA Annual Report 2024.

¹⁷ CBA, Financial Stability report 2024.

Sectorally, the system’s credit portfolio is almost evenly divided between household and business loans. There are notable concentrations in the mortgage (about 24 percent), consumer (about 23 percent), and construction and trade (about 11 percent each) segments (Figure 4).¹⁸ Historically, consumer lending has been a preferred product for banks due to its relatively high interest margins and short maturities. Mortgage lending has surged under the government’s income-tax refund program, which effectively reduced borrowing costs to zero. This policy fueled a rapid expansion of housing and lifted the mortgage share in total loans from 8.5 percent in 2011 to around 24 percent in 2025. Parallel developments occurred in the construction sector, where loan volumes nearly tripled between 2020 and 2025, increasing its share of total lending from 6.5 percent to about 11 percent.

FIGURE 4
Composition of the Armenian banking system’s loan portfolio



Source: Authors’ calculations based on unpublished CBA loan data.

The CBA has identified that the electricity sector has the highest sectoral transition risk score (see Table 1).¹⁹ The Risk Radar transition risk score considers an industry’s contribution to global emissions, regulatory developments (highly emitting industries often face increased regulatory pressure), and other factors including the availability of new and alternative technologies and public perceptions, especially customers/consumers. Sectors with a transition risk score above 2 are classified as high risk, between 1 and 2 as medium, and below 1 as low. The highest-risk sectors identified in the CBA’s Risk Radar (electricity, followed by agriculture, transport, water, and

¹⁸ Based on CBA’s internal data.

¹⁹ For more details on sectoral transition risk assessment in Armenia see [“ESG Risk Radar for Armenia: Assessment of Climate-Related and Other ESG Risks”](#).

construction) combine elevated transition risk with significant portfolio exposure. However, around 50 percent of the total loan portfolio (including mortgage and consumer lending) is not rated for transition risk. This suggests that while transition risks are identifiable and significant for certain sectors, the overall portfolio-level impact may be difficult to fully capture. It is worth noting that while transition risk impacts may be largely concentrated in a few institutions, their size relative to total sector assets determines the overall effect on the broader banking sector.

TABLE 1
Transition risk scores of Armenia’s banking sector (2024)

Riskiness	Sector	Transition risk score (0-4 [low-high])	Share in Loan Portfolio, Dec 2024 (%)	Share in Loan Portfolio (%)
High	Electricity	3.4	2.3	20
	Agriculture	2.8	5.7	
	Transport	2.6	1.1	
	Water	2.6	0.0	
	Construction	2.4	11.0	
Medium	Financial	1.8	3.2	15
	Manufacturing	1.8	4.9	
	Mining	1.7	2.2	
	Accommodation	1.3	3.0	
	Real Estate	1.3	1.7	
Low	Trade	0.7	11.2	14
	Profession	0.6	0.6	
	Education	0.6	0.1	
	Health	0.5	0.7	
	InfoComm	0.5	1.2	
	Entertainment	0.5	0.2	
Not assessed	Mortgage	No score available	23.7	51
	Consumer	No score available	22.5	
	Other	No score available	4.8	
Total			100	100

Source: CBA’s Risk Radar Report, combined with December 2024 loan data.

The banking sector has demonstrated resilience under conventional stress testing. Conducted over a three-year horizon, solvency stress testing simulating a strongly adverse macroeconomic contraction scenario including regional geopolitical shocks, sharp exchange-rate depreciation, and inflationary pressures, shows that aggregate CAR remains above 17 percent, above the current minimum requirement of 16.5 percent for systemic banks and 15 percent for non-systemic banks. Complementary liquidity stress tests, based on a six-month systemic deposit-outflow scenario, further confirm that banks’ liquidity buffers are sufficient to absorb potential funding shocks.

3 CTRST methodology and approach

This chapter outlines the technical framework used to assess the potential impact of a low-carbon transition on Armenia's banking sector. It describes the methodologies and assumptions employed to quantify transition-related financial risk.

3.1 The CTRST framework

Assessment of climate transition risks in the banking sector requires a comprehensive approach that links macroeconomic developments, sectoral vulnerabilities, and banks' individual exposures. The CTRST framework integrates these dimensions into a structured, forward-looking methodology, to evaluate how the transition to a low-carbon economy could affect the stability and resilience of Armenia's banking system.

To quantify the effects of climate transition risks on the Armenian banking sector, the CTRST applies the following steps:

1. **Scenario design:** The framework defines in total four scenarios – baseline assuming no policy change (counterfactual scenario) and three climate transition scenarios aligned with Armenia's NDC. Ranging from Orderly to Perverse Disorderly, these three scenarios specify the timing and roll out of carbon pricing policy, where the latter reflects a tail-risk scenario rather than a transition pathway.
2. **Macroeconomic and sectoral modelling:** Using the WB's climate-enhanced macrostructural model (MFMod), the macroeconomic and sectoral economic impacts of these scenarios is assessed.
3. **Credit risk transmission using satellite modelling:** A Bayesian Additive Regression Trees (BART) satellite model is used to evaluate how the scenario-driven macroeconomic changes translate into shifts in expected losses (EL) across loan portfolios. The approach links sector-level shocks to bank-level risk parameters using historical relationships between macro drivers and credit outcomes.
4. **Stress testing and capital impact:** The changes in EL feed into the stress testing model to estimate the resulting impact on banks' CAR.

3.2 Climate transition scenarios

The modelling is based on three low-carbon transition scenarios leading up to 2030. The scenarios define targets that are relevant for the five-year horizon of the exercise and are grounded in Armenia's actual policy commitments. The national NDC target, reducing total greenhouse gas emissions by 40 percent from 1990 levels by 2030, is assumed to apply equally to the power sector. The model considers achievement of the target in three alternative carbon pricing scenarios relative to a baseline no-additional-policies scenario.

The modelling uses carbon tax as the main policy instrument, as a proxy for a broader set of climate policies. Revenues from the carbon tax are assumed to feed into the general government budget, offsetting other expenditures. This allows the model to capture broad economic and sectoral effects of multiple climate policies (e.g., subsidies for renewables, regulations on emissions) while keeping the analysis tractable.²⁰

The economic costs of climate transition depend critically on how and when policies are implemented.

In practical terms, an orderly transition is one in which climate policies are introduced early, phased in gradually, and communicated clearly, giving households, firms, and financial institutions sufficient time to adjust their behavior, investment decisions, and portfolio composition. A disorderly transition, by contrast, is characterized by delayed or abrupt policy action that compresses the adjustment period, amplifies economic uncertainty, and increases the likelihood of asset quality deterioration and credit losses in transition-exposed sectors. The key distinction among the scenarios below is therefore not only the stringency of the carbon tax, but the timing, predictability, and enabling environment in which policy is introduced, factors that directly shape the magnitude of financial sector stress. The scenarios range from immediate and gradual implementation to significantly delayed policy reaction introduced in an unfavorable environment, and require different levels of taxation to achieve the same NDC target.²¹ Each transition pathway is calibrated to achieve Armenia's NDC target by 2030 to ensure comparability across scenarios.

The scenarios define targets that are relevant for the five-year horizon of the exercise and are grounded in Armenia's actual policy commitments.

To better capture the potential disorderly impacts, the macroeconomic forecasts for 2026-2030 are front-loaded by one year. They are used as 2025-2029 in the credit risk model's input data. Front-loading allows the exercise to reflect near-term economic shocks within the five-year horizon: Disorderly transitions are defined not only by what policies are introduced, but how abruptly they are imposed. Front loading only changes the timing of the policy activation, not the magnitude of the shock.

²⁰ However, it does not explicitly model the distributional or sector-specific mechanisms of all individual policies.

²¹ Differing the timing of carbon tax introduction aims to reflect types of [NGFS scenarios](#).

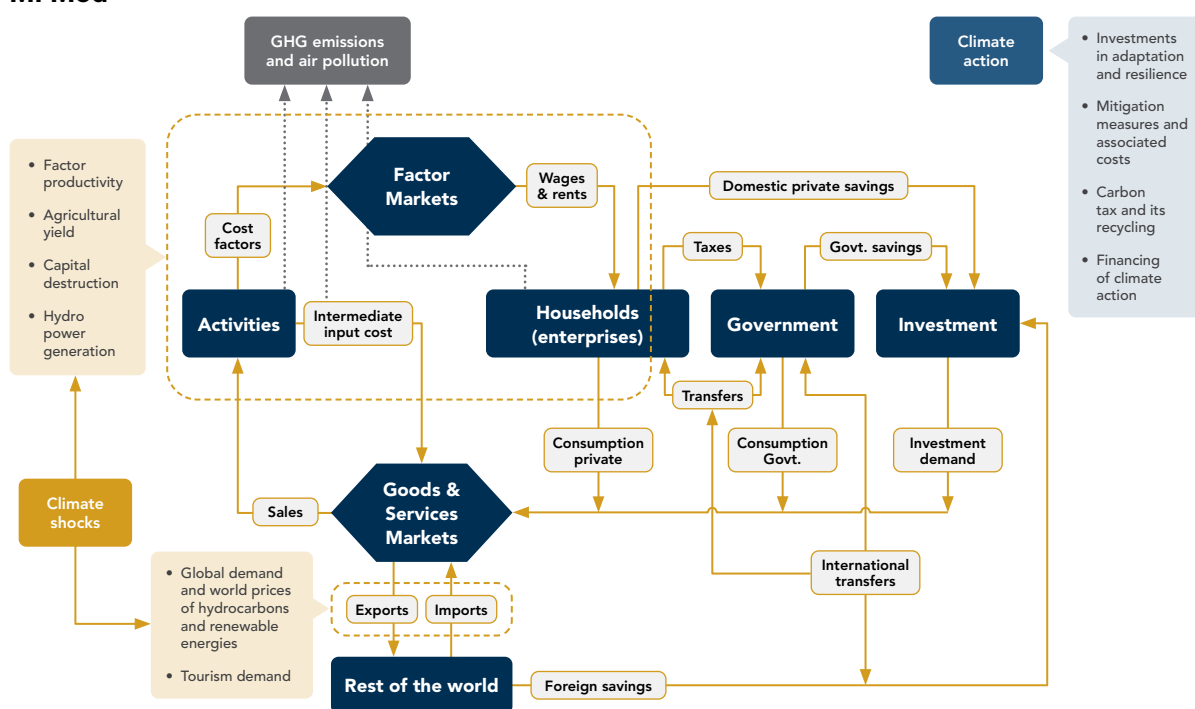
The four considered scenarios (including baseline) are summarized below:

1. **Baseline scenario:** The baseline represents CO₂ emissions in the power sector calculated endogenously by the model which assumes no new climate transition policies are implemented. Future macroeconomic growth is projected by extending historical trends.
2. **Orderly scenario:** In this scenario the policy instrument is introduced immediately. Armenia meets its NDC target by introducing a carbon tax in 2025 and increasing it gradually while clearly communicating this process. The carbon price starts at USD 35 per ton of CO₂ in 2025 and rises to USD 134 per ton by 2029.
3. **Disorderly scenario:** In this scenario the policy instrument is introduced but with a three year delay. Armenia still achieves its NDC target, but climate policies are postponed and then implemented abruptly in 2027. As a result, the carbon tax must be set higher and increase more sharply, beginning at USD 72 per ton of CO₂ in 2027 and reaching USD 141 per ton by 2029.
4. **Perverse Disorderly scenario:** In this scenario the policy instrument is introduced with delay and in the presence of additional unfavorable conditions at the point of introduction. It is similar to the disorderly scenario but introduces further challenge. In addition to the delayed and sudden policy rollout, the transition is more complex and expensive due to lack of coordination between local authorities and climate risk stakeholders. This is exacerbated by limited financing, political opposition, and supply chain delays. Such factors increase the economic uncertainty for households and firms to make and implement economic decisions, which is reflected as a higher carbon tax price in this scenario. Additionally, this scenario assumes a lower elasticity of substitution (sigma) compared to the other scenarios. This scenario describes a tail risk event and highlights that delayed action could be very costly, especially in a highly plausible global context characterized by rising protectionist trade policies and increasingly fragmented supply chains. As a result, the carbon tax must be set higher and increase more sharply, beginning at USD 150 per ton of CO₂ in 2027 and reaching USD 1,350 per ton by 2029.

3.3 Macroeconomic model for assessing climate transition impact

The MFMOD is used to quantify the economy-wide effects of carbon pricing and the transition to a low-carbon energy system. MFMOD, a general equilibrium, macro-consistent framework,²² has been calibrated to Armenia's national accounts and fiscal and balance of payments data. It links the behavior of households, firms, government, and the financial sector, ensuring market clearing in both product and factor markets, while accounting for existing frictions (see Figure 5). The model captures short term dynamics (through historical data, with potential output derived from a production function based on capital, labor, and total factor productivity) and economy steady state in the long term (driven by total factor productivity and population growth). The model calculates the speed of adjustment from short-term out of steady state equilibrium to the long-term steady state.²³

FIGURE 5
Overview of financial resource flows among households, firms, and the government in the MFMOD



Source: World Bank.

The standard MFMOD framework is modified for the CTRST to model the energy sector in more detail, focusing on volumes and prices to assess the low carbon energy transition's economic impact. Consumption and trade are divided into energy and non-energy components using a constant elasticity of substitution (CES) approach, allowing energy demand to respond to price sensitivity. A carbon tax is introduced as a key policy instrument to shift consumption and production away from fossil fuels toward renewables (See Appendix A for further details).

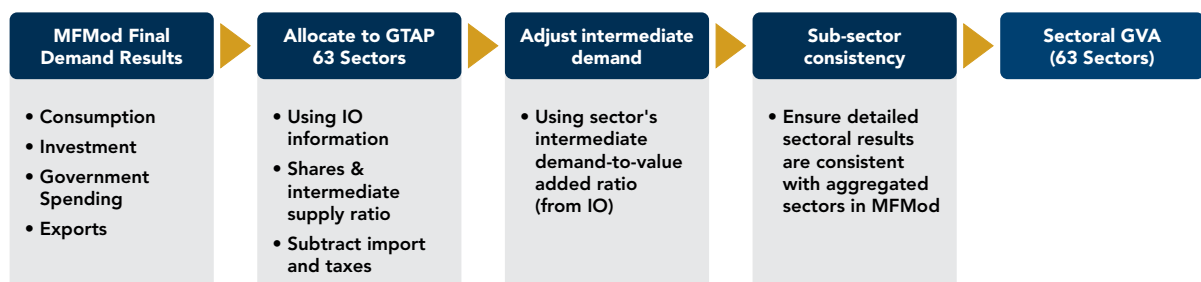
²² See Burns et al. (2019) and Hallegatte, Jooste, and McIsaac (2024) for a theoretical treatment of damages and a technical appendix that goes through the model's theoretical conditions.

²³ The MFMOD reflects Armenia-specific economic features while maintaining consistency in the interactions among key variables by combining theoretical rigor with empirical calibration.

Sectoral impacts under the transition scenarios in MFMod are calculated using a trans-log function. This specification ensures that sectoral shares add up to unity and allows substitution elasticities between sectors to vary with relative prices. The sectoral demand in the trans-log equation for each sector is derived by applying its share, obtained from the input-output/social accounting matrix, to total final demand categories (consumption, investment, government spending, and exports). This ensures that changes in aggregate components of demand are transmitted consistently to sectoral output.

Sectoral granularity is deliberately enhanced for the CTRST to support credit-risk transmission analysis. Macrostructural models such as MFMod rely on time series data, therefore the depth of sectoral disaggregation depends on data availability. In this case, availability of more granular sectoral breakdown is limited due to the absence of detailed sectoral data on labor, capital, wages, and rental rates. Consequently, the MFMod provides results for four broad sectors (Agriculture, Energy, Non-energy industry and Services). However, to circumvent this issue and to improve sectoral granularity, the four sectoral outputs from the MFMod are disaggregated to 63 sectors from GTAP's input-output framework (Figure 6). This method allows for deriving sectoral GVA estimates that are aligned with the input-output framework while remaining consistent with the macroeconomic and aggregated sector projections generated by MFMod (Appendix B maps this process in detail).

FIGURE 6
Disaggregation of MFMod sectors using the GTAP input-output framework



Source: Authors' own elaboration.

3.4 Credit risk transmission satellite model

A BART credit risk satellite model²⁴ is used to link macroeconomic outcomes obtained using MFMod to the PD for each sector as a target variable. The model estimates the expected PD for each sector conditional on macroeconomic variables and sector characteristics, providing a flexible, non-linear mapping from macroeconomic scenarios to credit risk outcomes. The BART model allows for automatic detection of interactions between predictors, capturing complex relationships that may not be adequately represented in traditional linear models.

Let $X_{s,t}$ denote a vector of macroeconomic indicators (GDP growth, inflation, unemployment, etc.) and sector identifiers for sector s at time t . The model expresses PD as:

$$PD_{s,t} = f(X_{s,t}) + \varepsilon_{s,t}$$

Where $f()$ is approximated by a sum of regression trees, capturing non-linearities and interactions among predictors. The target variable is bounded between 0 and 1.

To ensure comparability, the CTRST uses scenario-based forecasts of PD generated for each sector over a five-year horizon, which balances the need for meaningful stress-testing insights with the limitation of a static balance sheet assumption. To apply these forecasts to banks with heterogeneous exposures and asset qualities, the PDs are transformed into relative PD shifts. Using relative shifts rather than absolute values allows scenario-driven changes to be applied directly to each bank's portfolio regardless of the earlier PD levels. This assumes that shocks affect all borrowers within a sector similarly, hence, the initial PD of each bank's subportfolio remains the only differentiating factor when calculating the forecasted PD of a given sector for each bank. The PD forecasts from the BART model along with the LGD serve as key input for the calculation of EL in the stress-testing framework. LGDs will be shifted via a parameter in the assumptions sheet according to the rationale presented in Appendix C.



²⁴ For detailed description of the model see [Chipman, George & McCulloch \(2010\)](#).

3.5 Stress test model

The stress test evaluates how Armenia's banking sector would perform under the designed climate transition scenarios. It translates the scenario-driven macroeconomic paths (generated by MFMod) and the sector-level PD projections (generated by the BART satellite model) into bank-level impacts on credit losses, profitability, and capital adequacy.

The model focuses on credit risk, where transition policies affect borrowers unevenly across Armenia's sectors. The direction and magnitude of the effect vary by scenario. Carbon-intensive sectors may default at higher rates, increasing losses and provisions in case of disruptive policies, but they can also adapt and invest in low-carbon technologies, and reduce their defaults and provisions. The combination of scenario-specific PD shocks and LGD adjustments could be used to produce updated expected losses for each bank, using the granular credit register.

As a next step, shifts in losses per bank feed into banks' profit and loss accounts, where higher provisions, reduced NII from non-performing loans jointly reduce profitability, while scenario-consistent tax effects offset the results partly. Profits are updated iteratively over the projection horizon.

Finally, the model recalculates CARs using updated capital positions while holding risk-weighted assets (RWA) constant, isolating the effect of climate-driven credit deterioration. This provides a forward-looking assessment of which Armenian banks may face capital pressure under various transition pathways.

The robustness of this methodological approach depends on a number of key factors. The reliability of credit-risk model outputs is closely linked to the length and quality of available time series data, the availability of firm-level information to complement and validate sector-level estimates, and the granularity of inputs such as LGD values. Expert judgment remains an important complement to quantitative outputs, particularly where data are limited or model results are ambiguous. Additionally, the choice of stress-test horizon matters: where transition policies are introduced with a delay, adverse effects may extend beyond the assessment window, and static balance-sheet assumptions may not fully reflect how financial institutions adjust their portfolios over time. The extent to which these factors are binding will vary across country contexts; the specific implications for the Armenian case are discussed in the Chapter 5.2 and the rough recalculation for the dynamic balance sheet is presented in Chapter 5.1.

The reliability of credit-risk model outputs is closely linked to the length and quality of available time series data, the availability of firm-level information to complement and validate sector-level estimates, and the granularity of inputs such as LGD values.

BOX 2

How losses feed through to the bank capital

This analysis focuses on credit risk as the main way transition risk impacts banks. The goal is to estimate how much banks' credit losses could grow in different transition scenarios.

EL determines changes in LLP in the profit and loss (P&L) in each year, calculated as

$$EL_{i,j,t} = EAD_{i,j,t} \times PD_{i,j,t} \times LGD_{i,j,t}$$

where i , j and t index the bank, sector, and year, respectively, and EAD denotes the (remaining) performing loans amount. Owing to data gaps, the same LGD is applied for all banks and sectors within a given scenario.

Since the credit risk satellite model returns the sector-level PD shifts rather than the PD levels per se, bank- and sector- level PDs are obtained as

$$PD_{i,j,t} = PD_{i,j,t_0} \times PD_{j,t}^{Shift}$$

where $PD_{i,j,t}$ is the observed PD for bank i and sector j at the reference date t . As $PD_{j,t}^{Shift}$ is computed at the sectoral level, the same shift is applied to all banks in the given sector. Once PDs rise, EL increases. These higher EL must be recognized through higher LLPs, which reduce banks' profits and therefore their capital. Since the amount of RWA is kept the same throughout the stress test, any drop in capital will directly lower the bank's CAR compared to the baseline scenario. The stress test does not try to predict all profit and loss items, but it does make two logical adjustments to 2 profit and loss accounts – NII and Profit Tax:

- When loans become non-performing (NPL), they stop generating interest income, so the bank's net interest income is reduced.
- Tax expenses are calculated based on profit before tax, which already includes credit losses and NII reduction stemming from new NPLs. This means higher credit losses lead to lower profits and, as a result, lower taxes. This partially balances out the negative impact of credit losses on capital.

For simplicity, only loan loss provisions, net interest income, and tax expenses are adjusted in the model, since these have clear links to credit risk. All other profit and loss items are kept unchanged.

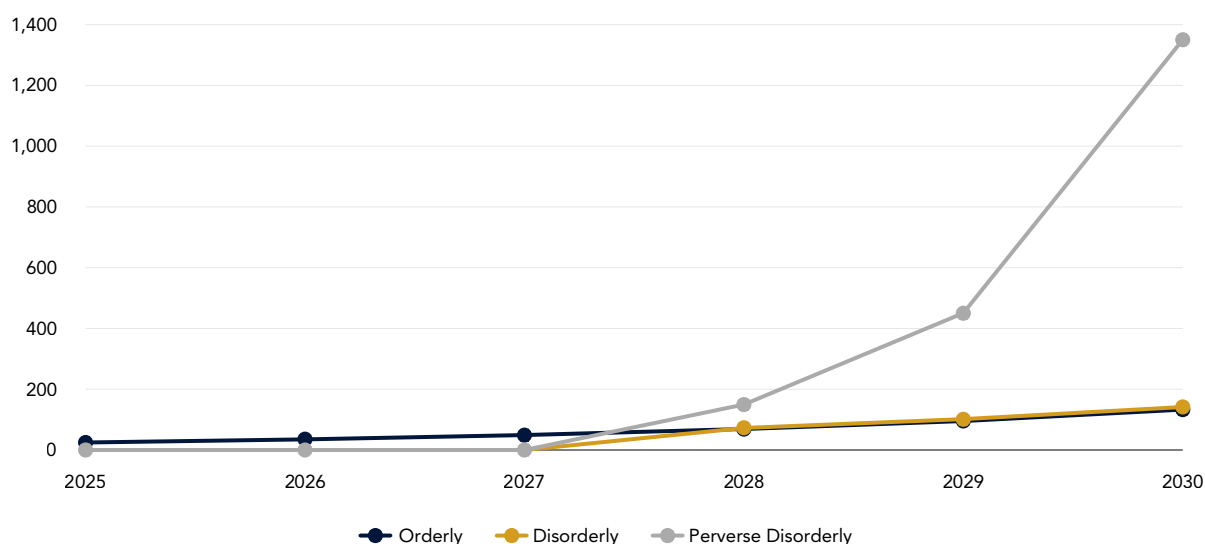
4 Macroeconomic and sectoral impacts of low-carbon transition scenarios

This chapter presents the modelling findings under the different transition scenarios described in Chapter 3 and their potential macroeconomic and sectoral impacts. The findings capture how carbon pricing (and related policies) could affect output and sectoral performance.

4.1 Modelling findings under different scenarios

The level of the carbon tax required to achieve the emissions reduction target varies under the different scenarios. The modelling determines the carbon price path required under each scenario to induce a decline in CO₂ emissions consistent with a 40 percent reduction by 2030 relative to 1990 levels (see Figure 7).

FIGURE 7
Carbon price to achieve NDC target under different scenarios (USD/tCO₂)

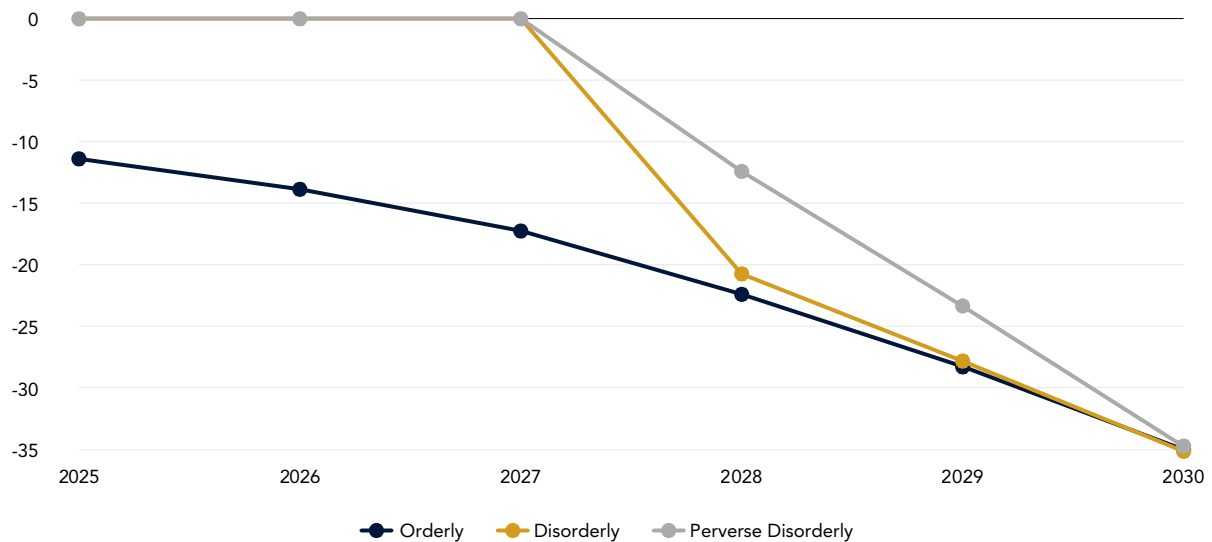


	Transition risk scenarios		
	Orderly (\$/tCO ₂)	Disorderly (\$/tCO ₂)	Perverse Disorderly (\$/tCO ₂)
2025	35	0	0
2026	49	0	0
2027	69	72	150
2028	96	101	450
2029	134	141	1,350

Source: Authors based on CBA data.

The rate of decline in CO₂ levels also varies under the different scenarios. The modelling uses the carbon tax levels to determine the CO₂ emissions reductions that could be expected in each scenario (see Figure 8).

FIGURE 8
Decline in CO₂ levels under various scenarios (% differences from baseline)



	Transition risk scenarios		
	Orderly (%)	Disorderly (%)	Perverse Disorderly (%)
2025	-13.84	0	0
2026	-17.22	0	0
2027	-22.36	-20.71	-12.38
2028	-28.22	-27.78	-23.31
2029	-34.95	-35.06	-34.70

Source: Authors based on CBA data.

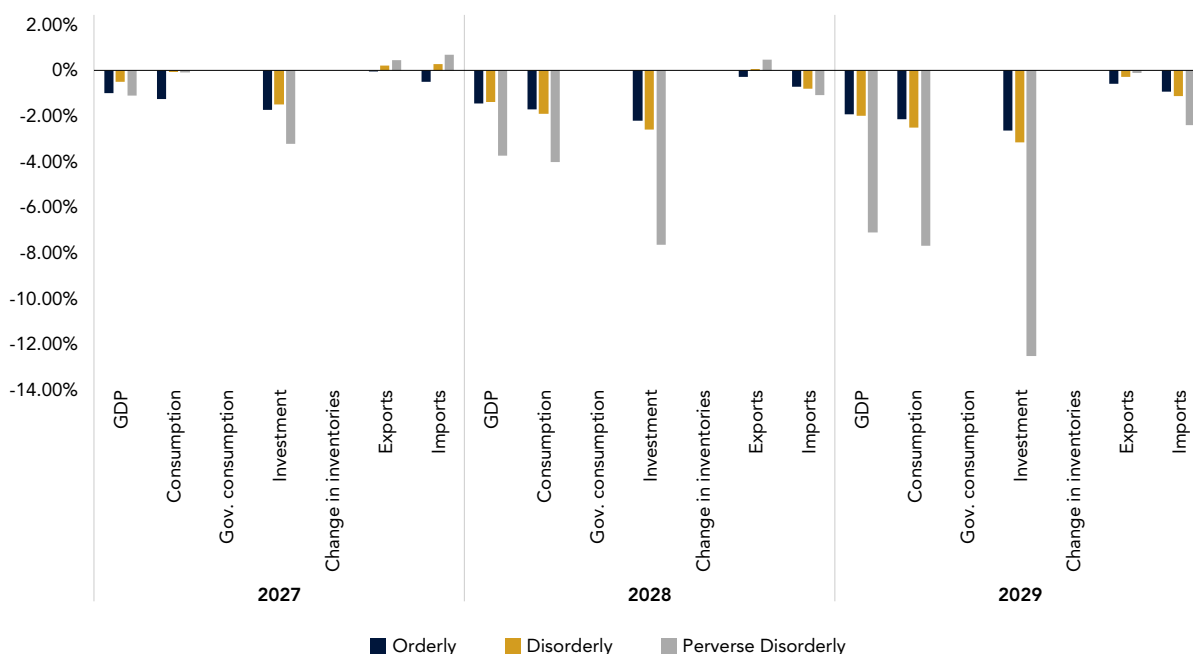
4.2 Macroeconomic impact of transition scenarios

Typically, the shift to a low-carbon economy influences macroeconomic and sectoral outcomes through established channels. Policies like carbon pricing and renewable energy subsidies raise the cost of carbon-intensive activities, prompting firms and households to adopt cleaner technologies and adjust consumption patterns. This drives investment away from carbon-heavy assets and toward low-carbon infrastructure, temporarily impacting productivity and output as capital is reallocated. While these changes may reduce aggregate output and employment in the short term, over time, increased efficiency, improved energy security, and new growth opportunities in low-carbon sectors can enhance productivity and resilience.

While all scenarios have some degree of negative impact on GDP by 2029, it is most affected by abrupt and poorly coordinated policy changes that disrupt market stability. The Perverse Disorderly scenario shows a decline of 7.1 percent, with much smaller reductions of around 2 percent in the Disorderly and Orderly scenarios (see Figure 9). This pattern reflects the disruptive nature of lower substitution between fossil fuel and renewable energy and poorly coordinated managed transition, where abrupt policy shifts and subsequent market shifts amplify negative effects in the economy (see below). However, the difference in GDP impacts between the Disorderly and Orderly pathways is relatively small. This indicates that the Armenian economy is likely to be more sensitive to how the transition is managed than the speed of transition per se.

FIGURE 9

Macroeconomic impacts of carbon pricing under various scenarios (% differences from baseline)



Source: Authors based on CBA data.

Uncertainty amplifies precautionary saving and suppresses consumption. A closer look at the GDP components in 2029 reveals that consumption is among the most negatively affected by the carbon price, with significantly larger declines under the Perverse Disorderly scenario, as uncertainty potentially amplifies precautionary saving and reduces spending. Consumer spending is not immediately affected after the introduction of a carbon tax, reflecting lags in price pass-through and in household consumption responses. Over time, however, rising prices reduce disposable income, leading to lower consumption.

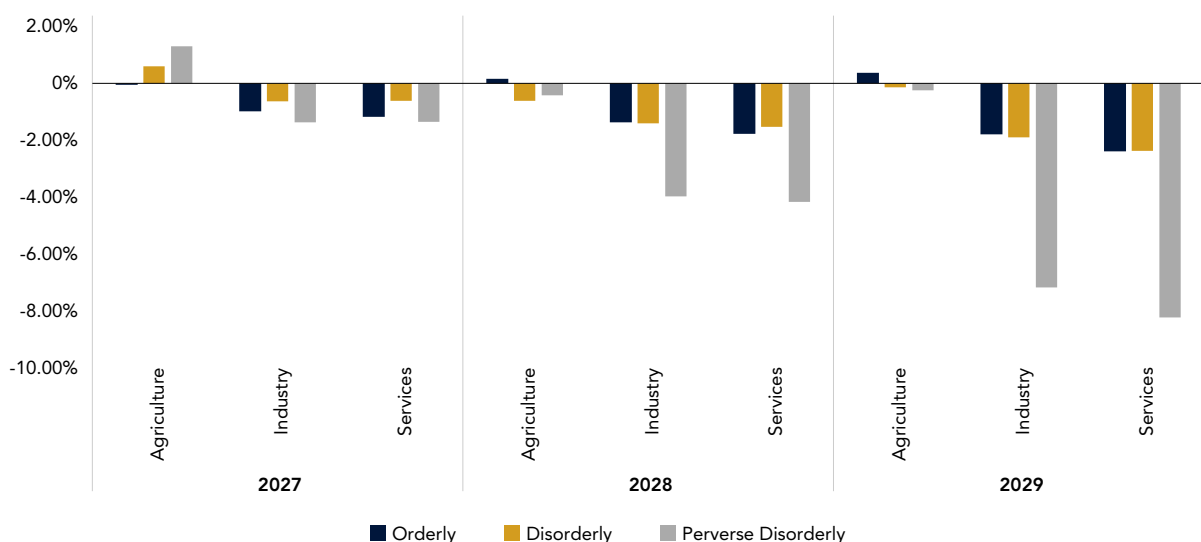
Abrupt policy shifts sharply undermine business confidence, causing investment to drop quickly and persistently. Investment sees the largest drop in the Perverse Disorderly scenario (about 13 percent), reflecting heightened uncertainty and reduced business confidence in the face of abrupt policy changes. Furthermore, unlike consumption, investment is negatively affected right away and continues to decline throughout the period because of the impact of carbon tax on expected returns and capital costs.

Imports shrink as domestic demand contracts, while exports weaken more gradually as rising production costs make Armenian goods less competitive internationally. Imports also decline in the same order, which partly offsets overall GDP losses, as reduced domestic demands lead to lower import volumes. Furthermore, following the introduction of the carbon tax, both the Disorderly and Perverse Disorderly scenarios initially show an increase in imports, likely driven by firms front-loading imported inputs, before weaker domestic demand eventually leads to a decline in imports. Exports, however, follow a contrasting pattern: they fall the most in the Orderly scenario and the least in the Perverse Disorderly scenario. This is likely explained by the fact that, in the short run, Armenian exporters are unable to raise prices to fully reflect higher production costs from the carbon tax. Under a more gradual transition (Orderly), export prices increase over time, leading to a decline in exports. Exports are less directly affected by the carbon tax, since Armenian exporters are unable to raise prices in global markets and international demand is not influenced by Armenia's domestic policy. However, over time, as export prices become less competitive compared to global peers, exports decline further compared to the baseline.

4.3 Sectoral impacts of transition scenarios

The services and industry sectors experience the largest decline in value added across all transition scenarios due to their larger roles in household consumption and investment, while agriculture remains largely insulated. Across all transition scenarios, the services sector experiences the largest decline in value added, followed by the industry sector (Figure 10). In contrast, agriculture shows near-zero effects and even small positive impacts in some years. Two factors explain these outcomes. First, demand structure: Services account for a large share of household consumption, while industry dominates investment demand; agriculture, on the other hand, has a relatively small share in the final demand components and is largely consumed as an intermediate input. Second, relative price effects: a carbon tax could lead to larger relative price increases in industry and services, which reduces their demand and create a substitution effect that partly benefits other sectors, including agriculture.

FIGURE 10
Aggregate Sector GVA under various carbon pricing scenarios (% change from baseline)



Source: Authors based on CBA data.

While these broad patterns hold across all sectors across scenarios, the magnitude of the impact varies within the services and industry categories as the shift becomes more abrupt and disorderly. The cumulative change in value added for the most affected sectors between 2024 and 2029 under the three transition scenarios (see Table 2) shows that the adverse effects deepen as the transition becomes more disorderly. Under the Orderly and Disorderly transitions, sectoral value-added declines by around 1-1.5 percent relative to the baseline. However, under the Perverse Disorderly scenario, losses become significantly larger, ranging from 2 to 4 percent across sectors.

Accommodation, Financial Services, and Real Estate sectors are among the most severely hit, reflecting their high exposure to overall economic slowdown and reduced investment activity.

The Information and Communication and Trade sectors face intermediate impacts, as weaker aggregate demand and investment ripple through the broader services network. The Construction sector also experiences declines due to lower capital formation and delayed investment projects.

TABLE 2

Differences in value added in the worst affected sectors between 2024 and 2029 (% change from baseline)

	Accommodation	Construction	Financial	Information and Communication	Trade	Real Estate
Orderly	-1.4	-1.3	-1.3	-1.1	-1.4	-1.3
Disorderly	-1.1	-1.2	-0.9	-0.8	-1.1	-1.0
Perverse Disorderly	-3.2	-3.9	-2.9	-2.4	-3.2	-3.2

Overall, the results suggest that the economic costs of the transition are highly sensitive to the manner in which climate policies are implemented. While all transition scenarios entail some short-term macroeconomic and sectoral adjustment costs, these effects are substantially amplified under disorderly and poorly coordinated policy pathways. In contrast, a more orderly and predictable transition helps contain output losses and limits adverse spillovers across sectors. The fact that these estimations cover only 5 years may underestimate the effects as it takes time for the economy to absorb the shock. However, these macroeconomic and sectoral dynamics can provide critical input into the banking sector stress testing framework.

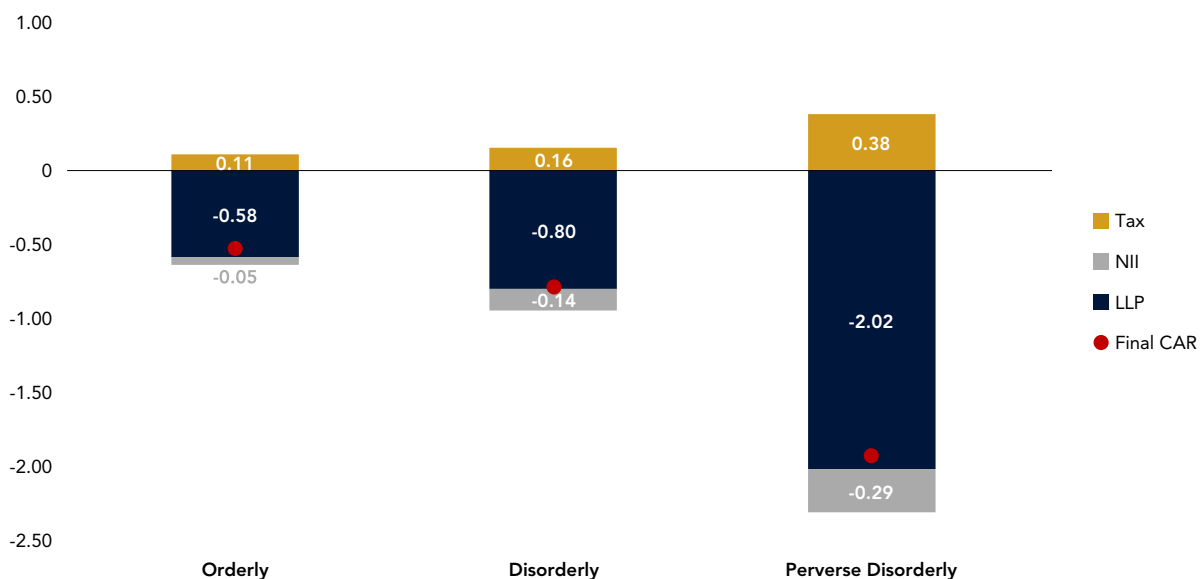
5 The impact of transition scenarios on the banking sector

This chapter evaluates how the macroeconomic effects of low-carbon transition scenarios impact the banking sector, with a particular emphasis on credit risk. Changes in economic activity, sectoral output, inflation and investment patterns shape borrower's repayment capacity, making macro-financial linkages central to stress-test results. Using these linkages, the climate-related transition scenarios are mapped into macroeconomic projections using MFMod, which are then fed into the stress-testing model to estimate how banks' financial results evolve under each scenario.

5.1 Mapping macro paths and sectoral shifts into credit outcomes

Overall, the results indicate that transition risk is manageable for the Armenian banking sector, but credit losses can increase considerably under an abrupt and weakly coordinated transition. By the end of the five-year horizon, the system-wide CAR declines by 0.5, 0.8, and 1.9 percentage points under the Orderly, Disorderly, and Perverse Disorderly scenarios, respectively, relative to the baseline (Figure 11). These declines are driven mainly by higher expected LLPs, which reach roughly 1.2, 1.3, and 1.7 times their baseline levels.

FIGURE 11
Impact on CAR per financial item



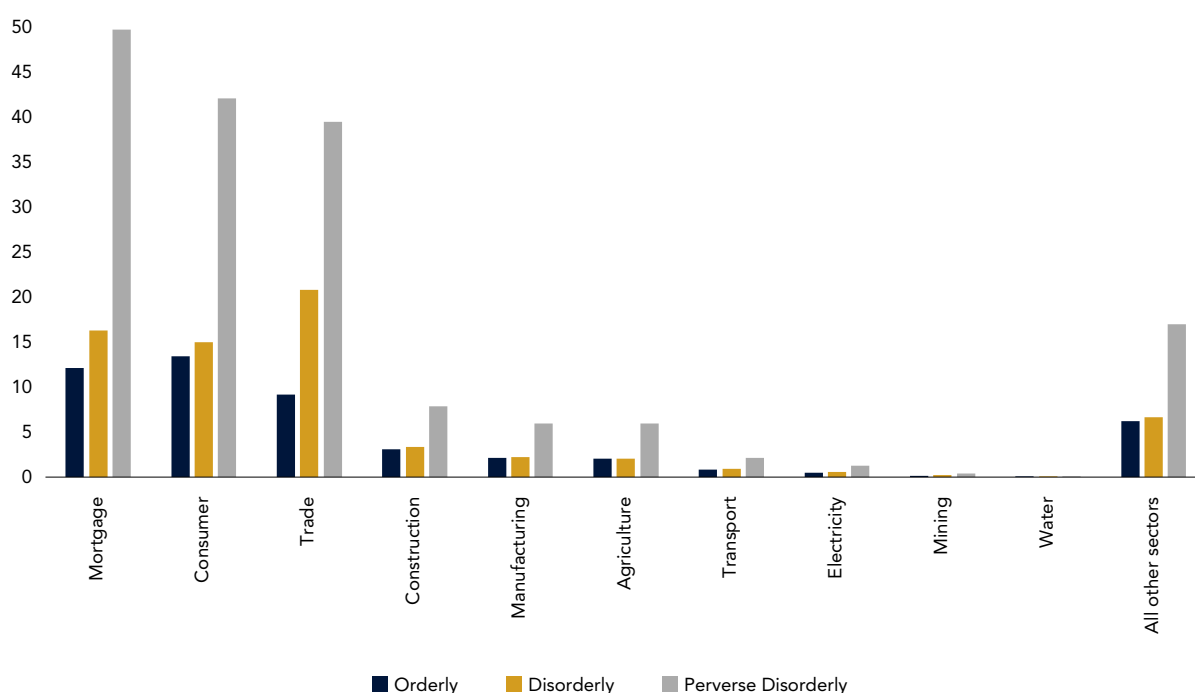
Note: Columns show the contributions of taxes on profits, NII, and LLP to the total capital impact in each scenario, with the final CAR relative to Baseline, p.p. indicated as a red dot.

Source: Authors' own calculations.

The severity of the capital drawdown is driven less by carbon pricing itself but rather by banks' underlying exposure to sectors and asset qualities as of December 2024 that become stressed under weakly organized transition. As shown in Figure 11, in Orderly and Disorderly scenarios, the profit tax burden and NII effects remain relatively smaller and largely offsetting each other, suggesting that banks can absorb gradual policy tightening. Instead, LLP are the main contributor to decline in capital. Consequently, the discussion below focuses on LLP and, in particular, its calculation through EL components, whose increase reflects a clear chain of events: stressed sectors lead to higher EL on the banks' portfolio; these losses increase LLPs on the balance sheet; higher LLPs reduce retained earnings, which in turn lowers CAR. This pattern suggests that transition risk for Armenian banks is primarily through credit losses.

System-wide credit risk is driven more by household and retail exposures than by classic transition-sensitive sectors. The main drivers of EL are the Mortgage, Consumer, and Trade sub-portfolios (Figure 12). Together they account for 57 percent of the banking sector's loan portfolio as of December 2024 and for 65-70 percent of total EL over the five-year stress-test horizon. This suggests that transition risks effect on retail segment through general macroeconomic variables (GDP, inflation) is stronger than the impact of economic sectors that considered more direct, sector-specific GVA (informed by the given sector's emissions). Construction, Agriculture, and Manufacturing follow in terms of contribution. The overall contribution to EL of sectors such as Water and Mining remains modest despite large shifts in PD. This is mainly due to their limited portfolio volumes and the low initial PDs (as at December 2024). This suggests that under the current portfolio structure, transition driven sectoral shocks have limited potential to generate systemic credit losses in the short term as they are currently concentrated in a few losses than across the system.

FIGURE 12
Banking sector's additional credit losses per economic sector

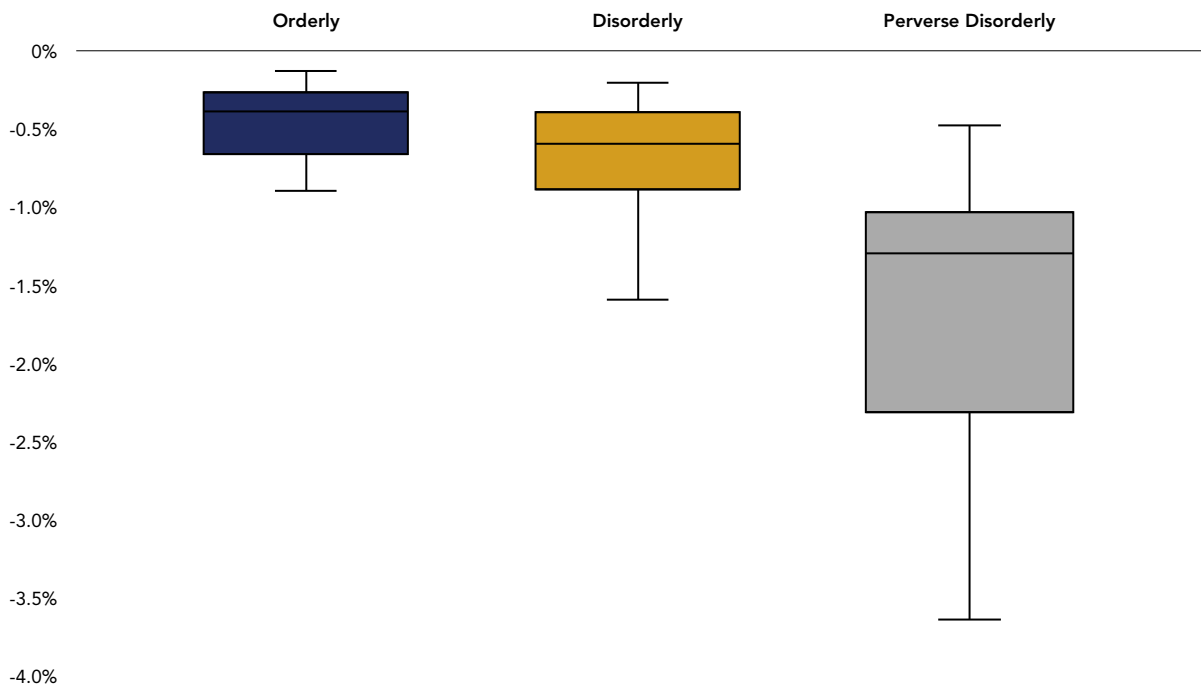


Note: Shown relative to baseline, cumulative for 5 years, in AMD, billion
Source: Authors' own elaborations.

Concentration risk matters far more at the bank level than at the system level. Even though sectors like Agriculture and Electricity contribute little to system-wide credit losses (Figure 12), the fact that 70 percent of loans in these sectors are concentrated in a few banks means that individual institutions may face material losses that do not show up in aggregate EL. This implies that while the system exhibits high resilience to the transition risk, certain banks could still face portfolio-specific vulnerabilities due to their concentration in transition-prone sectors, whose potential losses have not been fully captured in the current framework.

Interbank differences become even more pronounced under harsher stress. Not only is the CAR reduction larger under the Perverse Disorderly scenario, but the distribution of outcomes also widens, indicating that interbank differences become more pronounced under harsher stress (Figure 13). Since LGD and sectoral PD shifts are identical for all banks within a given scenario (the PD shifts have been calculated upon system-wide sectoral PDs and not individually for each bank, as the exercise focuses on system-wide risk), the differences between banks indicate variations in banks' loan portfolio mix and initial PD levels. Consequently, banks with larger exposures to more affected sectors or higher initial PDs experience stronger CAR declines. Depending on the bank, the contribution of high-risk transition sectors to the bank's total EL ranged from 0 to 23 percent, implying that for some banks these sectors can play an important role, even if their aggregate contribution at the system level is relatively modest.²⁵

FIGURE 13
The distributions of Armenian banks' CAR impacts per scenario



Note: By scenario relative to baseline, p.p.

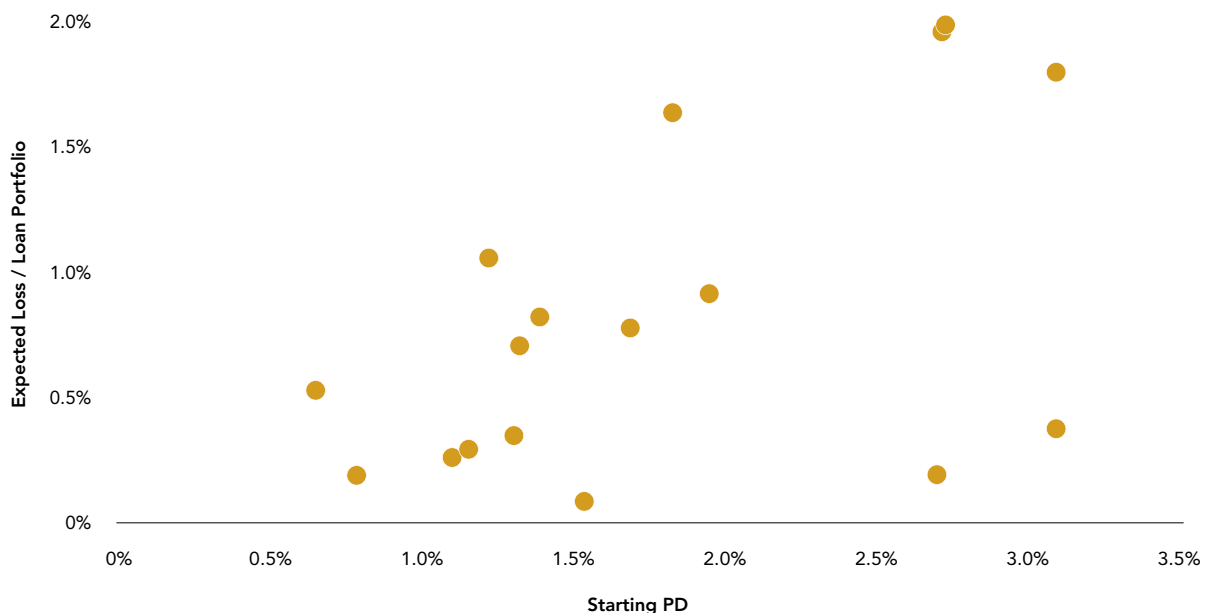
Source: Authors' own elaborations.

²⁵ Our simplified recalculation assuming dynamic balance sheet shows that the banking sector's CAR reductions due to transition risk become smaller for all transition scenarios when considering loan portfolio's natural growth (see Appendix D.2).

The additional credit losses at individual bank level (in the Perverse Disorderly scenario, scaled by their respective loan portfolio size), generally rise with the starting PD (Figure 14). This reflects the applied methodological approach. Each dot represents a bank, and the dispersion of points indicates substantial heterogeneity across banks: some banks with relatively low initial PDs still experience notable expected losses, while others with higher PDs do not necessarily have proportionally larger losses. Overall, the plot suggests that initial PD alone does not fully explain how severely banks are affected in this scenario; portfolio composition, exposures, and other risk factors likely play a significant role. These results indicate that climate shocks, that are generally weaker in nature than those used in standard stress testing, are unlikely to jeopardize the financial stability of the Armenian banking sector.

FIGURE 14

Bank-level expected losses (normalized) versus initial PD under the Perverse Disorderly scenario



Note: Expected losses (y-axis), scaled by loan portfolio, versus initial PD (x-axis). Each dot is one bank.

Source: Authors based on CBA data.

5.2 Factors which may impact modelling findings

These results should be interpreted with caution, as the current assessment is an initial attempt to quantify the effects of climate transition risk on the financial system without adjustments based on qualitative data. Indeed, the outcomes depend critically on the available data and the chosen methodology, hence, the assessment's main limitations are also linked to them. The results, particularly the sectoral PDs' predictions, depend on the available time series. Although the BART credit-risk satellite model can work with a relatively short time series, a longer and richer dataset would enhance the robustness of the estimates. Moreover, given the small exposures in several transition-prone sectors, system-wide PD estimates (based on counts) for these segments are less reliable than for larger portfolios, and forecasts based on past data may understate the full severity of transition policies. Furthermore, resulting PDs are recommended to make expert adjustments based on grounded quantitative insights, such as the CBA's Risk Radar. For example, incorporation of available transition risk scores or sub-portfolio specific insider insights (e.g., their nature, sectoral concentration) can help making expert adjustments to quantitative methods' output when the latter are contradictory or uninterpretable. Additionally, in the absence of Armenian historical data on the interaction between carbon prices, greenhouse gas emissions, and firms' financial health, constraints on the calibration of PD and LGD associated with transition risk are evident. Finally, another key limitation is the usage of system-wide LGD values; updated and more granular inputs would enhance the assessment's robustness.

A more granular sectoral breakdown or, ideally, the integration of corporate level assessments, would provide useful robustness checks and strengthen the credibility of the results. Currently applied macroeconomic approach considers only sector-level, system-wide asset-quality deterioration, whereas microeconomic approach via firm-level information could help validate and refine the estimates, especially for concentrated or quasi-monopolistic sectors such as Electricity and Mining. Additionally, for such sectors, volume-based indicators may be more informative than system-wide PDs derived from migration counts when it comes to capturing tail losses at the bank level.

The macroeconomic projections suggest that the adverse effects of the transition scenarios may extend beyond the five-year stress-test horizon. Under the static balance-sheet assumption, banks' loan-portfolio composition is held constant over the entire horizon,²⁶ although banks could reasonably be expected to adjust their portfolios in response to transition policies. In the disorderly scenarios, the carbon tax is introduced with a delay (in the third year of the horizon), implying that part of the negative impact is likely to continue to materialize on some degree beyond the fifth year (2029) according to the macroeconomic paths, which is outside the current assessment horizon.

²⁶ Bank of International Settlements (2018). [Stress-testing banks – a comparative analysis](#).

6 Conclusions and policy implications

This CTRST exercise constitutes an initial step toward quantifying climate-related financial risks. It lays the foundation for a consistent analytical framework, offers early insights into the potential scale of the risks, and highlights areas where methodologies, data, and coverage can be further strengthened.

More granular data across dimensions not fully captured by traditional banks' reporting frameworks would enhance the ability to quantify the effects of climate risks to financial sector.

There are data gaps at both the level of bank-specific exposures and in macroeconomic and sectoral information, constraining the scope for more detailed and institution-specific assessments. In particular, macroeconomic variables are typically available only at the national level, limiting the ability to precisely capture heterogeneous sectoral dynamics and transition effects. While transition risk analysis can be strengthened by moving beyond system-wide averages toward bank- and sector-specific parameters, such as bank-level LGD aligned with portfolio composition, greater granularity often comes at the cost of shorter and sparser PD and NPL time series, potentially weakening statistical robustness. Where appropriate, banks can make use of their NPL data alongside their current regulatory provisioning rates, as a complementary robustness check. Striking an appropriate balance between data granularity and data quality is therefore essential for producing reliable results, with banks' internal NPL data and regulatory provisioning rates providing useful complementary robustness checks where feasible.

Ongoing reporting initiatives at CBA could progressively solve key data gaps.

Identified data constraints are expected to ease as sustainability frameworks are implemented. For instance, banks have already begun reporting their sustainability information to the CBA, including financed emissions. By incorporating this data into stress test models, it will be possible to better estimate the sectors in the banks' portfolio that are most exposed to climate-related regulatory changes. The Ministry of Finance's planned country-wide sustainability reporting framework will also enable more granular, firm level analysis over time, which can complement and serve as additional robustness check for the transition risk stress tests.

There are data gaps at both the level of bank-specific exposures and in macroeconomic and sectoral information, constraining the scope for more detailed and institution-specific assessments.

Beyond data availability and granularity, a comprehensive assessment of climate-related financial risks also requires accounting for both transition and physical risk channels.

While this exercise focuses on transition risks, transition scenarios alone do not capture the full range of climate-related vulnerabilities relevant for Armenia. Physical climate hazards, such as heatwaves, floods, landslides, storms, mudflows, and droughts, can affect economic activity and credit risk through both acute shocks and longer-term impacts. Once sufficient data becomes available, complementing transition risk analysis with physical climate risk stress testing will therefore be

essential. In this regard, the CBA's forthcoming climate hazard mapping will provide a critical foundation for strengthening physical risk assessment and, over time, enable a more integrated and comprehensive climate risk stress testing framework.

Ultimately, the purpose of climate risk quantification is to inform supervisory expectations and, where necessary, support the development of targeted supervisory measures to help banks identify, measure, and mitigate climate-related financial risks. In this context, integrating transition and physical risk assessments within a unified climate stress testing framework would strengthen supervisory responses and expectations. While the CTRST results suggest that the banking system remains resilient, with CARs staying above critical thresholds, the projected increase in credit losses highlights the need for enhanced supervisory engagement. This, in turn, supports raising expectations for banks to conduct their own climate stress tests. In line with the Sustainable Finance Roadmap, the CBA plans to issue supervisory guidance covering governance, strategy, risk management, scenario analysis and stress testing, and disclosure, informed by transition and physical climate risk stress testing exercises.

Bank level transition planning is a key tool for managing long term transition risk. Differences in banks' credit portfolio structures and projected transition risk losses underscore the need for institution-specific transition plans. In this regard, financial institutions' transition plans should draw on good international practices to help achieve less emission intensive portfolios, thereby strengthening resilience to transition pathways and enhancing the credibility of future transition risk stress testing results. This could also support the mobilization of green financing, including from International Financial Institutions. Therefore, the CBA views it as a medium-term supervisory priority.

Effective management of climate-related financial risks, and the ability to unlock the opportunities arising from the transition, hinges on strong coordination across public authorities. Climate change mitigation and adaptation policies are designed and implemented by multiple institutions, often with complementary but fragmented mandates. Strengthening coordination among financial regulators and relevant ministries would improve data sharing, policy alignment, and joint target setting, including economy-wide transition objectives. Such coordination would help reduce transition costs and support a smoother adjustment for both the financial sector and the broader economy. For example, while the green taxonomy has been adopted by the Ministry of Economy, emissions reporting for the real sector falls under the responsibility of the Ministry of Finance. Establishing a coordinated platform involving the financial regulator and the Ministries of Finance, Economy, and Environment would facilitate more effective information exchange, help address any data gaps, subsequently generate one central climate and sustainability database and support the design of shared objectives, such as country-wide transition targets and transition planning frameworks for corporates beyond the financial sector. Armenia's existing Inter-Agency Climate Council, chaired by the Deputy Prime Minister and inclusive of a dedicated working group on finance, could serve as a natural foundation for such a platform, with clear guidance on the role of various entities within this broader coordination framework.

While preliminary in nature, this exercise represents an initial step toward developing a more comprehensive framework for assessing climate-related financial risks in the financial system. The conclusions and policy considerations emerging from the CTRST are consistent with the priorities outlined in the CBA's Sustainable Finance Roadmap and provide a practical basis for further strengthening climate risk analysis, supervisory approaches, and inter-institutional coordination going forward.

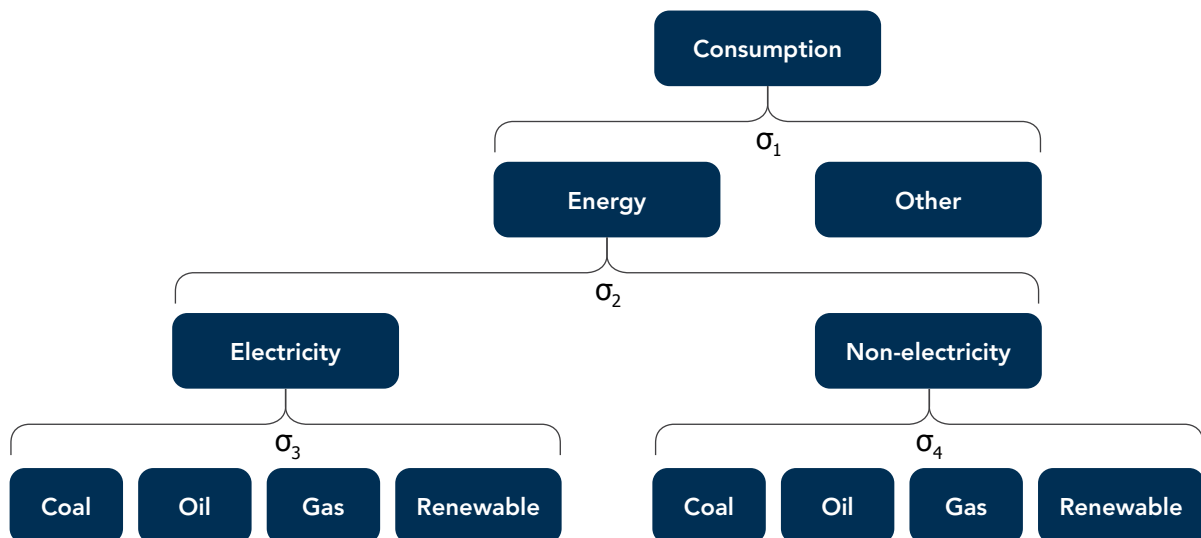


Appendix A: Use of MFMod to capture energy transition dynamics

For the purposes of the CTRST, the standard MFMod framework is modified to model the energy sector in more detail, focusing on volumes and prices to assess the energy low carbon transition's impact on the economy. Consumption and trade are divided into energy and non-energy components using a constant elasticity of substitution (CES) structure, which allows the model to reflect substitution patterns as relative prices change. This means energy demand depends on both the household and firm preference for energy goods and the degree of price sensitivity.

Consumption choices are determined by a constant elasticity of substitution (see Figure A.1), with σ parameters measuring price sensitivity at each decision stage. A carbon tax on fossil fuels creates a price difference between fossil fuels and renewables. If consumers are price-sensitive (σ_3 and σ_4), they will shift from fossil fuels to renewables, which in turn affects downstream production costs for energy-intensive goods and service. On the supply side, the energy sector distinguishes production activities from electricity and non-electricity production. This allows the model to quantify how carbon pricing, changes in energy mix, and shifts in demand influence sectoral output, energy imports, and overall macroeconomic outcomes.

FIGURE A1
Structure of consumption choices in MFMod



Source: Authors based on CBA data.

Appendix B: GTAP-based disaggregation of aggregate MFMod outputs

The GTAP input-output tables are used to break down aggregate MFMod demand components into detailed sector-level estimates. The disaggregation based on the GTAP input-output tables for Armenia serves to distribute the aggregate final demand components: Agriculture, Energy, Non-Energy Industry, and Services from the main MFMod framework across 63 individual sectors (Table B.1). Each sector's share of these components is then adjusted by its intermediate supply ratio to capture both the direct and indirect demand for its output. To isolate the domestically produced portion of demand, sector-specific shares of total imports and product taxes are removed. Sectoral intermediate input requirements are approximated using sector-specific intermediate-to-value-added ratios from GTAP, which scale MFMod sectoral value added to obtain implied intermediate demand. In the final step, the results are reconciled to ensure internal consistency between disaggregated sectoral estimates and the aggregate outcomes of MFMod.

TABLE B1
Mapping of sectors used in the stress testing

NACE	Accommodation	Agriculture	Construction	Consumer	Education	Electricity	Entertainment	Financial	Health	InfoCom	Manufacturing	Mining	Mortgage	Other	Professional	Real Estate	Trade	Transport	Water
A-B	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C-E	0	0	0	0	0	2	0	0	0	0	0	4	0	0	0	0	0	0	1
D	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0
F	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G-H	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
I	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0
J-P	0	0	0	0	1	0	1	2	1	0	0	0	0	2	1	1	0	0	0

Appendix C: Stress test framework

The CTRST uses credit risk as the main channel through which the transition scenarios affect the financial system. To capture this, EL are estimated under various scenarios. EL drive LLPs in the P&L, which in turn reduces profits and capital. With RWAs held constant, higher LLPs lower the CAR. In this stress test, only three items are affected: LLP, NII, and tax expenses. NII is adjusted when loans become non-performing and tax expenses partly offset credit losses by reducing profit-based taxes.

EL is calculated using the following formula:

$$EL_{i,j,t} = EAD_{i,j,t} \times PD_{i,j,t} \times LGD_{i,j,t}$$

where i , j and t index the bank, sector, and year respectively.

Due to data limitations, LGD is applied uniformly across banks and sectors within one scenario.

Bank and sector level PDs, are obtained by applying sectoral PD shifts to observed PDs:

$$PD_{i,j,t} = PD_{i,j,t_0} \times PD_{j,t}^{Shift}$$

where $PD_{i,j,t}$ is the observed PD for bank i and sector j at the reference date t . As $PD_{j,t}^{Shift}$ is computed at the sectoral level, the same shift is applied to all banks in the given sector.

PD specification and model calibration

Several BART specifications are estimated, varying the number of autoregressive lags for PD and the lags and selection of macroeconomic variables. The best-performing specification uses sectoral GVA and inflation as explanatory variables. The dependent variable (PD) is logit-transformed, while inflation enters in first differences, and four lags are included for both the dependent and independent variables.

Since the model is calibrated at the sectoral level, 19 sets of goodness-of-fit statistics are produced. Across sectors, the average R^2 is about 98 percent, with the exception of three sectors (Water, Education, and Electricity), where the fit is weaker. Judgmental adjustments are applied only in a few cases (e.g., for the financial sector, whose default behavior differs materially from that of other sectors).

PD calculation

The existing practice of risk migration matrices is used to calculate the PD. This tracks the migration of loans among five credit risk categories: standard loans (performing normally), watched (1 to 90 days overdue), non-standard (90 to 180 days overdue), doubtful (180-270 days overdue), and loss category (more than 270 days overdue). PDs are calculated based on loan counts, not volumes, to better capture systemic events. Count-based PDs ensure that significant worsening requires broad deterioration

across the portfolio; while volume-based PDs are more volatile, they can be distracted by a few large loans. However, we acknowledge the importance of volume-based indicators, especially when the objective is to assess the impact on individual banks. PDs are calculated for 19 sectors which are broadly in line with NACE classification. Figure C1 shows a sample risk migration matrix.

TABLE C1

Sample of risk migration matrix (counts of loans are normalized)

Date	Standard → Standard	Standard → Watch	Standard → Substandard	Standard → Doubtful	Standard → Loss	Watch → Standard	Watch → Watch
Jan-09	90.5%	6.3%	1.3%	0.7%	1.2%	34.4%	18.9%
Feb-09	91.4%	6.3%	1.2%	0.6%	0.5%	35.9%	21.7%
Mar-09	89.9%	7.3%	1.5%	0.7%	0.6%	32.1%	25.0%
Apr-09	86.5%	9.3%	2.2%	1.0%	1.0%	28.2%	23.4%
May-09	84.9%	10.0%	3.0%	1.1%	1.0%	30.1%	23.0%
Jun-09	83.7%	9.9%	3.8%	1.4%	1.3%	26.6%	22.6%
Jul-09	84.4%	8.7%	4.0%	1.6%	1.3%	25.1%	20.3%
Aug-09	84.9%	7.7%	3.7%	2.1%	1.6%	25.3%	18.2%
Sep-09	84.5%	7.6%	3.6%	2.6%	1.7%	25.3%	18.2%
Oct-09	84.7%	7.1%	3.4%	2.8%	2.0%	25.9%	17.5%
Nov-09	85.3%	6.7%	2.7%	2.5%	2.8%	24.1%	14.8%
Dec-09	85.6%	6.7%	2.3%	2.2%	3.1%	24.0%	15.5%
Jan-10	88.0%	5.0%	2.1%	1.8%	3.1%	30.0%	13.0%

PDs are calculated according to the following formula:

$$PD_{b,s,t} = \frac{\text{Worsened loans}_{b,s,t-1 \rightarrow t} + \text{special cases}}{\text{Performing loans}_{b,s,t-1}}$$

where b stands for bank, s for sector (19 sectors), and t is time.

- **Worsened loans** – the number of loans that have changed their risk category from either standard or watched to worse categories (non-standard, doubtful, or loss) during the previous year.
- **Performing loans** – number of loans in standard or watched category 1 year ago and remain in one of those categories.
- **Special cases** – cases capturing situations where loans may be either performing or non-existing at t and $t-1$, but worsened at least once during the year. They include:
 - » loans that were performing at the beginning of the period and are fully repaid at the end, but worsened at least once during the period.
 - » loans that did not exist at the beginning and are performing at the end of the period, but worsened at least once during that period.
 - » loans that did not exist at the beginning and are fully repaid at the end of the period but worsened at least once during that period.
 - » loans that were performing both at the beginning and the end of the period, but worsened at least once during that period.

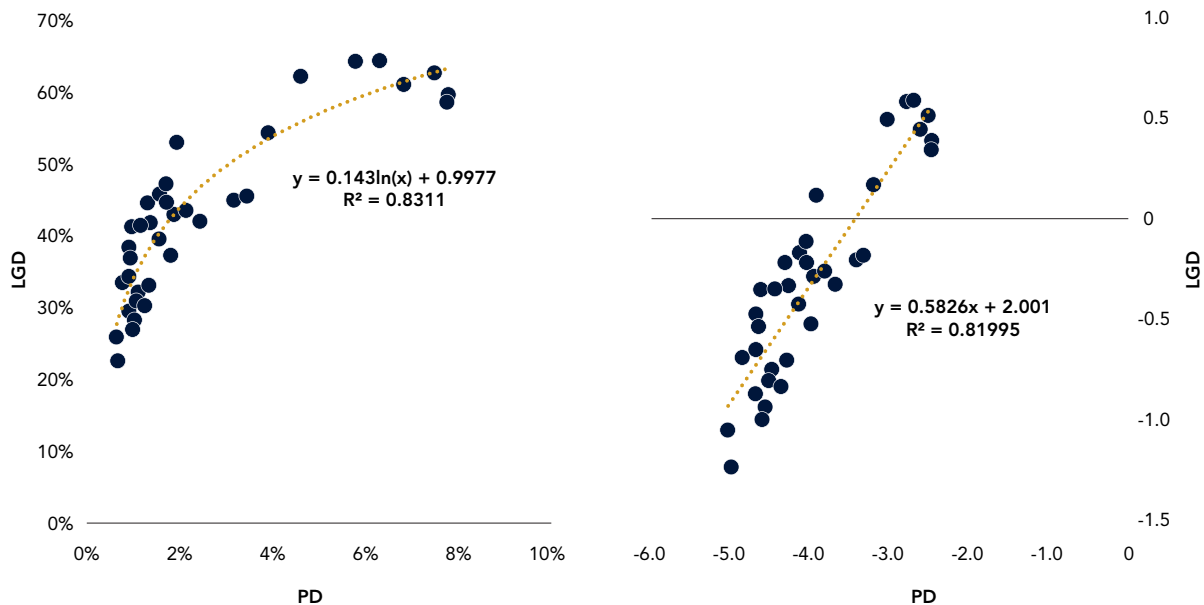
Loss given default calibration

LGD represents the share of default loans that ultimately become losses after recoveries. In contrast to PD, which can be easily approximated by the count or amount of loans that have migrated from the performing to non-performing category, the LGD parameter requires taking into account any collateral that backs the loan, its current value (which may be different from the value at the origination of the loan), and possible cash flows from its sale, among other things.

The CBA approximate LGD using risk migration matrices, as in the PD calculation process. It was practically implemented for the period of 2008-2017, involving a three-year rolling period, calculating recovery rates for initially worsened loans. However, one problem with its use is that the representative value of LGD is described for the three-year period as a whole, and it is difficult to assign that value to a specific date point at the beginning, the end, or any other point in the three years. As a compromise, the representative value is assigned to the mid-point of the period. The chart below (Figure C2) shows the dynamics of LGD parameter over time.

LGD values are very often tied to PDs for stress testing exercises, which means that during hard times more loans go to losses and vice versa. This is quite straightforward and logical from an economic perspective, and the approach is widely used by various central banks in their stress testing frameworks. In Armenia, the actual figures reveal that a relationship between PDs and LGDs exists and it is non-linear. Figure C2 below shows that connection both for raw PD-LGD values as well as their logit-transformed values.

FIGURE C2
PD-LGD relationship for raw and logit-transformed values



Source: Authors based on CBA data.

However, using the link between PDs and LGDs may be more appropriate for ordinary stress testing exercises, where the severity of stress scenarios may be variable over time and there might be a strong need for finer calibration. For the CTRST, given the clear-cut distinction among the severity of the scenarios, anchored LGD values are used for each, taking differentiated percentile values of the LGD distribution, specifically:

- Baseline scenario uses the 25th percentile (1st quartile) value which is approximately 32 percent;
- Orderly and Disorderly scenarios, given their severities' similarities (e.g., GDP, inflation) use the 40th percentile, which is around 38 percent;
- Perverse Disorderly scenario, designed to capture tail risks in transition pathways and constituting an adverse stress-test environment uses the 75th percentile or 3rd quartile value, which is close to 47 percent.

This approach balances realism with model simplicity, reflecting scenario severity while avoiding overfitting to historical extremes.

Using PD as a measure of credit risk

While there are many credit risk indicators, we have chosen PD counts its comprehensive nature and better quality. Credit risk can be measured in several ways including NPLs, loan loss provision to total loans and PDs. PDs are chosen for the CTRST as they are flow variables, capturing changes in portfolio quality over time, rather than slow moving stock variables like NPL. PDs also align well, given they could potentially account for intermediate worsening events within a year, serve as a recognized input for Basel II expected loss calculations, and are based on loan-level microdata, so the richness and quality of the underlying data is high. To develop an understanding of the NPL under the projected four scenarios, first, we should mention that the new NPL can be calculated as the product of the performing exposure multiplied by the PD in the given period. Hence, higher PD shifts and therefore PDs rise under transition scenarios, they would result in higher NPLs as well.

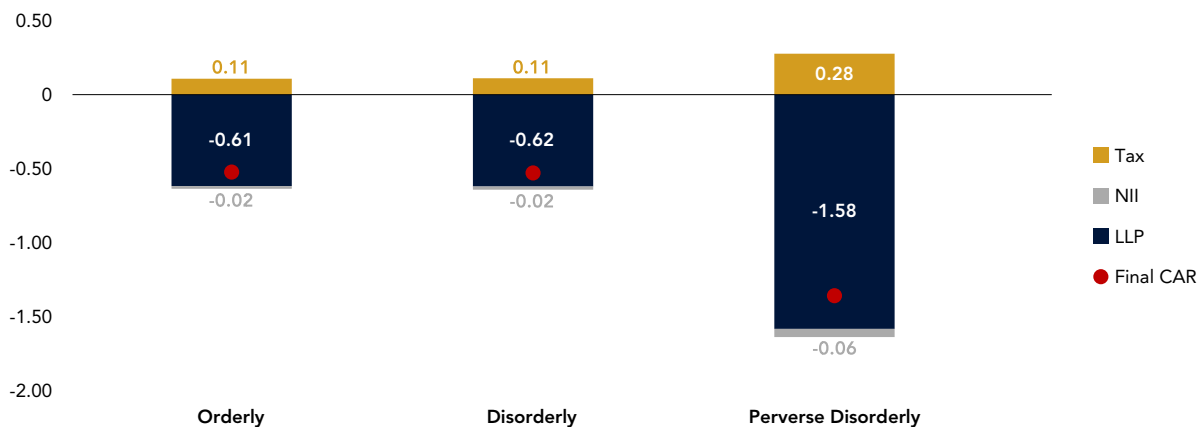
Appendix D: Robustness check and dynamic balance sheet assumption consideration

D.1 Robustness check

As a robustness check, the stress test was conducted using the OLS specification with sectoral GVA as the only driver of credit risk. This allows testing of whether the main results are sensitive to the model specification. Results show that transition under the Perverse Disorderly scenario hits the hardest, with Consumer, Trade and Mortgage sectors being the main drivers of EL. Figures D1 and D2 present the main outcomes of this specification. Overall, this robustness check confirms that the stress test findings are not driven by model complexity: even when only sector level economic shocks are considered, EL continued to be dominated by the same sectors, reinforcing the earlier conclusion that system-wide credit risk is shaped by portfolio composition and asset quality.

FIGURE D1

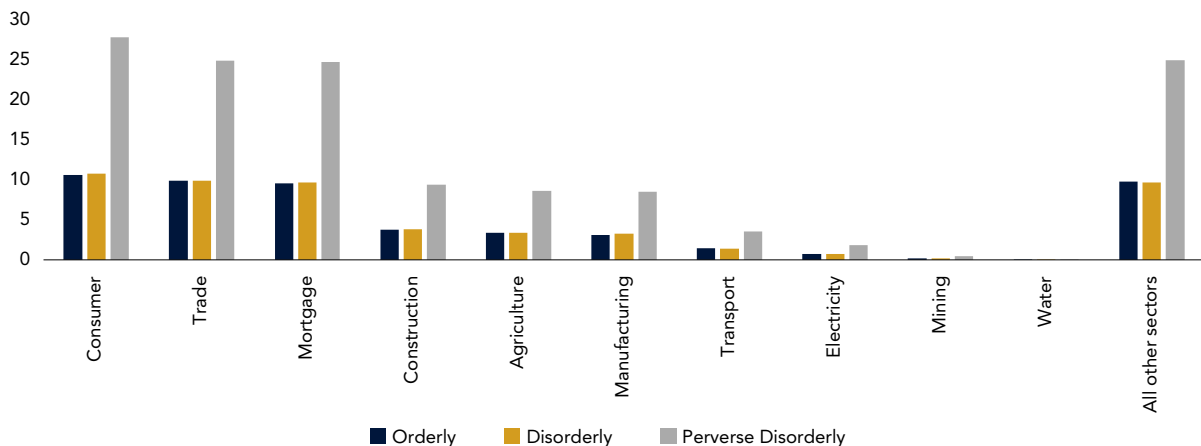
Resulting CAR reduction per forecasted drivers (OLS specification)



Source: Authors' own elaborations.

FIGURE D2

Banking sector's additional credit losses per economic sector relative to baseline



Note: Cumulative for 5 years, in AMD, Billion, OLS specification.

Source: Authors' own elaborations.

D.2 Dynamic balance sheet assumption consideration

To partly overcome the limitations regarding the static balance sheet and constant RWA assumptions, we explored the transition risk aggregate effects on the banking sector's CAR via simplified recalculation assuming dynamic balance sheet. As a starting point, the recalculation uses banking sector aggregate figures from the main results and applies simplified adjustments stemming from the loan portfolio's growth.

Our adjusted calculation assuming dynamic balance sheet shows that the impact of the transition risk on the CAR appears smaller in the broader picture when considering natural growth of the loan portfolio. To overcome the static balance and constant RWA assumptions' limitations, we explored the transition risk effects on the banking sector's CAR via adjusted calculations. To this end, in the spirit of dynamic balance sheet, we increase the overall banking sector's loan portfolio by the annual GDP growth year of the given scenario in the given year. Hence, within the four scenarios we have differentiated loan portfolio growth rates, which are later used for adjusting the other financial items and hence, influence the results. Thus, we adjust the NII, EL, RWA as well as other financial item (e.g., taxes, net non-interest income), which are later used to recalculate the adjusted CAR. First, we assume that EL would increase proportionally to the loan portfolio growth rate in the given scenario. Secondly, we increase proportionally the interest income and expenses, which results in the adjusted NII. Third, we adjust the RWA considering both the loan portfolio growth rate and the EL (in contrast to keeping RWA constant as it was done originally given the automated tool's technical capabilities). After further adjustments in connected financial items, we calculate the adjusted CAR, based on the adjusted Total Capital and the adjusted RWA. Surprisingly, the adjusted calculation shows lower reductions compared to the baseline at the end of the five-year stress test horizon – 0.2, 0.5 and 1.2 percentage points difference for Orderly, Disorderly and Perverse Disorderly scenarios, respectively. This suggests the capital depletion stemming from the transition risk becomes smaller on the banking sector's CAR as the faster RWA increase in baseline (due to natural growth of loan portfolio, that was higher in baseline compared to the other scenarios) naturally has a stronger effect to push the CAR down.

This exercise should be interpreted as exploratory, providing initial insights into dynamic balance sheet effects, and will be further refined and fully integrated in future iterations of the stress testing framework.

Appendix E: Applied loan classification against NACE 2 Level

Part of current Loan portfolio segmentation corresponding to NACE 2 level 1 sectors

NACE 2 level 1 sectors that are not used in current Loan portfolio segmentation

Part of current Loan portfolio segmentation, but outside of NACE 2 level 1 sectors

NACE code	Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organisations and bodies
#	Mortgage
#	Consumer
#	Other economic sectors



Central Bank
of Armenia



WORLD BANK GROUP