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The Case of Colombia

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Keywords: Banks, climate change, Colombia, credit risk, simulation, stress tests

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On the Impact of Climate Change Scenarios on Bank Solvency in an Emerging Economy: The Case of Colombia[1]

Abstract

Over the last few decades, climate change has become a pressing issue due to its potentially deleterious effects on economic and social conditions worldwide in the years to come. These impacts can be expected to spill over to many markets, including the financial system. This paper seeks to quantify the potential long-run impact of climate risk on bank solvency in Colombia. To that end, it describes and classifies the risks climate change poses to banking system stability. It also reviews recent research to quantify its effects, with a particular emphasis on the nascent literature on developing and emerging economies. The paper presents new evidence for Colombia by developing a straightforward stress test methodology that provides an initial estimate of potential effects related to climate change scenarios. To implement the simulation, sectoral elasticities of non-performing loans to sectoral GDP growth are estimated for the first time, to the best of our knowledge. Given the low depth of credit in economic sectors highly vulnerable to climate change, the impacts of extreme climate change scenarios are not sizeable. However, in extreme scenarios, there could be simultaneous bank failures that may raise concern about their impact on overall financial stability.

JEL Codes: G17, G21, O13, O54, Q54

Keywords: banks, climate change, Colombia, credit risk, simulation, stress tests

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1. Introduction and Literature Review

Climate change involves two sources of risk for financial stability: physical risk and transition risk (see ECB, 2020; Fabris, 2020; Rudebusch, 2021; Grippa, Schmittmann, and Suntheim, 2019). Physical risks encompass damage to property, infrastructure, and land caused by extreme weather events, such as floods and droughts, as well as the ensuing decline in productivity through lower output and higher costs. Additionally, they include slow-onset events, including environmental degradation and sea level rise. Transition risks refer to the unanticipated revaluation of carbon-intensive assets and the various effects associated with transitioning to a lower-carbon economy, including changes in the labor market and shifts in comparative advantages. These transition costs can be triggered by the sudden adoption of more stringent climate policies, reflected in new regulations and taxes; technological changes that reduce the costs of production of renewable energies; and changes in market sentiment and preferences that induce a further shift towards the supply and demand for more sustainable goods and services and away from fossil fuel-intensive industries.

Banks are exposed to climate change both directly (due to increasing costs of energy usage, compliance with climate-friendly building and regulatory standards, and data centers at risk from flooding or cyclones) and indirectly (through the disruptive effect of adverse macroeconomic conditions and transition paths on the creditworthiness of the bank's clients and the value of the assets they hold).

One fruitful avenue to assess whether banks can withstand the effects of climate change is stress testing. Stress tests are simulation exercises conducted by individual banks and central banks to assess the resilience of a bank or group of banks under alternative severe but plausible scenarios (see Baudino and Svoronos, 2021). The forward-looking nature of the stress test methodology makes it well suited to produce, under a few plausible scenarios, forecasts of exposures and losses that cannot be extrapolated from historical data, such as those related to the ongoing unprecedented climate risk. As climate hazards may manifest asymmetrically across sectors and geographical locations, the effect is also likely to differ across banks, depending on their specific balance sheet structures in general and their loan portfolios in particular.[2]

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[2] Here, the central bank also has a role in determining the parameters of the scenarios against which banks will test themselves. Otherwise, the results from each bank's stress test will not be comparable.

Translating climate change into financial impacts on bank exposures requires four central analytical steps. The first step deals with estimating greenhouse gas (GHG) emissions, which will determine the future temperature pathway. The next step involves mapping these climate metrics to traditional macroeconomic indicators, such as GDP growth. Thirdly, a more granular analysis should be conducted, as climate hazards manifest asymmetrically across economic sectors and geographical locations. Finally, all the previous elements must be combined to compute the impact on banks.[3]

Running a stress test entails a great deal of uncertainty, stemming from the difficulty of inferring the potential effects based on historical data, the non-negligible likelihood of tail events, and the emergence of second-round effects and feedback between climate change variables, macroeconomic variables, and financial outcomes (see Battiston et al., 2020; Monasterolo, 2020). The lack of clarity about the pathway of future emissions and their impact on climate and economic activity, and the pace of technological progress, not to mention the policies to be put forward in coming years and decades, all add uncertainty to this complicated task by forcing the analyst to ponder alternative outcomes under various scenarios. In this regard, the interaction between climate change and the economy, as well as the banking system, is highly dependent on the climate adaptation and mitigation policies chosen over time at both the national and international levels. Climate adaptation refers to the adjustment to new weather conditions to mitigate harm and capitalize on beneficial opportunities, such as building more resilient infrastructure and housing units and creating new crop varieties that can survive in a more hostile weather environment. Climate mitigation is the lessening of the potential adverse impacts of physical hazards, including, among other responses, the development of more sustainable technologies able to reconcile economic growth and lower GHG emissions.[4]

Relatedly, by leading the process, central banks are key in raising awareness among banks about the need to take measures to prevent the adverse impacts of climate change on bank solvency, profitability, and liquidity.

[3] This implies substantial modeling complexity and uncertainty, as it requires combining various models not initially designed to operate together. A more detailed description and comparison of the different modeling approaches can be found in Brunetti et al. (2022), BCBS (2021), and NGFS (2019). It must also be noted that banks and supervisors usually do not run all four steps. Still, they borrow most inputs from other sources (such as the NGFS scenarios, described later) and then focus on the bank-specific impact.

[4] It must be noted that technological advances have a dual role on the economic and financial outcomes: on the one hand, they support successful adaptation and mitigation, but on the other hand they may cause some assets to suffer a loss in value and become stranded. Stranded assets are assets that are unable to earn their original economic return due to changes in the landscape in which they operate. In the present context, in which the world is transitioning away from high-carbon activities, they comprise assets in the fossil fuel sector and in sectors that use that energy intensively.

With climate change increasingly becoming a topical issue on the global policy agenda, central banks and multilateral institutions have been leading a new wave of stress tests on the long-term impact of climate change. The Network of Central Banks and Supervisors for Greening the Financial System (NGFS, 2021) surveyed 31 central banks and supervisors that have stress tests planned (9), underway (18), or concluded (4). Advanced and emerging jurisdictions are represented in the sample, with three Latin American and Caribbean countries included (Chile, Colombia, and Mexico, all of which were in progress at the time of publication). The NGFS document summarizes some of the core features of all exercises, both planned and finalized, noting that most exercises:

a) adopt a 30-year span (as a compromise between long-term view and credibility) and three NGFS scenarios (namely, orderly transition, disorderly transition, and hothouse world);

b) cover transition risk more frequently than physical risk (as the former seems more pressing while the latter is expected to manifest itself more intensely in the second half of the century) and credit risk more often than market and other risks (justified by the overwhelming weight of loans in banks' portfolios);

c) focus on the banking system (even though several extend their scope to include insurance companies and pension funds);

d) favor a static balance sheet and focus on first-order effects (as opposed to the dynamic approach with second-round, or feedback, mechanisms, both of which would bring about more realism at the cost of additional modeling complexity); and

e) have an even split between top-down and bottom-up approaches, with a wide variety of data granularity.

The Financial Stability Board updated the previous survey by gathering responses from 53 member institutions in 36 jurisdictions. Its principal value lies in the review of existing international evidence from 35 exercises completed (out of a total of 67 applications, with the remaining 32 in progress or in the planning stage).[5]

Although a strict comparison of numerical results across studies is not feasible due to significant differences in the types of risks assessed, as well as in outcome metrics, assumptions, and methodologies, a common thread is that, despite the

[5] See FSB (2022).

short-term costs of transition, acting early is by far the best option. The short-term costs of the transition pale in comparison to the costs of unfettered climate change in the medium to long term (see ECB, 2022). Additionally, a consensus has emerged that a significant degree of climate-driven banking instability is unlikely, except for financial institutions with loan portfolios that are excessively concentrated in certain geographic regions and sectors. For instance, the studies reveal that an average of just 15 percent of the banking system's credit book has been issued to transition-sensitive sectors (i.e., high GHG emitters), which does not seem to pose a serious threat to solvency, even if a loan portfolio rebalancing is ruled out.[6] Nevertheless, the non-trivial level of uncertainty prevailing in these exploratory exercises calls for caution, as the materialization of tail risks may have potentially unmanageable consequences on banks across the board. Despite low exposure to the risks above, in several cases, raising concerns about potential risks through stress tests may raise awareness and lead to future proactive mitigating actions by financial intermediaries.

While the focal point of the above-described applications is credit risk, a recent body of research has begun examining the relationship between sovereign debt, climate change, and financial stability. As banks and other intermediaries invest a portion of their resources in government securities, the impact of climate change on public sector finances may spill over into the health of the financial system. Relative to an early transition, slower economic growth may induce investors to revise their expected default risk. Deghi et al. (2022) highlight the channels through which government debt affects the health of the banking sector in emerging markets. Cevik and Jalles (2020) conduct econometric research, showing that climate change vulnerability influences sovereign bond spreads for a broad sample, as well as other traditional determinants. Klusak et al. (2021) explore, through simulations for multiple countries, the potential sovereign and corporate credit rating downgrades that climate risks may lead to. Reinders et al. (2021) studied the Colombian case using granular data and concluded that, despite non-negligible loan and public debt losses being incurred in some scenarios, bank capital adequacy remains unaffected. In short, these results reinforce the general impression from the literature commented on in the previous paragraphs. As usual, caution is advised to distinguish between countries and financial institutions with high and low fragility to climate conditions in the decades to come, as the former may face steeper-than-average costs.

In this paper, we use publicly available bank and sector-specific data on loans and their performance to identify the potential impact of climate change on the

[6] FSB (2022) notes, however, that these exposures are not uniform across banks. As an example, they cite the Colombian case, where they range from 1 to 26 percent.

health of the Colombian banking system. Our main contribution is conducting stress exercises using sector-specific elasticities on non-performing loans (NPLs) to sectoral GDP growth, allowing for an increase in granularity and precision in the analysis. First, we use panel data VAR techniques to estimate these elasticities. Then, we use them to conduct climate stress tests by simulating the trajectory of NPLs using long-term growth projections under different climate change scenarios borrowed from Koch and Leimbach (2023), who run growth trajectories under five shared socio-economic pathways (SSPs) associated with different climate change conditions. We find that under most scenarios, the impact of climate change on the solvency of the Colombian financial system is low. However, there could be very extreme scenarios in which, despite not compromising the aggregate solvency of the system, low growth in specific sectors may lead to a few bank failures. Eventually, second-round effects not explicitly modeled here could lead to bank runs that could impact the overall stability of the system. As noted, however, this could occur in scenarios even more extreme than the most extreme scenario presented by Koch and Leimbach (2023). Section 2 describes the methodology used to conduct the stress tests and to estimate the sector-specific elasticities. Section 3 presents our results and estimates the amount of capital from the banking system at risk. Section 4 concludes.

2. Methodology

We propose a simple two-stage simulation approach to measure the stress that climate change could pose on bank capital and solvency in a nearly 30-year time frame.[7] In the first stage, the ratio of non-performing to private sector loans (henceforth, *NPL/L*, or just NPL ratio) in 2050 is projected as:

$$\left(\frac{NPL}{L}\right) = \sum_S \propto^S \times \ \varepsilon_{NPL,g_s} \times g_S \qquad (1)$$

where $\propto^S$ is the share of each sector *S* in total loans. To match the disaggregation on the GDP growth scenarios, we group bank loans into three economic sectors: manufacturing, primary, and services sectors. In turn, ε_{NPL,g_s} is the elasticity of sectoral NPL ratios to the corresponding GDP growth, which we estimate in this paper. Finally,

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[7] Key assumptions in the our methodology are: (a) In light of its overwhelming dominance in Colombia over other financial intermediaries, only the banking system is under scrutiny; (b) Although climate risks might have ramifications on market, liquidity, and operational risks, the exercise here focuses on credit risk, not only because it is more clearly defined and measurable but mainly because it appears prima facie as the most significant source of banking vulnerability; (c) The asset structure of the banking system does not change over the period of analysis. This assumption of a fixed balance sheet, whereby asset composition remains unchanged, is not fully realistic, as banks may gradually reduce their exposure to climate risks. However, a dynamic balance sheet approach would require equally strong assumptions, as these portfolio changes are extremely hard to foresee; and (d) All bank assets are denominated in local currency, so exchange rate considerations can be ruled out.

g_S is the projected sector GDP growth, taken from the dynamic neoclassical general equilibrium model estimated by Koch and Leimbach (2023) under the five SSPs in 194 countries.[8] In the second stage, in turn, we compute the additional loan losses in terms of the initial level of capital (*K*):

$$\left(\frac{\Delta LL}{K}\right) = \left(\frac{\Delta NPL}{L}\right) \times LGD \times \left(\frac{L}{A}\right) \times \left(\frac{A}{K}\right) \quad (2)$$

where *LL*, *A*, *K,* and *LGD* stand for loan losses, total assets, total capital, and loss-given default, respectively. For practical purposes, LGD is set to a value of 0.5, as suggested by Dagher et al. (2020).

The equation seeks to answer the following question: What proportion of their initial capital (as of December 2023) would banks lose due to additional loan defaults in a disorderly transition and a hothouse scenario compared to an orderly climate scenario?[9] The equation says that losses will be larger the larger the elasticity of NPL/L to GDP growth, the loss given default, the share of loans to assets (i.e., the overall exposure to credit risk), and the inverse of the capitalization ratio (i.e., higher capital banks are better prepared to absorb a given loan loss). We compute all relevant variables at a bank-specific level, and then we aggregate them to obtain system-wide results.

A key caveat is that we are estimating only the impacts coming through the corporate loan portfolios of banks, which means that we are likely underestimating the actual impacts. We are therefore omitting the household portfolio, such as consumer or mortgage loans, which, unlike the corporate loan portfolio, cannot be matched to GDP growth measures.[10] Another caveat is that we measure only the direct effects of a deteriorated loan portfolio of a bank on its solvency and do not capture second-round effects, coming, for example, from the impact of a failed bank

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[8] The model partly deals with climate change by explicitly considering energy and some natural resources (oil and gas) as productive inputs, which affect the GDP trajectory through energy prices and the cost-minimizing choice of energy sources by producers (see Château, Dellink, and Lanzi, 2014). Depending on the relative price of fossil and renewable energies, each sector, which has its own energy and other input intensity, decides whether to invest in sources alternative to conventional fuel. The sectoral breakdown enables the identification of sectors that are particularly affected by climate policies, such as emission-intensive industries. It is worth noting that the SSPs have been widely adopted by the various stakeholders in the area. For instance, they are the basis for the scenarios developed by the NGFS (see NGFS, 2020).

[9] We omit the trajectory in the years before 2050 because the main interest is in the long-term consequences and impacts of climate change, which, according to most projections, are unlikely to emerge in the next few years or decades, save for natural disasters with a local territorial scope. In the same spirit, we refrain from extending the time horizon to 2100, as some applications do. Although climate change impact measurement calls for a long-term perspective, such an extended window may widen confidence intervals to the point of questioning the credibility of the exercise.

[10] As of December 2023, enterprise credit represents approximately 53.8 percent of the total private credit portfolio of the banking establishments under analysis.

on the deposits and other liabilities of non-failed banks, which could eventually also affect the solvency of the non-failed institution. Namely, we are not addressing whether the failure of institutions could lead to bank runs that could hurt the whole system. Finally, our analysis should be considered indicative only, since we are still dealing with fairly aggregated data. In an ideal exercise bank, observed GDP data and climate simulations of GDP paths should be disaggregated by economic sector and geographical location to capture all possible nuances of climate change. In practice, this is not the case, and disaggregation is only available in a limited number of dimensions. While the Colombian bank-level data is disaggregated at a very detailed sub-sectoral level, it is not disaggregated geographically. The scenario data is only disaggregated in the three sub-sectors noted above; therefore, we group the bank-level sectoral data and the observed GDP data used for estimating the elasticities into three macro sectors—manufacturing, primary, and services—to ensure consistency.

Estimation of Sectoral Non-performing Loan Ratio Elasticities for Colombia

A key element in this exercise is the estimation of the elasticity of NPLs to GDP growth, ε_{NPL,g_s} in equation (1). Though it is customary to estimate NPL elasticities as a function of aggregate GDP growth (see, for example, Jakubik and Kadioglu, 2022; Macháček, Melecký, and Šulganová, 2018), there are reasons to expect sectoral asymmetries to arise due to, first, different GDP growth trajectories and, second, different initial liquidity and leverage conditions making repayment more or less unlikely, even for equal sectoral rates of GDP growth. In this context, we are developing novel NPL elasticity estimates at the sectoral level, utilizing a sectoral disaggregation that aligns with the climate change scenarios projected by Koch and Leimbach (2023).

The dataset for the corporate loan portfolio is constructed using quarterly reports from the Financial Superintendence of Colombia (Superintendencia Financiera de Colombia, or SFC), the supervisory body for financial entities in Colombia.[11] The data spans from Q1 2012 to Q3 2023, encompassing active operations reported by banking establishments.[12] This dataset provides sufficient granularity to estimate sectoral elasticities, while also accurately representing the overall corporate loan portfolio. As noted above, even if the data allows for a significant granularity at

[11] Enterprise loan portfolio data by economic sub-sector is extracted from the SFC, available here. Household and housing loan portfolio data are also extracted from the SFC, available here.

[12] Corporate data disaggregated by economic sub-sectors is reported for the top 5,000 private debtors. Although this represents a limitation due to the exclusion of smaller debtors, the sample remains representative, accounting for approximately 77 percent of the total enterprise loan portfolio as of the final quarter in the dataset.

the sector level, we group it only in the three large sectors to make it consistent with the GDP disaggregation of the climate change scenarios.

The SFC data for corporate loans includes the various risk portfolio classifications (A to E), but it does not explicitly identify NPLs. To address this limitation, the NPL ratios were approximated by aggregating loans classified from B to E and dividing them by the total loans per bank, sub-sector, and at quarterly levels. Although this approach provides a useful proxy, based on the Colombian regulatory framework, it remains an approximation that may not yield the exact NPL values. The observed GDP data were obtained from the National Administrative Department of Statistics (Departamento Administrativo Nacional de Estadística, or DANE).[13] This data includes seasonally adjusted real GDP series disaggregated by economic sector. From this, annual growth series were constructed at a quarterly frequency.[14]

We employ the panel data vector autoregressive (PVAR) model, as formulated by Love and Zicchino (2006), to estimate the elasticities. The PVAR framework leverages the panel structure of the dataset to exploit cross-sector variation while relying on contemporaneous movements in the series. This framework enables us to account for the simultaneity in interactions between GDP growth and NPLs across sectors, providing a dynamic approach to capture the impact of economic shocks on NPL ratios, while considering bank-specific fixed effects.[15]

Particularly, the PVAR models are estimated at the bank level for the NPL ratio and real GDP growth across the loan portfolios of the primary, manufacturing, and services macro sectors. To account for the shock to NPLs associated with the COVID-19 pandemic, a dummy variable representing this period is included as an exogenous factor. These models are estimated using the generalized method of moments. Impulse response functions (IRFs) are then generated for each sector to capture potential sector-specific reactions, assessing the cumulative effect of a shock to real GDP growth on the NPL ratio over a 16-quarter horizon, which is the elasticity used in our simulations. Confidence intervals for the IRFs are constructed through Monte Carlo simulations.

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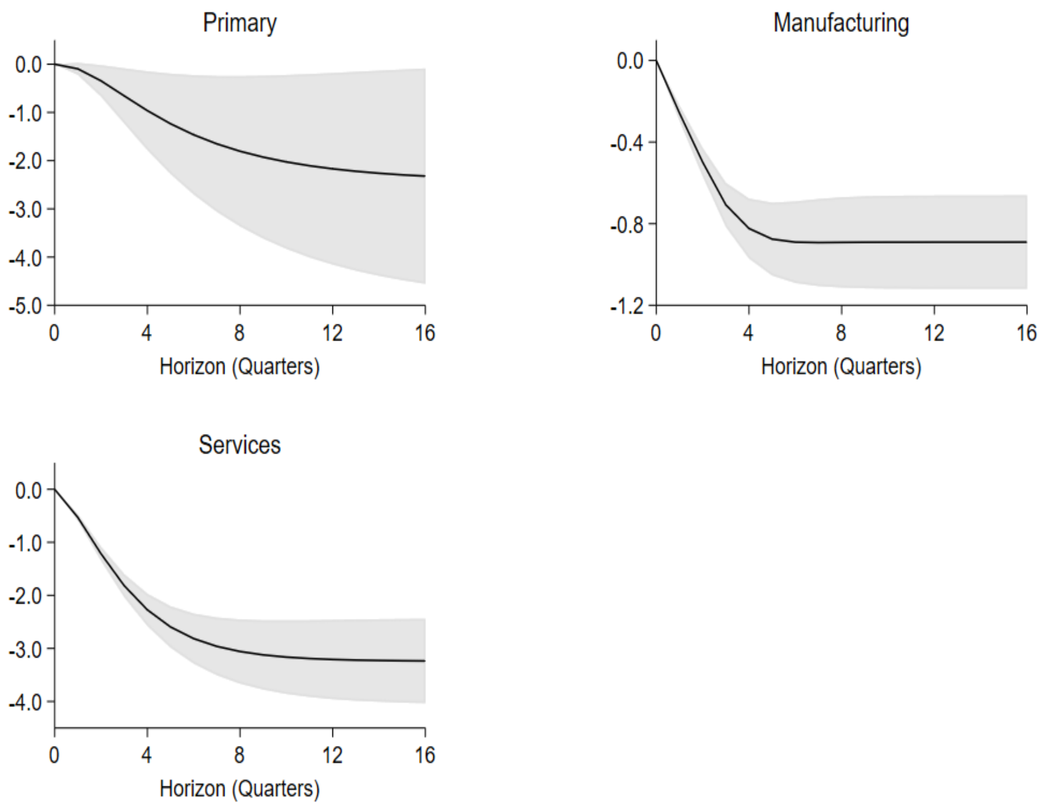
[13] GDP data is extracted from DANE's official website, available here.

[14] The series of NPL ratios and GDP growth were winsorized to limit the influence of outliers.

[15] Of course, other methodological approaches may also be suitable to tackle the issue at hand and explore economic causality, especially if detailed bank-level studies and country-level in international studies are available. However, in this context, it is implausible, on economic grounds, to expect any major reverse causality from bank NPLs on GDP growth.

Figure 1. Impulse Response Functions of NPL Ratios to GDP Growth Shocks Across Sectoral Enterprise Portfolios



Source: Authors' elaboration.
Note: The figure presents the IRFs for the NPL ratio in response to a positive GDP growth shock, disaggregated by enterprise portfolio sector: primary, manufacturing, and services. The IRFs are generated using a PVAR model. Confidence intervals at the 5 percent level obtained through Monte Carlo simulations are displayed.

Figure 1 displays the IRFs for the NPL ratio and economic growth with 5 percent confidence intervals, showing the cumulative impact of a 1 percent increase in GDP growth on the NPL ratio for each macro sector. In the services sector, the IRF indicates a significant sensitivity to economic fluctuations, with a positive shock to GDP growth leading to a notable cumulative decline in the NPL ratio over the 16-quarter horizon. The estimated elasticity at the end of the horizon is approximately -3.24. Similarly, the primary sector shows a substantial response on the NPL ratio following a GDP growth shock, with an elasticity of -2.32. In contrast, the NPL ratio for the manufacturing sector exhibits a relatively moderate response, with a smaller decline in the NPL ratio and an elasticity of -0.89, suggesting greater stability in its loan portfolio quality relative to the other two sectors.

The services sector's higher sensitivity may be attributed to its heavy reliance on consumer income, which is highly dependent on macroeconomic fluctuations. Moreover, this sector includes industries, such as tourism, which tend to be more volatile and sensitive to economic cycles. These results highlight the importance of considering sector-specific characteristics when estimating the elasticity of NPLs to GDP growth.[16]

The estimated elasticities from the PVAR models are relevant inputs for projecting capital losses under different climate change scenarios. These elasticities offer insights into how changes in economic conditions resulting from climate change may affect the NPL ratios of different sectors. If the banking system's exposure to these sectors is limited, the overall impact on NPL ratios may also be limited. These sector-specific elasticities highlight the need for differentiated stress-testing frameworks that consider the unique characteristics and vulnerabilities of distinct sectors.

3. Scenarios and Stress Results

Projected GDP growth up to 2050 is borrowed from Koch and Leimbach (2023), who simulate growth trajectories under five SSPs in 194 countries.[17] The SSPs are a set of scenarios developed by the climate change research community to promote integrated and consistent economic research in this area. We consider three of these scenarios (SSP1, SSP2, and SSP3): SSP1 is an orderly transition scenario with limited physical and transition risk. SSP2 is a disorderly transition scenario, where correction policies are delayed, resulting in high transition costs and medium physical costs. SSP3 paints a hothouse world where no additional advances are achieved on the mitigation and adaptation front, giving rise to low transition costs but extremely high physical risk.[18,19]

Table 1 presents the median annual GDP growth by sector for Colombia from 2023 to 2050. These figures must be interpreted cautiously, though. They do not display the GDP growth rates in a given scenario, but rather growth rates *relative* to

[16] In the same spirit, sectors with higher debt leverage are likely to display greater sensitivity to changes in GDP growth, leading to more pronounced changes in NPL ratios.
[17] We thank Prof. Marian Leimbach for generously sharing their dataset.
[18] In terms of the original SSP narrative, SSP1 can be dubbed the gold standard, featuring sustainable technologies driving economic growth and no major national and international conflicts that could hamper mitigation and adaptation policies; SSP2 is a "business-as-usual" scenario preserving historical socioeconomic patterns; and SSP3 is the least desirable case, in which nationalism, widening inequality within countries, and little care for climate-driven damage all give rise to disappointing economic growth.
[19] For example, the projected LAC average annual GDP per capita growth rate up in 2023-2050 stands at 3.5 percent, 2.5 percent, and 1.2 percent for SSP1, SSP2 and SSP3, respectively. Again, our analysis does not work with these projections directly but relative to SSP1, the most benign scenario.

the SSP1 benchmark scenario, as is customary in this type of research.[20] Some observers claim that these and similar climate change projections have an overly optimistic lower bound, as they do not account for potential growth disruptions deviating from historical trends and do not incorporate low-probability/high-impact climate events, among other shortcomings (see Buhaug and Vestby, 2019; Pindyck, 2013). This is why we are further stressing our simulations by including two additional *ad hoc* scenarios, in which we multiply the relative SSP3 growth rates by factors of 2 (henceforth, SSP3*2) and 3 (SSP3*3), respectively.

Table 1. Colombia: Annual GDP Growth Projections over the Period 2023-2050 for SSP2 and SSP3 Scenarios *Relative to SSP1 Scenario, in Percentage*

Sector	**Estimated NPL elasticity**	**GDP growth scenarios (relative to SSP1)**			
		SSP2	**SSP3**	**SSP3 times 2**	**SSP3 times 3**
Primary	-2.32	-0.36	-0.85	-1.71	-2.56
Manufacturing	-0.89	-0.77	-1.78	-3.57	-5.35
Services	-3.24	-1.19	-2.59	-5.17	-7.76

Sources: Estimated NPL elasticity: authors' elaboration. Relative sectoral GDP growth rates: Koch and Leimbach (2023).
Note: GDP growth rates are assumed to be equal to those of overall GDP.

Results are summarized in the following figures and tables, focusing on two of the most adverse scenarios: the standard SSP3 and the stressed SSP3*3 cases. Figure 2 illustrates the capital-to-risk-weighted assets ratio (hereafter referred to as the capital ratio) for each financial institution and the entire banking system. Three cases are presented: the initial ratio (as of December 2023) and the simulated values as of year 2050 in the SSP2 and the SSP3 growth scenarios. In turn, Figure 3 plots the same indicators under the more extreme scenarios (SSP3*2 and SSP3*3). The central message from these figures is that the system as a whole appears resilient enough to maintain capital ratios above the minimum Basel regulatory requirement of 10.5 percent. However, at the same time, they highlight the fact that a few banks would fail to comply with capital requirements, even under the standard SSP2 and SSP3 scenarios, suggesting that even if aggregated bank capital may seem sufficient, the

[20] For example, if growth is 5 percent under the SSP1 scenario and 2 percent under the SSP2 scenario, the table would feature -3 percent under the latter.

fact that individual bank failures may occur could lead to system-wide runs that could end up affecting the whole system. This finding alone should prompt supervisors to assess and address climate risks, particularly for small and potentially vulnerable banks.

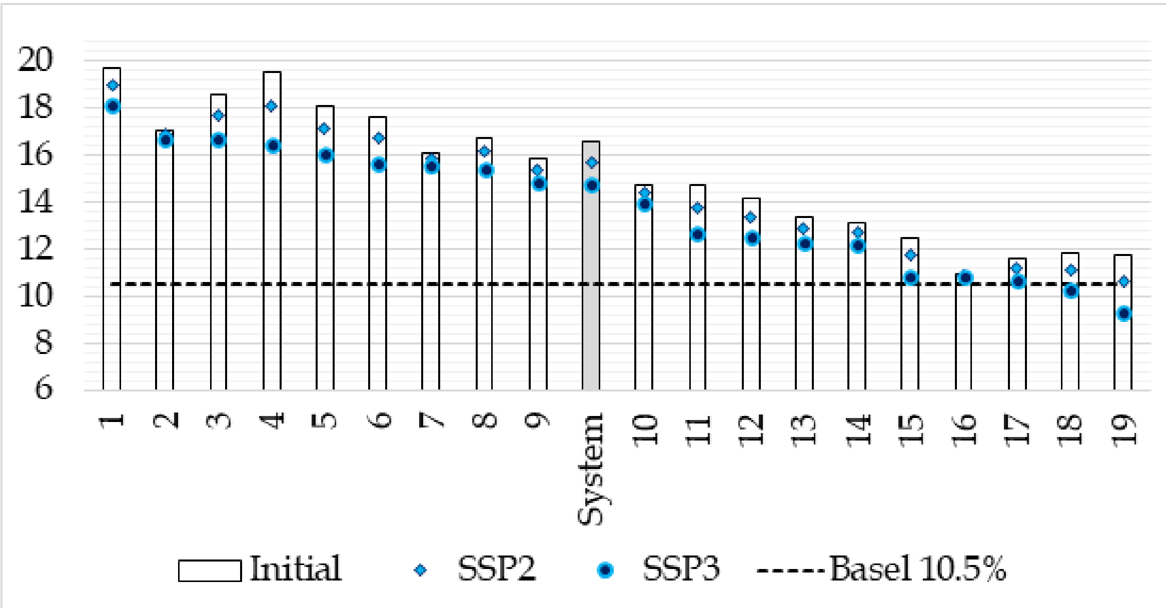
Table 2 offers additional insights into the heterogeneous response to capital losses across banks. First, note that at the system level, the NPL ratio increases from 9.6 percent to 13.1 percent under SSP3 and to 20 percent under SSP3*3. Despite such a drastic deterioration in loan portfolio quality, the capital ratio remains mostly within the regulatory limit, decreasing from 16.5 percent to 14.7 percent under SSP3 and to 11.2 percent under SSP3*3, indicating a high tolerance of the loan portfolios under analysis to climate change.[21] Again, such a conclusion calls for some qualification on an individual basis, as, under SSP3, two (out of the 19 institutions in our sample) fall in the red zone (capital ratio below 10.5 percent), which concentrates only 11.5 percent of the assets of the banking system. However, the numbers climb to nine institutions and 32.8 percent of the assets under SSP3*3.

What determines, in this exercise, which banks seem to pass this stress test comfortably and which ones see their solvency levels severely compromised? Table 2 shows that the banks above and below the 10.5 percent limit share several common traits, including similar shares of private credit to assets and loan portfolio compositions (primarily, manufacturing and services). Furthermore, because of this latter resemblance, the reduction in relative GDP growth rates under the alternative scenarios affects them similarly, as reflected in the evolution of NPL ratios.

This leaves us with a direct explanation: the more vulnerable banks are those that start with lower capital levels, as evident from equation (2). Capital losses depend, for a given increase in NPL and LGD levels, on the initial ratio of loans to capital, or L/K. This is the single ratio that significantly differs between the subsets of banks above and below the 10.5 percent mark: the initial L/K ratio is 4.2 for the system, but it stands at 4.1 and 6.2 for the banks above and below the 10.5 percent ratio, respectively, under the SSP3 scenario, and to 3.8 and 5.7 times under the SSP3*3 scenario. In other words, the differential effect stems from the fact that a much larger proportion of capital would be at stake if climate change led to a higher volume of bad loans.

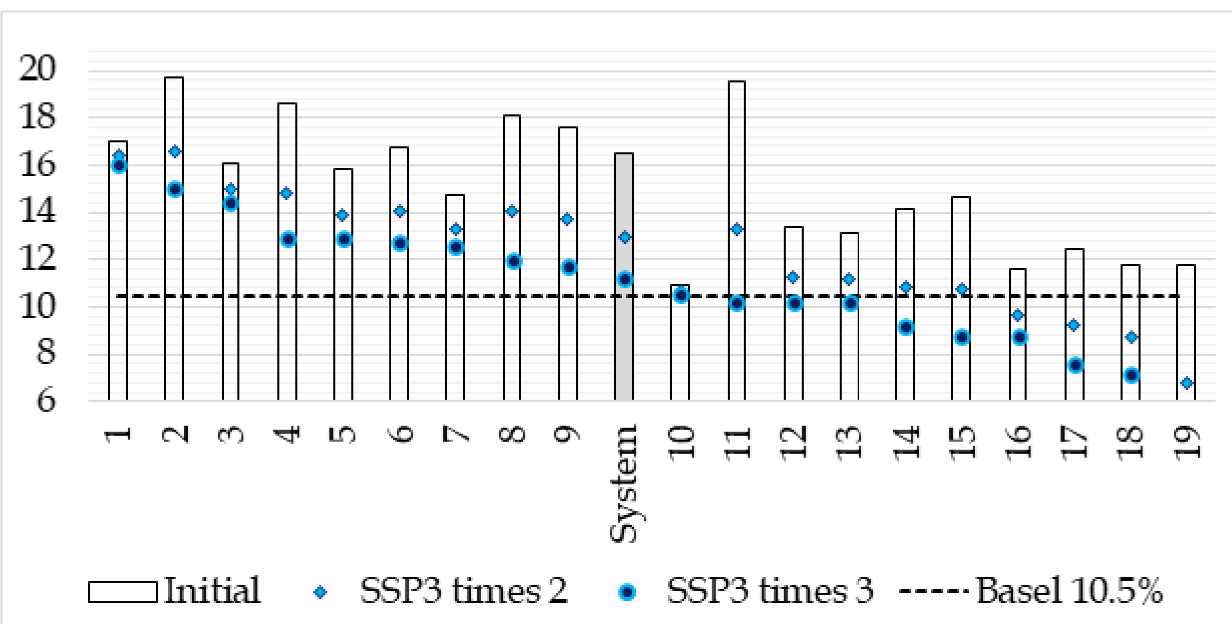
[21] Even though we are restricting the analysis to the corporate loan portfolio, the conclusions have clear system-level implications, as that portfolio represents a sizable 53.8 percent (22.6 percent of GDP) of total private credit (42 percent of GDP).

Figure 2. Capital to Risk-Weighted Assets by Bank under Alternative Scenarios (SSP2 and SSP3) in Descending Order by Values under SSP3



Source: Authors' elaboration.

Figure 3. Capital to Risk-Weighted Assets by Bank under Alternative Scenarios (SSP3 times 2 and 3) in Descending Order by Values under SSP3*3



Source: Authors' elaboration.

Table 2. Bank-level Indicators: Banks Above and Below Minimum Capital Requirements under Alternative Scenarios

Indicator	SSP3 scenario			SSP3 times 3 scenario		
	System	Above 10.5%	Below 10.5%	System	Above 10.5%	Below 10.5%
Count	19	17	2	19	10	9
Assets (% of system)	100	88.5	11.5	100	67.2	32.8
Initial NPL	9.6	9.5	9.6	9.6	10.2	8.4
NPL	13.1	13.0	13.5	20.0	21.2	17.8
NPL Change	3.5	3.5	3.8	10.5	11.0	9.4
Initial capital to weighted assets	16.5	16.8	11.8	16.5	17.8	12.6
Capital to weighted assets	14.7	15.1	9.7	11.2	12.6	7.4
Regulatory capital ratio change	-1.8	-1.7	-2.1	-5.3	-5.2	-5.2
Average market share (% of total assets)	5.3	5.2	5.7	5.3	6.7	3.6
Private credit to assets (%)	69.3	68.7	73.3	69.3	68.2	71.4
Private credit to capital (times)	4.2	4.1	6.2	4.2	3.8	5.7
Corporate credit to private credit (%)	30.3	30.1	31.5	30.3	25.8	38.9
Primary credit to private credit (%)	16.0	16.5	12.1	16.0	16.9	14.2
Corporate credit to private credit (%)	53.8	53.4	56.5	53.8	57.3	46.9
Primary credit to private credit (%)	1.9	1.9	1.9	1.9	2.3	1.3
Manufacturing credit to private credit (%)	12.7	13.0	11.0	12.7	14.0	10.3
Services credit to private credit (%)	39.2	38.5	43.5	39.2	41.0	35.3

Source: Authors' elaboration.

4. Conclusions

This study conducted a simple stress test of the Colombian banking system in response to climate change, based on the deterioration of the loan portfolio in a context of prospective lower GDP growth resulting from climate change over the period 2023-2050. As the analysis encompasses a substantial portion of Colombia's total bank loan portfolio, the results indicate a relatively manageable systemic effect, even in extreme scenarios, but a more concerning impact on certain individual institutions. Ultimately, the fragility of specific institutions could lead to systemic bank runs and aggregate financial distress, which are not captured in this analysis. Based on the analysis, the fragility of first-round effects is linked to low initial capital ratios compared to the rest of the system. The logical conclusion is that to shield these banks and make them more resilient, higher capital requirements for banks more exposed to climate-related risks would be the most effective approach, specifically to account for the growing climate risks.

Even if this exercise and other stress-testing efforts in various countries hint that systemic effects regarding bank solvency disruptions would be mild, such findings should be interpreted cautiously. The field of research on the interaction between climate change and economic and financial developments is still in its infancy, and there is a lack of historical evidence to support sound projections.

Regarding policy responses, this uncertainty calls for a leading role of financial regulatory and supervisory authorities to collect and process detailed data, by bank, geography, and borrower, about exposure to these new sources of risk, run thorough stress tests, and raise awareness among intermediaries under their jurisdiction. The existing body of evidence, including the present paper, does not suggest that the general regulatory framework should be drastically reformed in the near term. This could lead to counterproductive regulatory overkill. Over time, if new empirical results or unanticipated events necessitate it, this regulatory standby may be reconsidered. Meanwhile, they should focus their efforts on data gathering and training technical staff to conduct these complex prospective analyses.

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