How climate physical risks affect banking stability? The Latin American experience with strong ENSO events [1]

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Abstract

This paper investigates how climate shocks affect banking stability in a large panel of 1208 banks observed at annual frequency over the period 2005-2019 for 16 Latin American countries. We use strong *El Niño Southern Oscillation* (ENSO) events as a natural experiment for climate shocks related to climate change, as they produce quasi-periodic climate oscillations that can lead to unpredictable natural disasters. Our results show that, when considering Latin American countries, weather shocks associated with strong ENSO events can have adverse financial consequences that lead to a decline in banking stability. We also reveal that strong *El Niño* and *La Niña* shocks have asymmetrical effects on banking stability. Strong *El Niño* shocks are associated with lower banks' stability, resulting from decreased performances associated with increased credit and liquidity risks. In contrast, strong *La Niña* shocks appear to have economic benefits, with no significant impact on banking stability, but higher banks' performances and lower credit risk. Finally, further estimates identify some key characteristics of "climate-resilient banks". Banks with a larger size, a higher capital ratio, and less market-oriented activities are more resilient to adverse climate shocks resulting from ENSO events. As climate change should intensify the frequency and magnitude of ENSO's cyclical pattern, these findings can help estimate the potential adverse effects of climate change-induced physical risks on banking stability and inform future mitigation and adaptation policies.

JEL: G21; Q54; C33

Keywords: ENSO; climate shocks; banking stability; climate finance; panel data

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[1] Corresponding author: julien.thavard@univ-lorraine.fr. We are grateful for the valuable suggestions provided by participants of the Quantitative Sustainable Economics and Finance seminar at CMAP (École Polytechnique) and CREST (ENSAE Paris and Ecole Polytechnique), the International workshop CLIFIRIUM 2023 at Banque de France, and the BETA and Chaire RENEL seminars.

I. Introduction

In November 2023, *National Oceanic and Atmospheric Administration* (NOAA) meteorologists confirmed the imminent occurrence of "*strong El Niño*" events. Simultaneously, Ralph Keeling, director of the CO2 Program at UC San Diego's *Scripps Institution of Oceanography*, reported that "we continue to break records in the CO2 rise rate," attributing this to the ongoing global growth in fossil fuel consumption. The confluence of strong *El Niño* events and record CO2 rise rates has ushered society into a period of global temperature increases exceeding 1.5 degrees Celsius. According to the *Intergovernmental Panel on Climate Change* (IPCC) reports (Masson-Delmotte *et al.*, 2021), this temperature rise will lead to a sustained increase in extreme weather phenomena, which is already having a detrimental impact on the global economy. The natural disasters of 2023 have particularly affected developing and rural countries. For example, since June 21, Chile has experienced its most severe weather front in a decade, with heavy rainfall causing significant river flooding.

In response, the effects of climate change on society and the economy are increasingly being studied (Dell *et al.*, 2014; Carleton & Hsiang, 2016). From this perspective, the ability of the financial sector to facilitate adaptation and recovery plays a crucial role in mitigating the effects of climate change (Klomp, 2014; Keerthiratne & Tol, 2017; Ritchie *et al.*, 2021). For instance, financial institutions play a fundamental role in financing post-disaster recovery and reconstruction (Hallegatte, 2014). Moreover, inadequate insurance markets exacerbate direct losses (Koetter *et al.*, 2020; Wagner, 2022).

Consequently, an increasing number of studies are devoted to the analysis of the impact of climate change-related natural disasters on the stability of financial institutions (Noth & Schüwer, 2023). Climatic disruptions can lead to natural disasters and extreme weather events that are likely to impact financial institutions (Chabot & Bertrand, 2023) due to their exposure to households, businesses, and governments. In this context, policymakers worldwide have launched initiatives aimed at analyzing and mitigating the consequences for the financial sector of these adverse climate shocks (BIS, 2020, 2021), for instance, through climate stress testing (Jung *et al.*, 2021; Acharya *et al.*, 2023).

Climate, ENSO and financial stability in Latin America. The vast array of physical risks associated with climate change, spanning from droughts to hurricanes and flooding, coupled with their unpredictable outcomes and the existence of tipping points, entail radical uncertainty regarding their impact on the economy, depending on sectors and geographical areas concerned

(NGFS, 2019). Bolton *et al.* (2020) coined the term "Green Swan" to characterize this phenomenon, emphasizing the underestimation of climate change's impact on the financial sector, and especially banking institutions. Against this backdrop, our paper proposes a novel approach to assess, at a microeconomic level, how climate shocks may affect banking stability. At the core of our investigation lies the use of a recurring climatic phenomenon that deeply influences local weather conditions and natural disasters worldwide, and especially in Latin American countries, namely, the *El Niño-Southern Oscillation* (ENSO) (Cai *et al.*, 2020). The magnitude and duration of the ENSO teleconnection determine the extent of its impact among countries. For instance, Collier *et al.* (2011) showed that the 1997-98 *El Niño* had detrimental effects on vulnerable microfinance intermediaries in northern Peru, due to a significant surge in non-performing loans. These findings underscore the critical need to understand the intricate relationship between climate-induced natural disasters and banking stability, especially in emerging regions like Latin America that are disproportionately vulnerable to such events. Hence, our objective is to assess the relationship between adverse climate shocks and banking stability, shedding light on the transmission channels through which ENSO events can affect the performances and risk exposure (in terms of both credit and liquidity risks) of the Latin American banking sector. More generally, we aim to contribute to a deeper understanding of the resilience of financial institutions in the face of climate-related challenges, particularly in vulnerable regions.

The choice of ENSO instrument. By using ENSO as a proxy for the physical risks induced by climate change, similar to the approach of Hsiang *et al.* (2011), our paper provides deeper insights into how climate change could impact banking stability. Previous literature has predominantly focused on the effects of natural disasters rather than climate change. However, by considering ENSO as a climatic shock, we are able to capture unpredictable quasi-periodic climatic oscillations, i.e., structural climatic oscillations, which, at specific times, frequencies, and magnitudes, can induce natural disasters. Additionally, considering that the frequency and magnitude of ENSO events are expected to increase with climate change (Cai *et al.*, 2014, 2021; Yeh *et al.*, 2022), focusing on ENSO provides a relevant means to approximate the potential effects of climate change on banking activity in the near future.

Literature and gaps. Natural disasters induced by climatic oscillations can affect the solvency of financial institutions. Indeed, the damage caused by a catastrophe reduces the value of borrowers' collateral and their solvency, leading to business interruptions and negative effects on the economic growth in areas where banks operate. A body of work initially focused on the effects of natural disasters on economic growth (Noy, 2009; Cavallo & Noy, 2009; Strobl, 2011; Cavallo *et al.*, 2013; Botzen *et al.*, 2019), as well as the negative effects of ENSO events on economic growth (Smith & Ubilava, 2017; Generoso *et al.*, 2020; Callahan & Mankin, 2023). Recently, in the case of Latin American countries, Damette *et al.* (2024b) document that sovereign risk increases following strong ENSO events, which might hinder the ability of governments located in this region to act as a "climate rescuer" of last resort in the aftermath of these adverse climate shocks. More specifically, some empirical studies have tested the effects of natural disasters on credit and liquidity risks (e.g., Brei *et al.*, 2019; Koetter *et al.*, 2020; Marco & Limodio, 2023; Noth & Schüwer, 2023). However, for now, no study has sought to assess the effect of adverse climate shocks associated with ENSO events on banking stability and the transmission mechanisms at work in terms of banks' performances and risk exposure. In addition, despite the critical importance of understanding the determinants of financial institutions' resilience in the face of adverse climate shocks, there is a notable gap in the literature regarding the specific factors that could contribute to their ability to withstand climate-related physical risks. This issue is particularly critical in developing and emerging countries, where banks are more vulnerable to natural disasters due to greater geographic and sectoral concentration in their portfolios (Brei et al., 2019).

Contribution. This paper aims at contributing to the existing climate finance literature by studying for the first time the relationship between ENSO-induced natural disasters and banking stability in a sample of Latin American countries. Moreover, to deepen the study of the determinants of Latin American banks' financial fragility in response to adverse ENSO events, we consider different financial mechanisms that could be at work, in terms of performances and risk exposure (focusing on credit and liquidity risks), and also account for three key banks' characteristics that could influence their resilience to these shocks, namely, their size, capitalization and business model. Therefore, three questions are addressed in this paper, corresponding to its three contributions: 1) What is the impact of ENSO events on the stability of Latin American banks? 2) What are the transmission channels that could explain the impact of ENSO events on the stability of Latin American banks? 3) What are the resilience factors at the bank level that could explain the impact of ENSO events on the stability of Latin American banks?

To this end, we use a large panel of 1208 banks observed at annual frequency over the period 2005-2019 for 16 Latin American countries. Based on panel fixed-effects estimates, we use strong *El Niño Southern Oscillation* (ENSO) events as a natural experiment for climate shocks related to climate change, as they produce quasi-periodic climate oscillations that can lead to unpredictable natural disasters. We consider several indicators to assess the stability (z-score), the performances (ROE and ROA) and the exposure to credit risk (non-performing loans) and liquidity risk (bank deposits to total assets) of Latin American banks in response to ENSO events. To account for the heterogeneous effect of these climate shocks depending on banks' characteristics, we carry out further subsample estimates based on three key features of banks included in our sample: their size (total assets), capitalization (total equity to total assets) and business model (non-interest income to total income). This econometric set up enables to assess the effect of ENSO-induced climate shocks on banking stability, the financial transmission channels at work and the resilience factors that could dampen these adverse effects in a sample of emerging countries that are particularly vulnerable both climatically and financially.

Our results show that, when considering Latin American countries, weather shocks associated with strong ENSO events can have adverse financial consequences that lead to a decline in banking stability. We also reveal that strong *El Niño* and *La Niña* shocks have asymmetrical effects on banking stability. Strong *El Niño* shocks are associated with lower banks' stability, resulting from decreased performances associated with increased credit and liquidity risks. In contrast, strong *La Niña* shocks appear to have economic benefits, with no significant impact on banking stability, but higher banks' performances and lower credit risk. Finally, further estimates identify some key characteristics of "climate-resilient banks". Banks with a larger size, a higher capital ratio, and less market-oriented activities are more resilient to adverse climate shocks resulting from ENSO events.

As climate change should intensify the frequency and magnitude of ENSO's cyclical pattern, these findings can help estimate the potential adverse effects of climate change-induced physical risks on banking stability and inform future mitigation and adaptation policies. This issue is even more critical as banks are a key source of external financing for post-natural disaster reconstruction, economic recovery, and the implementation of measures aiming at dealing with the consequences of physical risks associated with climate change.

Outline. The remaining sections of the paper are organized as follows. Section II provides an overview of the potential mechanisms explaining the impact of ENSO events on the stability of Latin American banks. Data and stylized facts are presented in section III. The econometric methodology is detailed in section IV. Section V presents and discusses our main results regarding the ENSO events-banking stability relationship in Latin America and the potential financial transmission channels at work. Section VI checks the robustness of our main findings. Section VII presents the result associated with the extension of our baseline econometric set-up when considering how banks' size, capitalization, and business model could play a role in offsetting the impact of ENSO events on banking stability. Section VIII concludes the paper.

II. From climate physical risks to banking stability: overview of mechanisms at work

We first review the literature studying the impact of climate physical risks on banking stability, considering the main financial mechanisms at work. Then, we summarize the main findings associated with the empirical literature dealing with the economic consequences of ENSO events and derive testable hypotheses for our econometric analysis.

2.1. Climate and banking stability

The existing literature indicates that natural disasters influence banking stability through various channels. Klomp (2014) shows that natural disasters, especially meteorological (e.g., storms and hurricanes) and geophysical (e.g., earthquakes, tsunamis and volcanic eruptions) are associated with a significant decrease in banking sector distance-to-default. The author also shows that these natural disasters have a significantly smaller impact on banking sector instability in countries with a developed financial system and a well-functioning regulation and supervision of the financial sector. Complementing these findings, Noth & Schüwer (2023) show that, in the case of the United States, weather-related disasters (meteorological, hydrological and climatological) have an adverse short-term (up to one year) significant effect on banks' return-on-assets, solvability (equity-to-asset ratio), non-performing assets, distance-to-default and probability of default. However, these adverse effects are short-lived and not significant in the medium-term (from two to three years following a given disaster). Similarly, Özsoy *et al.* (2020) found that drought periods in the United States lead to more frequent branch closures, higher default probabilities, and lower z-scores, despite the presence of insurance payouts and government aid. Furthermore, Brei *et al.* (2019) assess the impact of hurricanes strikes on banking sector stability and performances. Their results show that the banking sector of Caribbean countries is significantly and negatively impacted by these natural disasters, with a decrease in banks' external sources of financing (deposits, interbank and money markets) associated with a contraction in credit supply and banks' return-on-equity, which in the end, reduce the banking sector's distance-to-default.

These effects of adverse climate shocks on banking stability can be explained by three main risk channels: a direct operational risk channel and two indirect credit and liquidity risk channels.

Operational risk. Extreme weather events adversely impact both physical capital and human resources (Zheng et al., 2022). These hazards can directly disrupt bank operations by damaging critical infrastructure, such as office buildings, telecommunications, and information systems, including data centers. Such damages can reduce staff productivity, interrupt financial operations, and hinder customer access to banking services.[2]

Credit risk. Natural disasters indirectly increase banks' credit risk due to borrowers' reduced ability to service their debts as a result of decreasing income and wealth. At the firm level, key impacts include reduced profits and cash flows, heightened investment costs, and asset depreciation (Hugon & Law, 2019; Lanfear *et al.*, 2019), as extreme climate events impair business operations and disrupt supply chains (Abe & Ye, 2013; Pankratz & Schiller, 2021). Such events are also associated with a decrease in household income, particularly in agriculture and fishing, leading to lower private consumption (Batten *et al.*, 2020). Temperature anomalies can diminish labor supply and productivity (Burke *et al.*, 2015; Day *et al.*, 2019; Letta & Tol, 2019), while property values suffer from climatic damages like flooding (Bin & Polasky, 2004; Ortega & Taşpınar, 2018). Moreover, due to increased non-performing loans (NPLs), adverse climate events can lead banks to proactive loan loss provisioning (Schüwer *et al.*, 2019). Thus, by elevating NPL ratios, and diminishing banks' capital ratios and returns on assets, these conditions threaten banks' solvency and thus their financial stability (Dafermos *et al.*, 2018; Noth & Schüwer, 2023).

Liquidity risk. Following a natural disaster, banks may suffer from solvency issues because of liquidity shortages associated with significant withdrawals from households, firms, and financial institutions. Indeed, climatic shocks can increase banks' liquidity risk by triggering increased liquidity demands from customers for repairs, withdrawal of deposits, or access to emergency credit (Chabot & Bertrand, 2023). In this case, banks can be unable to meet their obligations without incurring significant losses due to important asset liquidations. In response, central banks may intervene to maintain banks access to liquidity and preserve financial stability. For instance, Brei *et al.* (2019) documented rapid and substantial deposit withdrawals

[2] For instance, following the 2011 Tōhoku earthquake in Japan, banks in the affected areas faced operational challenges, impacting their ability to process loans and imposing borrowing constraints on firms outside the earthquake zone (Hosono *et al.*, 2016).

in the Caribbean following hurricanes, while Ichimura *et al.* (2009) found that savings were used to offset asset losses after the 1995 Hanshin-Awaji earthquake. Similarly, Barth *et al.* (2019) observed increased lending and deposit rates in affected US bank branches, while Steindl & Weinrobe (1983) noted deposit increases post-floods, alongside increased demand for emergency loans.

2.2. ENSO and banking stability

ENSO stands as one of the Earth's most influential climate phenomena, significantly impacting weather patterns and natural disasters, particularly in Latin American countries (Cai *et al.*, 2020). The severity and duration of these events, coupled with the strength of the ENSO teleconnection, dictate their repercussions. Different weather patterns emerge during *El Niño* and *La Niña phases*, affecting various regions differently. Empirical studies indicate that severe climate shocks tied to ENSO events often affect economic growth (Cashin *et al.*, 2017; Smith & Ubilava, 2017; Generoso *et al.*, 2020). Emerging and developing countries reliant on agriculture face more pronounced adverse impacts on GDP from ENSO, stemming from reduced productivity and production in agriculture and fishing (Adams *et al.*, 1999; Hsiang & Meng, 2015). Furthermore, Atems & Sardar (2021) and Dufrénot *et al.* (2021) find that *La Niña*-induced ENSO shocks increase global food and agricultural commodity prices, potentially propagating aggregate inflation. Additionally, the tourism sector suffers adverse effects, as evidenced by Oduber & Ridderstaat (2017) showing a decreased tourism demand in the USA, Venezuela, and the Netherlands during ENSO events. On the financial front, Damette *et al.* (2024b) find that strong *El Niño* or *La Niña* shocks correlate with short- to medium-term increases in sovereign spreads in a sample of seven Latin American countries. These results suggest heightened volatility in sovereign spread dynamics that may reflect investor overreactions to ENSO-related macroeconomic and financial consequences, which can hinder governments' ability to act as a 'climate rescuer' of last resort. Finally, political and social factors can exacerbate the macroeconomic and financial effects of ENSO, with Hsiang *et al.* (2011) highlighting a link between ENSO events and increased civil conflicts.

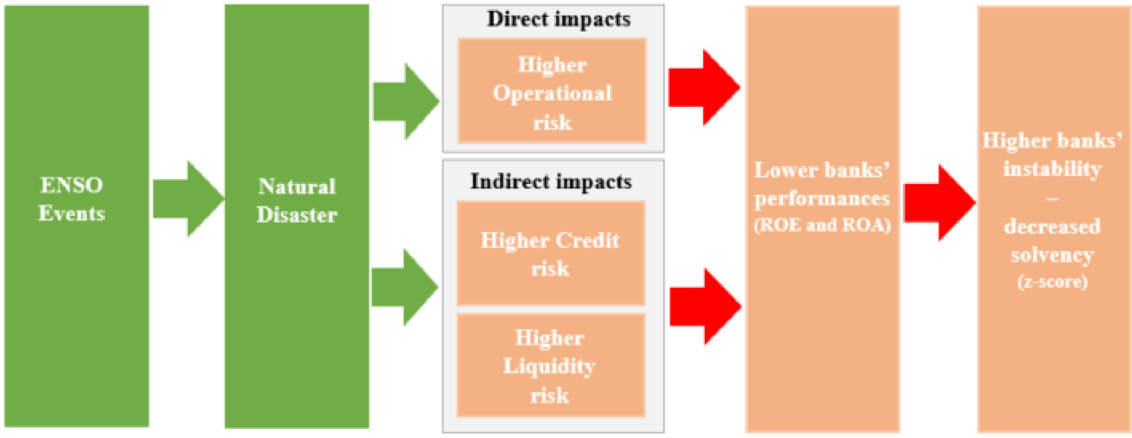
As a result, in line with the analysis carried out in section 2.1, severe climate shocks linked to ENSO events can impact banking stability and performances through various channels, including operational, liquidity, and credit risks. Firstly, weather extremes and natural disasters stemming from ENSO can damage bank assets and hinder staff productivity, resulting in an increased operational risk. Secondly, due to adverse macroeconomic and financial consequences affecting firms' profits, cash flows, and investment costs, and households' income, ENSO events can elevate credit risk in response to reduced borrowers' collateral value and solvency. For instance, Collier *et al.* (2011) highlight the adverse effects of the 1997-98 *El Niño* event on microfinance institutions in northern Peru, where NPLs significantly surged. Lastly, in response to ENSO-induced climate shocks banks can face liquidity risk due to increased demands from customers for repairs, withdrawals, or emergency credit that can entail significant losses associated with important asset liquidations. Overall, as summarized in Figure 1, ENSO events are likely to have adverse effect on banking stability and performances through several channels associated with direct physical exposures and indirect credit and liquidity risks. The expected effects, however, are asymmetrical: while the effects of *El Niño* are expected to be predominantly negative, the effects of *La Niña* are likely to be neutral or even positive. Indeed, the previous literature has shown that there are more adverse climatic and macroeconomic consequences associated with *El Niño* shocks (Smith & Ubilava, 2017; Generoso *et al.*, 2020; Callahan & Mankin, 2023). The climate banking literature has demonstrated that there is no symmetry in the effect of ENSO events on the banking sector, particularly regarding the distance-to-default (Damette *et al.*, 2024a). De Marco & Limodio (2022) note that the top 5 *La Niña* events are much weaker than the top 5 El Niño events and find that US banks with a one standard deviation higher exposure to *La Niña* do not have different loans or total assets than others. In contrast, they show that during a top 5 *El Niño* event, total assets of highly exposed banks decline by about 0.8%, and bank lending decreases by about 1.6%. Real estate lending falls by 1.5% and commercial and industrial loans by 2.7%.

Based on this analysis relating climate physical risks, ENSO events, and banking stability, we formulate the following two testable hypotheses:

Hypothesis 1. Climate-induced ENSO shocks have a significant negative impact on bank stability and performances, especially when associated with *El Niño* phases.

Hypothesis 2. Considering potential transmission channels, climate-induced ENSO shocks significantly increase both credit and liquidity risks, especially when associated with *El Niño* phases.

Figure 1. ENSO and banking stability: summary of key financial mechanisms



III. Data and stylized facts

Data used in this paper are based on climatic and banking indicators observed at annual frequency from 2005 to 2019 for 16 Latin American countries and covering a large panel of 1208 banking institutions.[3] Apart from data availability, our choice of these countries was also motivated by their level of exposure to strong ENSO events, since they are known to be significantly impacted by ENSO events, especially in terms of adverse effects on their economies (Cashin *et al.*, 2017).

3.1. ENSO as a proxy for the physical risks associated with climate change

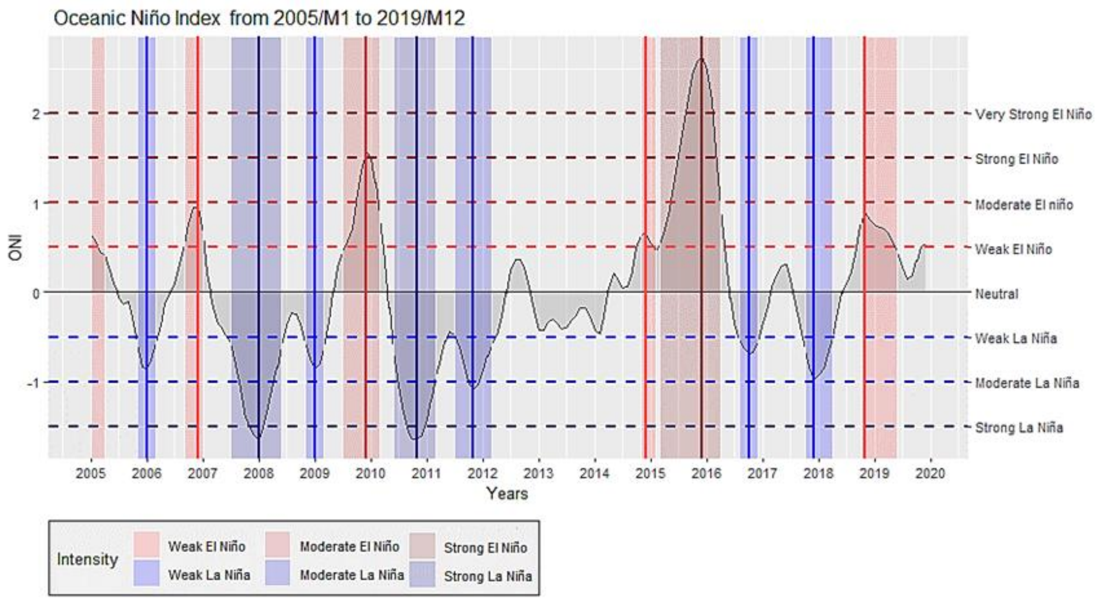
Definition. ENSO entails abnormal sea surface temperature (SST) fluctuations and alterations in Pacific basin atmospheric circulation. During *El Niño*, the eastern tropical Pacific region experiences unusually warm SST, disrupting typical atmospheric circulation with weakened trade winds and altered precipitation patterns. Conversely, *La Niña* involves abnormally cold SST in the eastern tropical Pacific, strengthening trade winds and increasing precipitation in the western Pacific's tropical regions. These *El Niño* or *La Niña* phases are determined by abnormal ocean surface temperature and wind circulation pattern variations. Depending on the amount of heat (cold) transferred from the ocean to the atmosphere, *El Niño* (*La Niña*) events can be classified as neutral, moderate, strong or very strong. Recurring *El Niño* and *La Niña* phases represent the largest fluctuations in the global climate system, influencing local climates near the eastern and western Pacific and exerting global climatic effects via teleconnections with other climate phenomena (Trenberth *et al.*, 1998).

[3] Our sample includes the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Jamaica, Mexico, Panama, Paraguay, Peru, Trinidad and Tobago, and Uruguay.

Identification and classification of ENSO events. In line with existing literature (Santoso *et al.*, 2017; Timmermann *et al.*, 2018; Cai *et al.*, 2020), the Oceanic Niño Index (ONI) is widely accepted as a reliable measure for tracking ENSO events by assessing anomalies in sea surface temperatures (SST).[4] Thus, ONI provides a clear visualization of *El Niño* (warm) and *La Niña* (cold) periods in the tropical Pacific region based on average SST anomalies, calculated as a three-month moving average for the Niño 3.4 region (Yang *et al.*, 2021). Then, based on ONI, *El Niño* (*La Niña*) events are identified if the absolute value of its three-month moving average is equal to or above (equal to or below) + 0.5°C (-0.5°C).

In addition, event strength is determined by the peak value of the ONI index, corresponding to the month when the absolute value of the three-month moving average reaches its maximum during a given *El Niño* or *La Niña* event. An *El Niño* (*La Niña*) event strength is categorized as weak if the peak falls between 0.5°C and 1°C (-0.5°C and -1°C), moderate between 1°C and 1.5°C (-1°C and -1.5°C), strong between 1.5°C and 2°C (-1.5°C and -2°C), and very strong if the peak exceeds 2°C (-2°C). Figure 2 displays the average monthly dynamics of ONI from January 2005 to December 2019. Over the sample period, we notice three weak *El Niño* events (2006, 2014, and 2018), one moderate (2009), and one very strong (2015). As for *La Niña* events, four were of weak amplitude (2005, 2009, 2016, and 2017), one of moderate amplitude (2011), and two of strong amplitude (2008 and 2010).[5]

Figure 2. Dynamics and phases of the Oceanic Niño Index (ONI)



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[4] ONI displays strong correlation (exceeding 90%) with other commonly used indicators like the Niño 3.4 index and the Southern Oscillation Index (SOI) derived from surface atmospheric pressure (Bamston *et al.*, 1997).
[5] See Table A1 in appendix 1 for a detailed classification of ENSO events included in our sample.

Note: Figure 2 displays, on a monthly basis, the dynamics of ENSO based on the Oceanic Niño Index (ONI) and the associated *El Niño* and *La Niña* events during the study period. The ONI index is sourced from the NOAA database. The occurrence of an ENSO event is determined by the three-month moving average of the ONI index. *El Niño* is indicated by values of 0.5°C or higher, while *La Niña* is indicated by values of -0.5°C or lower. Based on the peak in monthly temperature anomaly, an *El Niño* (*La Niña*) event strength is categorized as weak if the peak falls between 0.5°C and 1°C (-0.5°C and -1°C), moderate between 1°C and 1.5°C (-1°C and -1.5°C), strong between 1.5°C and 2°C (-1.5°C and -2°C), and very strong if the peak exceeds 2°C (-2°C).

A quasi-random phenomenon. *El Niño* and *La Niña* are quasi-periodic and quasi-random phenomena, exhibiting complex behavior that makes them difficult to predict due to their unpredictable impacts on local climates (Timmermann *et al.*, 2018). This "quasi-random" nature stems from their high variability (Cobb *et al.*, 2013). Characterized by varying intensities and irregular frequencies (occurring every 2 to 7 years), these phases involve cyclical mechanisms and atmospheric teleconnections that unevenly affect global meteorological patterns (Trenberth & Hoar, 1996). ENSO is considered the most significant annual climate variation on Earth, posing a substantial challenge for prediction, especially as human activities alter its frequency, amplitude, and teleconnections (Cai *et al.*, 2018; Yeh *et al.*, 2018). In this paper, we consider the peak years of ENSO events to capture their "quasi-random" properties. By considering ENSO as a climatic shock, we are able to monitor quasi-periodic climatic oscillations that occasionally lead to natural disasters. Given the expected increase in frequency and magnitude of ENSO events due to climate change (Cai *et al.*, 2014; Yang *et al.*, 2021; Yeh *et al.*, 2022), focusing on ENSO offers a valuable lens to assess potential impacts on banking stability associated with climate change-induced physical risks.

Duration of the event. *El Niño* and *La Niña* phenomena are not symmetrical opposites but differ in their temporal and seasonal patterns, exhibiting distinct evolutionary cycles (An *et al.*, 2020). An ENSO event, typically starting with *El Niño*, begins in the northern hemisphere's spring, intensifies through summer and fall, peaks in winter, and gradually wanes by the following spring, potentially transitioning to *La Niña* in the summer. Unlike *El Niño*, which usually lasts about a year, *La Niña* can persist for several years. In our analysis, for consistency with the banking data, we account for the duration of these ENSO events on a yearly basis, considering their contemporaneous and one-year lagged impacts on banking stability to capture their full dynamics in terms of physical risk. Indeed, ENSO events include two phases: the ascendant phase from approximately March to December, which is crucial for understanding the associated major climatic oscillations leading to natural disasters, and the descendant phase from approximately January to March, reflecting the waning effects. Furthermore, in years with multiple ENSO events of varying intensities, classification is based on the event with the highest amplitude.

Coding of strong ENSO events. Based on the above criteria, we consider two dummy variables to measure ENSO events. Our analysis focuses on strong ENSO events due to their critical impact on weather anomalies and natural disasters in Latin American countries, with significant adverse economic consequences (Damette *et al.*, 2024b). The dummy for strong *El Niño* shocks equals 1 in year *t* if ONI is at its peak value for a given strong *El Niño* event, and equals 0 otherwise; leading to the identification of one strong *El Niño* shock over the studied period in 2015. Similarly, the dummy for strong *La Niña* shocks equals 1 in year *t* if ONI is at its trough value for a given strong *La Niña* event, and equals 0 otherwise; leading to the identification of two strong *La Niña* shocks over the studied period in 2008 and 2010. In appendix 2, Tables A2.1-A2.2 provide a comprehensive overview of the weather anomalies and natural disasters associated with the strong *El Niño* and *La Niña* shocks covered in our sample.

3.2. Banking data

To assess banking stability, performances, and associated credit and liquidity risk channels, we use bank-level data at annual frequency coming from the Moody's Analytics BankFocus database. Our sample includes a large unbalanced panel of 1208 banks located in 16 Latin American countries from 2005 (the starting year of BankFocus's data for Latin American countries) to 2019, with heterogeneous sizes and business models, enabling a comprehensive assessment of the relationship between banking stability and ENSO events in this region. In this section, we first present the data treatment we implemented to account for differences in banks' business model, as well as missing and outlier values. Then, we detail the different banking indicators we selected as dependent variables to assess the impact of ENSO events on banking stability, performances, and risk channels.

Data treatment

Business model. To account for financial institutions with strong traditional (lending and deposit-taking) banking activities, we selected from BankFocus the following four categories of banking institutions: 1) bank holding companies, 2) commercial banks, 3) cooperative banks, and 4) saving banks.[6] In addition, to include in our database financial intermediaries with different funding access strategies, we consider both listed and unlisted banks.

[6] Saving and cooperative banks tend to be less diversified than bank holding companies and commercial banks, with a more concentrated geographical scope in their activities (Koetter *et al.*, 2020). Thus, they can be considered as financial institutions based on stronger relationship banking activities at the regional level.

Missing and outlier values. To ensure data reliability, we implemented several adjustments consistent with banking literature standards in order to address missing and outlier values. Firstly, we account for banking institutions with consolidated accounting data according to IFRS standards.[7] This group-level measurement avoids double-counting issues and offer a more accurate representation of banks' activities (Kim & Sohn, 2017). Secondly, due to the limited availability of consolidated accounting data and the lack of accounting standards harmonization in emerging countries like Latin American ones, we expanded our sample to banking institutions with non-consolidated accounting data.[8] Notably, it enables accounting for small, independent cooperative banks without subsidiaries and with a regional focus, which are an important source of external financing for both households and small firms in Latin America. Thirdly, to assess the contemporaneous and lagged effects of ENSO events on banking stability, while having a sufficient number of available observations, we only kept banks with at least three consecutive years of non-missing data over the period 2005-2019. Fourthly, to address potential outlier values, a logarithmic transformation was applied to all bank-specific variables.[9] Fifthly, we excluded data after 2019 to avoid accounting for the consequences at the macroeconomic and financial levels associated with the Covid-19 crisis in the following years. Finally, for robustness purposes, we defined a dummy variable controlling for bank failures, as well as a dummy variable controlling for banks experiencing a merger and acquisition over the studied period.[10]

Banking dependent variables

Banking stability. Developed by Roy (1952), the z-score is commonly used as a proxy for banking stability (Lepetit & Strobel, 2015; Noth & Schüwer, 2023) and is defined for each bank *i* at time *t* as follows:

$$Zscore_{i,t} = \log\left(\frac{ETA_{i,t} + RoA_{i,t}}{\sigma_{RoA_{i,t}}}\right)$$

It is calculated by dividing the sum of the equity-to-asset ratio (*ETA*) and the return on assets (*ROA*, before tax) by the standard deviation of the ROA (before tax). Thus, the z-score gauges the number of standard deviations a bank's ROA can decline in a single period before reaching

[7] In BankFocus database, it corresponds to the C1 and C2 consolidation categories.
[8] In BankFocus database, it corresponds to the U1, U2, U* and C* consolidation categories.
[9] For variables expressed as a growth rate, we applied the following transformation : $\bar{x} = \text{sign}(x) \cdot log(1 + |x|)$. The use of $\bar{x}$ mitigates potential extreme values of *x*, while preserving its negative values and thus the size of our sample.
[10] See Tables A3.1-A3.4 in appendix 3 for details about the definition, sources and descriptive statistics of these variables.

insolvency, serving as a distance-to-default metric. Higher bank's z-score indicate higher distance-to-default, thus better banks' solvency and stability.

Banking performances. We assess banking performances based on two indicators (Brei *et al.*, 2019; Noth & Schüwer, 2023): the return on assets (ROA) and the return on equity (ROE). Return on assets (ROA) represents pre-tax profits divided by total assets. Following an adverse climate shock, the decline in the quality bank's credit portfolio can decrease earnings derived from assets, mainly due to an increase in non-performing loans and a decrease in the credit supply. As for return on equity (ROE), it indicates pre-tax profits divided by total equity. ROE is a crucial measure of bank performance, principally reflecting shareholder returns. An adverse climate shock can impact bank's return on equity by reducing profits due to increased operating costs, disrupted business activities, and deteriorated access to external sources of financing.

Credit risk. Based on Brei *et al.* (2019), we assess credit risk based on the ratio of non-performing loans to gross customer loans. An adverse climate shock can reduce borrowers' ability to generate income and meet their financial obligations, leading to an increase in banks' non-performing loans.

Liquidity risk. To gauge banks' liquidity risk, we use the following three variables. We first use the ratio of total customer and bank deposits to total assets as a general indicator of bank's liquidity (Beltratti & Stulz, 2012; Laeven *et al.*, 2014, 2016). Then, we subdivide this variable and consider the ratio of total customer deposits to total assets and the ratio of bank deposits to total assets as more specific indicators of the source of bank's liquidity risk. In each case, higher values of these variables mean more bank's liquidity. In the aftermath of an adverse climate shock, bank's liquidity risk can increase due to a surge in deposits outflows from households and firms needing funds for repairs and increased demand for emergency loans. Additionally, in this situation, banks can face heightened refinancing pressure on the interbank market, as deposits outflows may prompt an important increase in banks' demand for short-term funds that can lead to higher borrowing costs, and thus lower performances and higher instability.

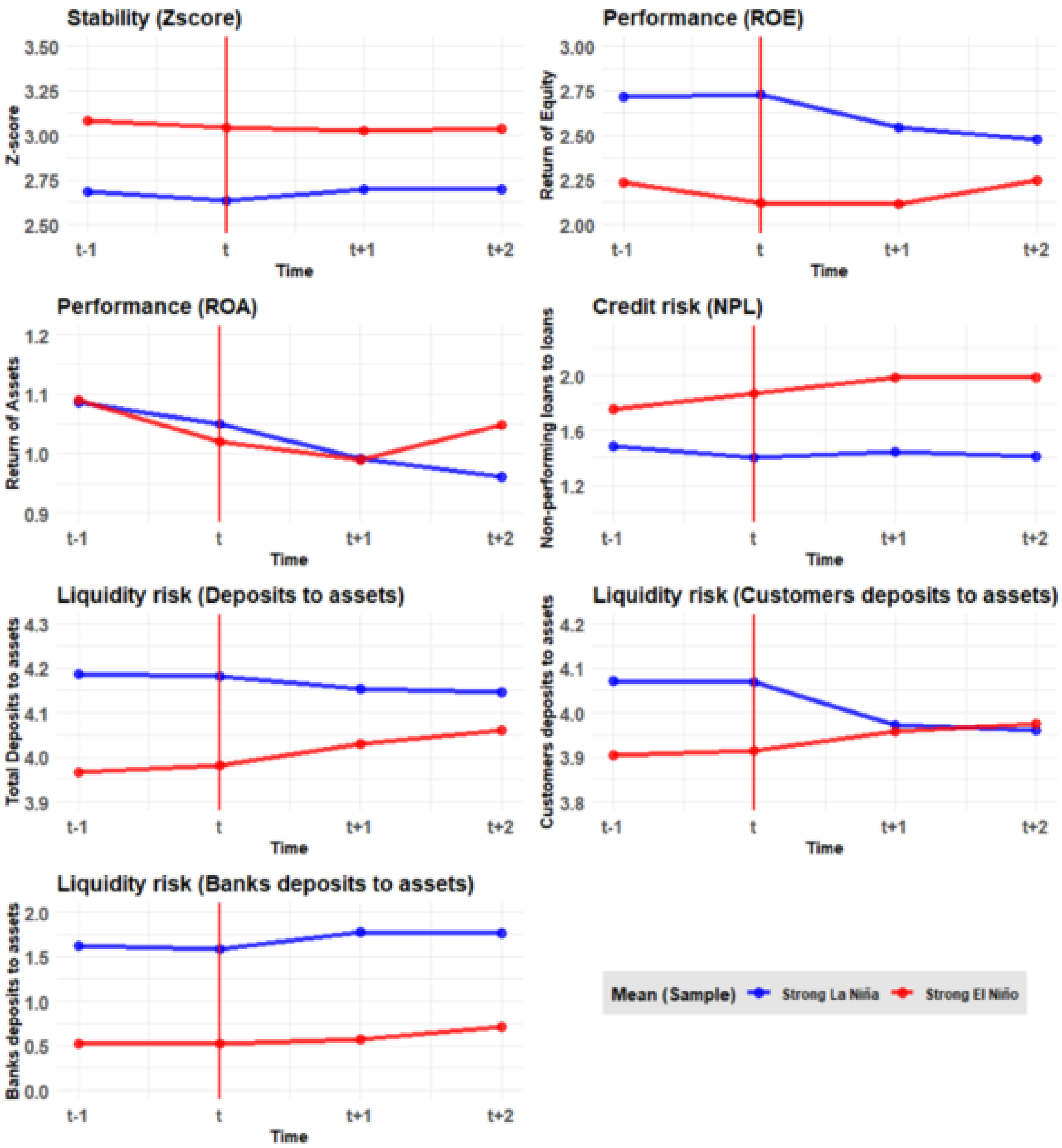
3.3. A first look at the relationship between strong ENSO events and banking stability

Figure 3 displays the average annual dynamics of banking stability, performances, and associated credit and liquidity risks over the period 2005-2019 for the 1208 banks from 16 Latin American countries included in our sample in response to strong ENSO events.

Strong *El Niño* shock. A strong *El Niño* event is associated with a contemporaneous reduction in bank stability, as evidenced by a lower z-score, and this effect is persistent, which is well documented (Klomp, 2014; Noth & Schüwer, 2023), especially in less developed regions like the Caribbean (Brei *et al.*, 2019, 2024). This lagged effect may be due to the fact that financial losses induce by a strong *El Niño* event, such as non-performing loans, are declared after a 90-days late payment period. In this case, the adverse impact of a strong *El Niño* event can span two calendar years, even though the peak effect occurs from December to February (Cai *et al.*, 2020). Related to banking stability, we also notice a contemporaneous and one-year lagged decrease in banks' ROE, returning to its initial levels two years after the strong *El Niño* events, in line with Brei *et al.* (2019), as climate shocks can reduce profits due to increased operating costs and business disruptions. We also observe a contemporaneous and lagged decrease in return on assets (ROA) associated with a significant and persistent increase in non-performing loans, corroborating results obtained by Noth & Schüwer (2023). Increasing non-performing loans signal a weakened loan portfolio, reducing ROA, worsening banks' equity and thus their stability. As for liquidity risk, we find no significant decrease in the banks' deposits-to-asset ratio and its subcomponents, but a slight lagged increase in banks' liquidity potentially due to precautionary behaviors by customers to face the adverse consequences of climate shocks, and also by factors like government and municipal deposits for disaster recovery, and insurance payouts.

Strong *La Niña* shock. A strong *La Niña* event is associated with a contemporaneous decrease in banking stability, as evidenced by a lower z-score, and this effect is followed by a subsequent recovery. Moreover, we find a contemporaneous increase in banks' financial performances (ROE) associated with reduced credit risk, and no significant variations in liquidity risk, which may be attributed to potential favorable climatic conditions during the peak year of a *La Niña* event, with positive effects on macroeconomic conditions across Latin American countries (see section 2.2.). Then, except for the z-score, banks experienced a reduction in their performances (ROE and ROA) and an increase in both credit and liquidity risks in the aftermath of a strong *La Niña* event. However, the two strong *La Niña* events in our sample occurred in 2008 and 2010, thus, in a period of important financial instability associated with the consequences of the *subprime* crisis. Therefore, we need to deepen these preliminary results with econometric estimates that enables to identifies more precisely the specific impact of these climate shocks on banking stability.

Figure 3. Dynamics of banking stability in responses to strong ENSO events



Note: This graph illustrates the dynamics of the annual average of several indicators of banks' stability, performances, and associated credit and liquidity risks in response to a strong *El Niño* shock (red lines) and a strong *La Niña* shocks (blue lines). The sample includes 1208 banks located in 16 Latin American countries and observed at annual frequency over the period 2005-2019. The graph displays data from one year prior to a strong ENSO event (*t-1*), up to two years after (*t+2*). The red vertical bars indicate the peak year of the *strong* ENSO event. All banking variables are expressed in logarithms to account for potential outlier values.

IV. Econometric methodology

This section presents the econometric methodology used to empirically assess the impact of strong ENSO events on banking stability for a sample of 1208 banks located in 16 Latin American countries and observed at annual frequency over the period 2005-2019.

4.1. Identification issues

The empirical evaluation of the economic consequences from physical risks induced by climate change has long been recognized as a challenge in the econometrics literature (Auffhammer, 2022; Kolstad & Moore, 2019). As a result, our identification strategy relies on two key methodological points. Firstly, following Noth & Schüwer (2023), we rely on a panel data model with fixed effects at country, bank, and banking business model levels, to account for different sources of unobserved heterogeneity that could bias the estimated effects of climate shocks on banking stability.[11] Secondly, in line with Damette *et al.* (2024b), our identification strategy is based on the time series variability created by ENSO. Capitalizing on the usual practice in the climate literature, we characterize the occurrence and intensity of ENSO events as "quasi-random" due to their unpredictability and orthogonality with respect to economic and financial conditions. Thus, ENSO events can be considered as exogenous shocks resulting from random or quasi-random trials, thereby mitigating concerns regarding endogeneity when estimating their impact on banking stability. By considering ENSO events as a climate shocks, we capture quasi-periodic climatic oscillations, i.e., structural climatic fluctuations that, at certain times, frequencies, and magnitudes, can result in natural disasters. Moreover, since the frequency and the magnitude of ENSO events are expected to increase with climate change, using ENSO as a proxy for the potential physical risks induced by climate change, like Hsiang *et al.* (2011), offers a relevant approach to get empirical insights regarding the impact of climate change on banking stability.

4.2. Baseline model specification

To assess the relationship between strong ENSO events and banking stability, we estimate the following fixed effects OLS regression model with standard errors clustered at the bank level:

$$Y_{i,c,t} = \alpha_0 + \beta_1 EN_t + \beta_2 EN_{t-1} + \beta_3 LN_t + \beta_4 LN_{t-1} + \theta_i + \nu_c + \gamma_m + \varepsilon_{i,c,t} \qquad \text{Eq. (1)}$$

[11] We cannot account for time fixed-effects due to perfect collinearity issue with ENSO events that are global shocks with no country-specific dimension.

We consider a set of seven dependent variables ($Y_{i,c,t}$) for bank i in country c in year t to evaluate the effect of strong ENSO events on banking stability, accounting for the main financial mechanisms at work: 1) z-score, 2) return on equity (ROE), 3) return on assets (ROA), 4) non-performing loans (NPL), 5) total deposits to total assets, 6) customer deposits to total assets, 7) bank deposits to total assets.

EN and *LN* are contemporaneous and one-year lagged dummy variables for strong *El Niño* and *La Niña* shocks respectively. As mentioned in section 3.1, the adverse physical risks induced by strong ENSO events cover two calendar years, typically extending from November of the peak year to March of the following year (Cai *et al.*, 2020). Specifically, the peak year captures the period when ENSO entails the most severe natural disasters. Then, the impact of ENSO decreases in intensity the subsequent year, reflecting the waning effects of a given ENSO phase (Cai *et al.*, 2018, 2021). Thus, to account for the potential seasonal effects associated with strong *El Niño* and *La Niña* shocks, we consider both their contemporaneous and the one-year lagged effects on banking stability. Considering banking data, this specification choice appears even more important due to the timing of registration in banks' balance sheet and income state of losses stemming from the adverse economic and financial consequences of strong ENSO events. For instance, non-performing loans are typically reported after a 90-day period of late payment. In this case, we expect a heightened credit risk in the year following the peak of a strong ENSO event.

θ_i represents bank fixed-effects that account for time-invariant unobserved heterogeneity at the bank level, such as management quality, governance, and risk preference. v_c denotes country fixed-effects that control for time-invariant unobserved heterogeneity at the country level. The inclusion of fixed effects for both banks and countries also help mitigate potential bias arising from differences in state or private insurance systems across countries. In addition, γ_m represents banking business model fixed-effects accounting for time-invariant unobserved heterogeneity associated with the different types of banks included in our sample (i.e., bank holding companies, commercial banks, cooperative banks, and saving banks). $\varepsilon_{i,c,t}$ is an *i.i.d.* error term with zero mean and constant variance. For robustness purpose, given the potential strong correlations of banking instability at country and regional levels, due to contagion effects, we also estimate our baseline fixed effects OLS regression model using the Driscoll-Kraay's (Driscoll & Kraay, 1998) heteroskedasticity-robust standard errors adjusting for temporal and spatial dependence.[12] Finally, given the relatively short time dimension of our annual panel (with T = 15), to avoi d any Nickel bias inherent to dynamic panel models with country or bank fixed-effects, we do not include as regressors the lagged values of our banking dependent variables.

V. Main results

Baseline results associated with the estimates of equation (1) are displayed in Table 1. Overall, three main results can be highlighted, in line with our testable hypotheses:

1. Our findings indicate a significant negative impact of strong *El Niño* events on banking stability, associated with decreased banks' performances and heightened credit and liquidity risks.

2. In contrast, we observe a positive effect of strong *La Niña* events on banks' performances, associated with reduced credit risk.

3. Strong *El Niño* and *La Niña* shocks thus have asymmetrical effects on banking stability, as they can vary depending on geographical areas and seasonal factors in which they occur.

Table 1. Banking stability and strong ENSO events: baseline results

	Stability		Performances				Credit risk		Liquidity risk					
	Zscore		ROE		ROA		NPL		Total Deposits to total assets		Customer Deposits to total assets		Bank Deposits to total assets	
	OLS	DK	OLS	DK	OLS	DK	OLS	DK	OLS	DK	OLS	DK	OLS	DK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Strong El Niño	0.004	0.004	-0.084**	-0.084**	-0.015	-0.015	-0.085***	-0.085***	-0.053***	-0.053***	-0.035***	-0.035***	-0.173***	-0.173***
	(0.006)	(0.006)	(0.035)	(0.036)	(0.018)	(0.018)	(0.013)	(0.013)	(0.006)	(0.006)	(0.006)	(0.006)	(0.020)	(0.019)
Strong El Niño (t-1)	-0.016***	-0.016***	-0.089**	-0.089***	-0.047**	-0.047***	0.037***	0.037***	-0.007	-0.007	0.007	0.007	-0.111***	-0.111***
	(0.006)	(0.005)	(0.035)	(0.034)	(0.019)	(0.018)	(0.013)	(0.012)	(0.005)	(0.005)	(0.005)	(0.005)	(0.017)	(0.017)
Strong La Niña	-0.018	-0.018	0.163**	0.163**	0.069**	0.069**	-0.097**	-0.097***	0.017	0.017	0.020	0.020	0.003	0.003
	(0.019)	(0.017)	(0.075)	(0.078)	(0.034)	(0.034)	(0.038)	(0.031)	(0.014)	(0.011)	(0.017)	(0.014)	(0.055)	(0.047)
Strong La Niña (t-1)	-0.003	-0.003	0.030	0.030	0.024	0.024	0.027	0.027	0.009	0.009	0.004	0.004	-0.014	-0.014
	(0.017)	(0.014)	(0.073)	(0.069)	(0.031)	(0.029)	(0.031)	(0.029)	(0.014)	(0.011)	(0.018)	(0.016)	(0.043)	(0.040)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.86	0.86	0.43	0.43	0.48	0.48	0.67	0.67	0.87	0.88	0.89	0.89	0.71	0.71
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. DK columns stand for fixed-effects OLS regressions with Driscoll & Kraay robust standard errors in brackets. All regressions include bank, country, and banking business model fixed-effects.

[12] Table A3.5 in appendix 3 shows the results of the Pesaran (2015, 2021) cross-sectional dependence test applied to our seven banking dependent variables and confirms the presence of significant cross-sectional dependence within our panel.

El Niño. A strong *El Niño* event is associated with a significant lagged decline in banks' z-score, as evidenced in columns (1)-(2), which is in line with previous studies highlighting the adverse effects of natural disasters on banking stability due increased losses threatening banks' solvency (Klomp, 2014; Brei *et al.*, 2019; Noth & Schüwer, 2023). Quantitatively, a strong *El Niño* event is associated with a 1.6% decrease in banks' z-score. As mentioned in section 4.2, this lagged decline in stability, may be attributed to the delayed accounting of financial losses resulting from the adverse economic and financial consequences of a strong *El Niño* event, typically overlapping two calendar years from November of the peak year to March of the following year.

Based on the analysis presented in section II, several factors can explain this reduction in banking stability. Firstly, as shown in columns (3)-(4), we notice a significant contemporaneous and lagged decrease in banks' return on equity (ROE). Considering marginal effects, a strong *El Niño* event is associated with a 8.4% contemporaneous and a 8.9% lagged reduction in banks' ROE. This reflects the *El Niño*'s adverse effects on banks' profit due to increased operating costs, disrupted business activities, and deteriorated access to external sources of financing. Secondly, in columns (5)-(6), we notice only a significant lagged decrease in banks' return on assets (ROA), with an estimated marginal effect of – 4.7%. However, there is no significant reduction in ROA in period t, indicating that ROA takes longer to adjust to the ENSO shock than ROE. This is because ROA measures the average profitability of a bank's assets. Thirdly, this decline in both ROE and ROA is associated with an increase in credit risk, suggesting a deterioration in the quality of banks' loan portfolio with adverse effects on asset returns. Indeed, estimates in columns (7)-(8) show that a strong *El Niño* event is associated with a significant 3.7% lagged increase in non-performing loans. However, we notice a significant contemporaneous decrease in credit risk. This might be explained by the fact that NPLs are only accounted for after 90 days. Considering the dynamic, particularly seasonal, nature of El Niño, the negative impact of the shock on NPLs will only be visible and significant the following year (thus in t-1 considering the estimates). Therefore, our coefficients at t most likely capture the positive climatic consequences of the end of the previous *La Niña* phase. Finally, as shown in columns (9)-(14), there is a significant contemporaneous increase in liquidity risk, as reflected by a 5.3% decrease in the ratio of total deposits to total assets in columns (9)-(10), which is explained by a 3.5% decline in customers' deposits in columns (11)-(12) and a 1.7% reduction in banks' deposits in columns (13)-(14). These results suggest increased customer withdrawals for repairs and reconstruction following the outbreak of a strong *El Niño* event, with heightened refinancing pressures, as deposits outflows may prompt an important increase in the needs of banks for short-term funds, which intensifies competition on the interbank market, potentially increasing refinancing costs. We also notice that this significant adverse effect of a strong *El Niño* event on banks' deposits is persistent, as indicated in columns (13)-(14). Contrary to what we observe for customers' deposits in columns (11)-(12), which could be explained by factors such as government aid and insurance payouts.

La Niña. A strong *La Niña* event does not appear to significantly affect banking stability, as evidenced in columns (1)-(2). Further examination reveals a noteworthy pattern. Indeed, we notice in columns (3)-(6) that a strong *La Niña* event is associated with a contemporaneous increase in both banks' ROE and ROA. Similarly, columns (7)-(8) show a significant decline in banks' non-performing loans in the year of occurrence of a strong *La Niña* event. However, in columns (9)-(14), we find no significant relationship with liquidity risk. In line with the analysis carried out in section II, this contemporaneous improvement in banks' performances and the associated reduction in credit risk may be attributed to the potential short-run positive climatic effects of strong *La Niña* events for Latin American countries included in our sample, such as rain surplus in the agricultural sector for instance, with beneficial consequences on macroeconomic conditions.

Overall, these estimates show that, regarding Latin American countries, strong ENSO events can have adverse financial consequences that lead to a decline in banking stability. Indeed, strong *El Niño* shocks are associated with lower banks' stability, resulting from decreased performances associated with increased credit and liquidity risks. In contrast, we find that strong *La Niña* shocks have no significant impact banking stability and is associated with higher banks' performances and lower credit risk. This suggests important asymmetric effects on banking stability from *El Niño* and *La Niña* shocks depending on geographical areas and seasonal factors in which they occur.

VI. Robustness

Based on the same econometric set-up we used in section V, we now implement several robustness checks. To save space, all results are presented in appendix 4 Tables A4.1-A4.4.g.

6.1. Alternative classifications of ENSO events

In the baseline estimates, we focused on the impact of strong *El Niño* and *La Niña* shocks on banking stability. Now, we present robustness checks assessing the effects of moderate *El Niño* and *La Niña* events as an alternative classification of ENSO events based on the methodology outlined in section 3.1.[13] We identify one moderate *El Niño* event in 2009 and one moderate *La Niña* event in 2011. Results in Table A4.1 indicate that a moderate *El Niño* event is not associated with a significant decrease in banking stability and performances (both ROE and ROA). However, we notice a significant contemporaneous increase in credit risk, which is likely to be the result of the adverse macroeconomic and financial consequences induced by the 2008-2009 *subprime* crisis. Conversely, lower credit and liquidity risks are observed in the year following the occurrence of the 2009 moderate *El Niño* event, possibly reflecting the decrease in financial instability at the international level in the aftermath of the 2008-2009 *subprime* crisis. In addition, estimates reveal no significant effect of a moderate *La Niña* event on banking stability, performances and associated credit and liquidity risks. Overall, in line with our testable hypotheses, these findings confirm that only strong *El Niño* events are associated with a significant decrease in banking stability,

6.2. Accounting for additional control variables

We now assess if our baseline results are robust when considering three different sets of control variables that could influence banking stability, especially in the case of Latin American countries: 1) bank-specific controls, 2) country-specific macro-financial controls, 3) country-specific macroeconomic controls.[14] This choice of controls enables to ensure that our baseline estimates are not influenced by different potential sources of omitted variables biased. For each of these three sets of controls, we proceed in two steps. First, we re-estimate equation (1) by sequentially including each control variable. Then, only significant controls in the first step are jointly introduced in equation (1). This two-step procedure is applied to the seven dependent variables we consider in baseline to assess the impact of strong ENSO events on banking stability, performances, and risk channels.

Bank-specific controls

First, we evaluate the robustness of our baseline panel estimates by controlling for the effect of seven additional microeconomic bank-specific variables considered as key determinants of banking stability (e.g., De Jonghe, 2010; Betz *et al.*, 2014; Laeven *et al.*, 2016; Chen *et al.*,

[13] We do not consider weak ENSO events for robustness checks due to their higher frequency and lower magnitude, which provides the identification of a significant impact on banking stability for Latin American countries because of their limited macroeconomic impacts. As shown in appendix 1 Table A1, we identify three weak *El Niño* events (2006, 2014, and 2018) and four weak *La Niña* events (2005, 2009, 2016, and 2017).

[14] In appendix 3, Table A3.1 details the definition and source of each of these controls' variables, whereas Table A3.2 provides their descriptive statistics.

2021): bank size (log of total assets), asset growth (growth rate of total assets), capital ratio (total equity to total assets), cost to income (total operating expenses to total operating incomes), net interest margin (net interest income to total interest earning assets), loans to total assets, and non-interest income to total assets. Moreover, we account for the following three categories of dummy variables: a dummy for years of banks failures, a dummy for years in which banks undergo or engage in a merger and acquisition, and a set of dummies controlling for each type of consolidation code used to extract banking data from BankFocus (see section 3.2).[15] Results are displayed in appendix 4 Tables A4.2.a-A4.2.g and show that overall our baseline findings regarding the adverse effects of strong *El Niño* events on banking stability, performances, and associated credit and liquidity risks are robust to the inclusion of a large array of bank-specific controls. We also confirm the positive effect of *La Niña* events on banking performances and credit risk.

Country-specific macro-financial controls

Then, we assess the robustness of our baseline panel estimates by controlling for the effect of nine additional country-specific macro-financial variables also considered as key determinants of banking stability(e.g., Betz *et al.*, 2014): banks' total assets to GDP, the ratio of bank credit to deposits, banking sector concentration (the ratio of assets held by the five largest banks as a share of total banking assets), the average real bank lending rate, total private credit to GDP, growth of private credit, a dummy for the years 2007 to 2009 associated with the *subprime* crisis[16], the annual S&P 500 Volatility Index (VIX), and the FED funds rate. Results are displayed in appendix 4 Tables A4.3.a-A4.3.h and show that overall our baseline findings are robust when including this large set of country-specific macro-financial controls.

Country-specific macroeconomic controls

Finally, we evaluate the robustness of our baseline panel estimates by controlling for the effect of nine additional country-specific macroeconomic variables considered as key determinants of banking stability (e.g., Demirgüç-Kunt & Detragiache, 1998; Demirguc-Kunt *et al.*, 2013; Demirgüç-Kunt & Huizinga, 2010; De Jonghe & Öztekin, 2015; Laeven *et al.*, 2016): real GDP,

[15] To account for the fact that a bank failure may take several years (from liquidation to bankruptcy), we consider the contemporaneous and the two lagged values of the bank failures dummy. Regarding the dummy for merger and acquisition, we follow the standard practice in the banking literature and consider that a bank experiences a merger and acquisition in a given year if its total assets growth is equal to or above 15% (De Jonghe & Öztekin, 2015; Bakkar *et al.*, 2020). Since a merger and acquisition may be preceded by several stages impacting banking activity, we also consider the contemporaneous and the two lagged values of the merger and acquisition dummy.

[16] To control for the country-specific impact of the *subprime* crisis on banking stability, we also estimate equation (1) with the inclusion of a set of dummy variables corresponding to the interaction between the *subprime* crisis dummy and country fixed-effects. Results are displayed in appendix 4 Table A4.3.h and corroborate our baseline findings.

real GDP growth, real GDP per capita, inflation, the growth of the nominal exchange rate, the growth of the current account balance, the growth of terms of trade, a dummy for years of sovereign debt crisis outbreak, and a dummy for years of currency crisis outbreak. Results are displayed in appendix 4 Tables A4.4.a-A4.4.g and show that overall our baseline findings are once again robust when including this large set of country-specific macroeconomic controls.

VII. Heterogeneity: strong ENSO events and banking resilience indicators

In this section, we extend our baseline results by considering potential sources of heterogeneity at the bank-level in the relationship between strong ENSO events and banking stability. We want to assess if some key banks' characteristics may influence their resilience to these adverse climate shocks. To this end, we focus on three potential factors, namely, banks' size, capitalization, and business model.[17] Then, for each of these three variables, we define a threshold value and re-estimate our baseline econometric specification associated with equation (1) based on two subsamples depending on either bank in our sample has observations above or below this threshold. To save space, in appendix 5, Table A5.1 displays descriptive statistics for our seven dependent variables of banking stability, performances, and associated credit and liquidity risks depending on the threshold values define for banks' size, capitalization, and business model.

7.1. Banks' size

We consider a given bank as large if the averaged value of its total assets over the period 2005-2019 is equal to or above 1 billion US dollars.[18] Do *et al.* (2023) point that larger banks are more resilient because they have more expertise in risk management, they also have more branches in diversified geographical areas and they can more easily increase their liquidity buffer through intra-group liquidity transfers. Thus, we expect larger banks to be more resilient to the adverse consequences resulting from strong ENSO events, especially *El Niño* ones.

Regarding strong *El Niño* events, Table 2.a show that results for the subsample of small banks closely mirror those obtained in baseline for the entire sample. We notice a significant lagged decline in banks' z-score, associated with a decrease in banks' performances (both ROE and ROA) resulting from a lagged increase in credit risk and a contemporaneous increase in

[17] In appendix 3, Table A3.1 details the definition and source of these three variables, whereas Table A3.2 provides their descriptive statistics.

[18] This corresponds to the standard criterion used in the banking literature to categorize large banks (e.g., Lepetit *et al.*, 2008; Noth & Schüwer, 2023).

liquidity risk caused by a reduction in both customers' and banks' deposits. When considering results for the subsample of large banks, we observe a significant contemporaneous and lagged decrease in banks' z-score, associated with a decrease in banks' ROA and an increase in liquidity risk. Conversely, for strong *La Niña* events, we notice positive effects, except a contemporaneous decline in banks' z-score for the subsample of large banks that might be explained by the adverse consequences of the *subprime* crisis at the international level during the 2008 strong *La Niña* event. Overall, these results suggest that both small and large banks are adversely affected by a strong *El Niño* event, but small banks appear less resilient due to their simultaneous exposure to credit and liquidity risks. This aligns with existing literature indicating that small banks, being less geographically diversified, face higher credit risk and customer deposit withdrawals in response to adverse climate shocks, deteriorating their profitability and depleting their capital further, leading to decreased stability (Koetter *et al.*, 2020; Noth & Schüwer, 2023).

Table 2.a. Banking stability and strong ENSO events: banks' size subsamples

	Stability		Performances				Credit risk		Liquidity risk					
	Zscore		ROE		ROA		NPL		Total Deposits to total assets		Customer Deposits to total assets		Bank Deposits to total assets	
	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large	Small
Strong El Niño	-0.058***	0.017***	-0.106	-0.081**	-0.067**	-0.005	-0.046*	-0.093***	-0.066***	-0.050***	-0.059***	-0.029***	-0.054	-0.199***
	(0.013)	(0.006)	(0.066)	(0.041)	(0.026)	(0.021)	(0.025)	(0.015)	(0.021)	(0.006)	(0.017)	(0.006)	(0.048)	(0.022)
Strong El Niño (t-1)	-0.028**	-0.012**	-0.037	-0.100**	-0.030	-0.051**	0.043	0.035**	-0.031*	-0.001	-0.015	0.013**	-0.105**	-0.114***
	(0.012)	(0.006)	(0.045)	(0.041)	(0.021)	(0.022)	(0.028)	(0.014)	(0.017)	(0.005)	(0.016)	(0.005)	(0.046)	(0.018)
Strong La Niña	-0.042*	0.030	0.024	0.576***	-0.014	0.300***	-0.036	-0.263***	0.032*	-0.037*	0.038*	-0.047*	-0.047	0.183
	(0.021)	(0.041)	(0.072)	(0.188)	(0.030)	(0.089)	(0.045)	(0.055)	(0.017)	(0.020)	(0.021)	(0.025)	(0.062)	(0.114)
Strong La Niña (t-1)	-0.033	0.057**	-0.029	0.192	-0.016	0.120*	0.033	0.020	0.019	-0.029	0.028*	-0.071	-0.071	0.168*
	(0.021)	(0.026)	(0.084)	(0.145)	(0.033)	(0.071)	(0.033)	(0.074)	(0.015)	(0.025)	(0.016)	(0.046)	(0.048)	(0.086)
N	2001	6289	2001	6289	2001	6289	2001	6289	2001	6289	2001	6289	2001	6289
R-squared adj.	0.75	0.85	0.36	0.41	0.54	0.47	0.59	0.63	0.81	0.89	0.90	0.89	0.60	0.65
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects. A given bank is considered large if the averaged value of its total assets over the period 2005-2019 is equal to or above 1 billion US dollars.

7.2. Banks' capitalization

To get balanced subsamples, we consider a given bank as having a high level of capitalization if its averaged capital ratio (total equity to total assets) over the period 2005-2019 is equal to or above the sample median. A higher level of capitalization plays a key role in banks' resilience as it strengthens their ability to absorb losses resulting from adverse climate shocks. For instance, Collier *et al.* (2014) shows that micro-banking institutions in Peru have high capital ratios to prevent losses from non-performing loans resulting from natural disasters associated with ENSO events. Thus, we expect banks with a higher capital ratio to be more resilient to strong ENSO events, especially *El Niño* ones.

Considering strong *El Niño* events, Table 2.b indicates that results for the subsample of banks with a low capital ratio are very similar those obtained in baseline. We notice a significant contemporaneous and lagged decline in banks' z-score, associated with a decrease in banks' performances (both ROE and ROA) resulting from a lagged increase in credit risk and a contemporaneous increase in liquidity risk caused by a reduction in both customers' and banks' deposits. Regarding the results for the subsample of banks with a high capital ratio, we notice a significant contemporaneous and lagged improvement in banking stability (increase in banks' z-score), combined with an increase in banks' performances (ROA) and a reduction in credit risk. Interestingly, this increase in banking stability allows for the absorption of losses associated with an increase in liquidity risk concerning both customers' and banks' deposits. As for strong *La Niña* events, similar to our baseline results, in both subsamples, we find few instances of positive effects, except from the significant lagged increase in credit risk for banks with a high capital ratio, possibly reflecting the adverse effect of the *subprime* crisis on non-performing loans during the 2008 strong *La Niña* event. Thus, these results suggest that banks with higher capital ratios exhibit greater resilience to adverse climate shocks induced by strong *El Niño* events, due to better losses absorption capacities, despite potential exposure to liquidity risk. This is in line with the existing literature. For instance, in the context of floods in Germany, Rehbein & Carbo-Valverde (2020) find that the most affected firms are linked with banks having lower regulatory capital.

Table 2.b. Banking stability and strong ENSO events: banks' capitalization subsamples

	Stability		Performances				Credit risk		Liquidity risk					
	Zscore		ROE		ROA		NPL		Total Deposits to total assets		Customer Deposits to total assets		Bank Deposits to total assets	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Strong El Niño	0.050***	-0.052***	0.034	-0.231***	0.065**	-0.115***	-0.138***	-0.018	-0.083***	-0.016*	-0.050***	-0.016**	-0.249***	-0.080***
	(0.007)	(0.009)	(0.044)	(0.057)	(0.026)	(0.023)	(0.019)	(0.018)	(0.009)	(0.008)	(0.009)	(0.008)	(0.029)	(0.027)
Strong El Niño (t-1)	0.016***	-0.053***	-0.075	-0.104**	-0.029	-0.067***	0.022	0.054***	-0.015**	0.003	0.009	0.005	-0.147***	-0.070***
	(0.006)	(0.010)	(0.049)	(0.048)	(0.029)	(0.020)	(0.018)	(0.017)	(0.007)	(0.007)	(0.007)	(0.008)	(0.024)	(0.023)
Strong La Niña	-0.040	-0.023	0.218	0.142*	0.116	0.052	-0.044	-0.099***	0.042	0.018	-0.001	0.025	0.174	-0.010
	(0.065)	(0.020)	(0.228)	(0.079)	(0.124)	(0.035)	(0.150)	(0.037)	(0.046)	(0.015)	(0.051)	(0.018)	(0.157)	(0.058)
Strong La Niña (t-1)	0.065**	-0.024	-0.047	0.031	0.052	0.008	0.201*	0.000	-0.040	0.022*	-0.079	0.022	-0.044	0.004
	(0.030)	(0.019)	(0.163)	(0.082)	(0.071)	(0.035)	(0.103)	(0.031)	(0.049)	(0.013)	(0.081)	(0.015)	(0.104)	(0.047)
N	4149	4141	4149	4141	4149	4141	4149	4141	4149	4141	4149	4141	4149	4141
R-squared adj.	0.82	0.59	0.41	0.44	0.42	0.48	0.62	0.68	0.87	0.87	0.88	0.90	0.62	0.75
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects. A given bank is considered as having a high level of capitalization if its averaged capital ratio (total equity to total assets) over the period 2005-2019 is equal to or above the sample median.

7.3. Banks' business model

Finally, the relative importance of traditional (lending and deposit taking) banking activities compared with more market-oriented activities (e.g. investment banking, proprietary trading, securities brokerage, insurance sales) in banks' business model is an important feature that may also influence their resilience to adverse climate shocks. To assess the relative importance of market-oriented activities in banks' business model, we follow the usual practice in the banking literature and consider the ratio of non-interest income to total income (e.g., Lepetit *et al.*, 2008; De Jonghe, 2010; Bakkar *et al.*, 2020). To get balanced subsamples, we consider a given bank as having a high level of market-oriented activities if its average non-interest income to total income ratio is equal to or above the sample median. High levels of market-oriented activities can have ambiguous effects on banking stability. On the one hand, banks with more market-oriented activities are able to better diversify the risks resulting from traditional banking activities, allowing more resilience in response to adverse shocks (Lepetit *et al.*, 2008). On the other hand, banks with more market-oriented activities are less prone to develop long-term relationship with their customers, resulting in less careful risk assessments and financing granted to potentially more risky firms and households (Beck *et al.*, 2014; Laeven *et al.*, 2016), which could reduce the resilience of banks in response to adverse climate shocks.

Regarding strong *El Niño* events, Table 2.c show that results for the subsample of banks with high levels of market-oriented activities are close those obtained in baseline. We notice a significant lagged decline in banks' z-score, associated with a decrease in banks' performances (both ROE and ROA) resulting from a lagged increase in credit risk and a contemporaneous increase in liquidity risk caused by a reduction in both customers' and banks' deposits. When considering the results for the subsample of banks with low levels of market-oriented activities, we observe a significant lagged decrease in banks' z-score, associated with an increase in liquidity risk, caused by a reduction in both customers' and banks' deposits, but without significant decline in banks' performances and increase in credit risk. Concerning strong *La Niña* events, in both subsamples, we find again few instances of positive effects, except from the significant lagged increase in liquidity risk for banks with a high level of market-oriented activities when considering the banks' deposits to total assets ratio. These results suggest that both market-oriented and non-market-oriented banks are adversely affected by a strong *El Niño* event, but banks with high market-oriented activities appear less resilient due to a decrease in performances and their simultaneous exposure to credit and liquidity risks.

Table 2.c. Banking stability and strong ENSO events: banks' business model subsamples

	Stability		Performances				Credit risk		Liquidity risk					
	Zscore		ROE		ROA		NPL		Total Deposits to total assets		Customer Deposits to total assets		Bank Deposits to total assets	
	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
Strong El Niño	0.005	0.003	**-0.104****	-0.066	-0.027	-0.005	**-0.063*****	**-0.106*****	**-0.058*****	**-0.048*****	**-0.034*****	**-0.036*****	**-0.250*****	**-0.097*****
	(0.008)	(0.008)	(0.048)	(0.052)	(0.023)	(0.028)	(0.017)	(0.021)	(0.008)	(0.010)	(0.007)	(0.009)	(0.030)	(0.027)
Strong El Niño (t-1)	**-0.016****	**-0.015***	**-0.165*****	-0.013	**-0.090*****	-0.004	**0.071*****	0.003	0.001	**-0.014***	**0.014****	0.001	**-0.120*****	**-0.104*****
	(0.008)	(0.008)	(0.049)	(0.050)	(0.026)	(0.027)	(0.016)	(0.020)	(0.007)	(0.008)	(0.006)	(0.009)	(0.024)	(0.024)
Strong La Niña	-0.014	-0.023	0.070	**0.289****	0.021	**0.134****	**-0.086***	**-0.110***	0.014	0.021	**0.032***	0.003	-0.079	0.110
	(0.020)	(0.037)	(0.083)	(0.135)	(0.034)	(0.066)	(0.046)	(0.063)	(0.014)	(0.029)	(0.017)	(0.034)	(0.061)	(0.099)
Strong La Niña (t-1)	0.007	-0.016	0.040	0.013	0.021	0.025	-0.022	0.093	0.012	0.004	0.015	-0.010	**-0.097***	0.091
	(0.018)	(0.032)	(0.086)	(0.127)	(0.034)	(0.056)	(0.034)	(0.058)	(0.013)	(0.027)	(0.022)	(0.030)	(0.050)	(0.072)
N	4148	4142	4148	4142	4148	4142	4148	4142	4148	4142	4148	4142	4148	4142
R-squared adj.	0.84	0.86	0.48	0.37	0.54	0.44	0.72	0.62	0.87	0.88	0.90	0.89	0.69	0.74
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects. A given bank is considered as having a high level of market-oriented activities if its averaged non-interest income to total income ratio over the period 2005-2019 is equal to or above the sample median.

In summary, these additional estimates point to interesting policy implications regarding the types of banks' characteristics that may influence their resilience to adverse climate shocks. Indeed, results derived from Tables 2.a-2.c indicate that banks with a larger size, a higher capital ratio, and less market-oriented activities are more resilient to adverse climate shocks resulting from strong *El Niño* events. However, these results should be considered only as an illustration of the potential heterogeneities that could drive the response of banking stability to strong ENSO events depending on some key banks' characteristics. A further in-depth analysis would be necessary to precisely identify these heterogeneities, but it is beyond the scope of this paper.

VIII. Conclusion

This paper aims at contributing to the existing climate finance literature by studying for the first time the relationship between ENSO-induced natural disasters and banking stability in a sample of Latin American countries. To this end, we use a large panel of 1208 banks observed at annual frequency over the period 2005-2019 for 16 Latin American countries. Based on panel fixed-effects estimates, we use strong *El Niño Southern Oscillation* (ENSO) events as a natural experiment for climate shocks related to climate change, as they produce quasi-periodic climate oscillations that can lead to unpredictable natural disasters. We consider several indicators to assess the stability (z-score), the performances (ROE and ROA) and the exposure to credit risk (non-performing loans) and liquidity risk (bank deposits to total assets) of Latin American banks in response to ENSO events. To account for the heterogeneous effect of these climate shocks depending on banks' characteristics, we carry out further subsample estimates based on three key features of banks included in our sample: their size (total assets), capitalization (total equity to total assets) and business model (non-interest income to total income).

Our results show that, when considering Latin American countries, weather shocks associated with strong ENSO events can have adverse financial consequences that lead to a decline in banking stability. We also reveal that strong *El Niño* and *La Niña* shocks have asymmetrical effects on banking stability. Strong *El Niño* shocks are associated with lower banks' stability, resulting from decreased performances associated with increased credit and liquidity risks. In contrast, strong *La Niña* shocks appear to have economic benefits, with no significant impact banking stability, but higher banks' performances and lower credit risk. Finally, further estimates identify some key characteristics of "climate-resilient banks". Banks with a larger size, a higher capital ratio, and less market-oriented activities are more resilient to adverse climate shocks resulting from ENSO events.

These findings underscore the critical need to understand the intricate relationship between climate-induced natural disasters and banking stability, especially in emerging regions like Latin America that are disproportionately vulnerable to such events. Moreover, as climate change should intensify the frequency and magnitude of ENSO's cyclical pattern, these findings can help estimate the potential adverse effects of climate change-induced physical risks on banking stability and inform future mitigation and adaptation policies. This issue is even more critical as banks are a key source of external financing for post-natural disaster reconstruction, economic recovery, and the implementation of measures aiming at dealing with the consequences of physical risks associated with climate change.

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How climate physical risks affect banking stability? The Latin American experience with strong ENSO events

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SUPPLEMENTARY MATERIAL

Appendix 1. Classification of ENSO events

Table A1. Classification of ENSO events

Enso	Type	Intensity	Start date	End date	Monthly Peak	Yearly Peak
La Niña	CP	Weak	11/2005	03/2006	12/2005	2005
El Niño	EP	Weak	09/2006	01/2007	12/2006	2006
La Niña	CP	Strong	07/2007	06/2008	01/2008	2008
La Niña	CP	Weak	11/2008	03/2009	01/2009	2009
El Niño	CP	Moderate	07/2009	03/2010	12/2009	2009
La Niña	CP	Strong	07/2010	03/2011	11/2010	2010
La Niña	CP	Moderate	07/2011	03/2012	11/2011	2011
El Niño	Mix	Weak	11/2014	02/2015	12/2014	2014
El Niño	Mix	Strong	03/2015	04/2016	12/2015	2015
La Niña	CP	Weak	08/2016	12/2016	10/2016	2016
La Niña	EP	Weak	10/2017	04/2018	12/2017	2017
El Niño	CP	Weak	10/2018	06/2019	11/2018	2018

Note: This table presents the different types of *El Niño* and *La Niña* events over the studied period according to their intensity (weak, moderate or strong) and according to whether the maximum warming in the tropical Pacific SST is located in the Eastern Pacific (EP) or the Central Pacific (CP). This classification is consistent with the ENSO literature (Agus Santoso *et al.*, 2017; Cai *et al.*, 2020; Timmermann *et al.*, 2018).

Appendix 2. Latin American natural disasters associated with the strong ENSO events over the period 2005-2019

Table A2.1. Latin American natural disasters associated with the strong *El Niño* event from 2015-2016

Location	Disaster type	Date	Notable event	Estimated Damage	Additional information
North of America					
Mexico					
Central region	Climatological	Summer of 2015	Drought		The reduced summer rainfall in Mexico's central highlands, attributed to El Niño, resulted in decreased crop yields.
Pacific coast	Meteorological	Oct 2015	Hurricane Patricia	940	Hurricane Patricia holds the distinction of being the most powerful hurricane ever recorded in the eastern North Pacific basin. It formed on October 20th and rapidly intensified to a Category 5 hurricane on the Saffir-Simpson scale. The estimated number of individuals affected by Hurricane Patricia is approximately 15 000.
Central America					
Pacific Slope of Central America	Hydrological	Up to 6 Oct 2015	Extreme below average rains	NA	Affected countries: Azuero Peninsula, Panama; Guanacaste, Costa Rica; Pacific slopes of Nicaragua, El Salvador, Honduras, and Guatemala. Approximately 3.5 million individuals impacted, with over 2 million requiring assistance in food, medical, and sanitation.
Panama					
The Pacific slope	Climatological	Sep 2015	Drought	Millions	The drought associated with El Niño has resulted in crop damage and the loss of 2500 cattle.
The Atlantic slope	Meteorological	2015	Extreme temperature	NA	NA
Costa Rica:					
The Atlantic slope	Hydrological	Oct-Nov 2015	Floods	173	The Central Valley, Sarapiqui, and Turrialba cantons, as well as the province of Limon, have experienced floods and landslides triggered by heavy rainfall. These events have resulted in five fatalities and economic losses amounting to USD 173 million.
The Pacific slope	Climatological	2015	Drought	NA	Dry and low-level moisture conditions made worse by El Niño has led to drought.
Guatemala					
	Hydrological	Aug Oct 2015	Riverine flood and Landslide	6	Province: Livingston, El Estor (Izabel department), Livingston, El Estor (Izabel department) and El Cambray village (Santa Catarina Pinula district, Guatemala province) for Landslide
Caribbean					
Caribbean Island	Meteorological	August 27-29 2015	Tropical storm Erika	550	
Dominican Republic					
	Hydrological	Sep 22 2015	Riverine flood	NA	Santiago district (Santiago province), Total Deaths 250
	Meteorological	Aug 28 2015	Hurricane Erika	NA	Total Deaths 250
South of America					
Argentina					
	Hydrological	Aug 2015	Riverine flood	NA	
	Hydrological	Dec 2015 to jan 2016	Riverine flood	NA	
Brazil					
Northeast	Climatological	2015	Drought and heat wave	2	The drought, exacerbated by El Niño, resulted in heightened wildfire activity, crop damage, and a scarcity of potable water resources.
Southeastern and West central	Meteorological	Oct 2015	Heat wave	NA	A deviation of approximately 4°C–5°C from the normal temperatures has been observed.
Southern	Hydrological	2015	Floods and riverine floods	200	Significant floods were caused by the overflow of the main rivers due to abundant rainfall over Southern Brazil and most of the La Plata basin.
Chile:					
Central region	Meteorological	June to August 2015	Extreme temperature	NA	In Chile, positive anomalies ranging from +1°C to +1.5°C were recorded for maximum temperatures.
	Climatological	June 2015	Drought	NA	Santiago, the capital of Chile, experienced its most arid conditions.
Colombia:					
Country (Global)	Climatological	2014/2015	Drought and Wildfire	608	The estimated total government expenditure amounts to USD 608 million.
Caribbean coast (Cesar)	Meteorological	Sep to Dec 2015	Extreme temperature	NA	On the Caribbean coast, maximum temperatures registered positive anomalies of +5°C.
Central and Northern regions	Climatological	Sep 2015	Drought and Wildfire	170	The severe drought, attributed to El Niño, has resulted in water supply restrictions for consumption, agriculture, and hydro-power generation. The El Niño phenomenon has also contributed to widespread forest fires, which have ravaged approximately 68,000 hectares of forest and impacted 12 out of the country's 32 provinces.
Peru:					
Pacific Coast	Meteorological	July to November	Extreme temperature	NA	El Niño-related elevated temperatures (ranging from +1°C to +4°C) have been systematically observed in the coastal zone, surpassing, in certain cases, the record-high temperatures recorded in 1998. The intensified El Niño event resulted in reduced productivity of coastal ecosystems, impacting fisheries and marine aquaculture. Notable changes were observed in the migration patterns of demersal species (Bacheler et al., 2019) and fishing practices (Radway, Manley, and Mangubhai, 2016).
Ecuador					
	Hydrological	Jan 2015	Riverine and flash flood	12	Total Deaths 9
Paraguay					
	Hydrological	Nov 2015 to Jan 2016	flood	NA	Total Deaths 12
Uruguay					
	Hydrological	Nov to Dec 2015	Riverine flood	NA	NA

Note: compiled by authors with data from IMF's "State of the climate" reports from 2007 to 2019, OECD and the World Bank reports, Aon Benfield's "Annual Global Climate and Catastrophe" reports from 2010 to 2017, EM-DAT database and national government reports. Natural Disasters classification follows the EM-DATA guidelines. The EM-DAT was created by the Center for Research on the Epidemiology of Disasters (CRED). Total affected corresponds to the sum of injured, affected and homeless.

Table A2.2. Latin American natural disasters associated with the strong *La Niña* events from 2007-2008 and 2010-2011

Location	Disaster type	Date	Notable event	Estimated Damage	Additional information
North of America					
Mexico					
Southern	Hydrological	2010	Flood and landslide	250	The intensified rainfall due to La Niña resulted in numerous floods and landslides across multiple states in Mexico. For instance, significant damage occurred, with at least 150,000 homes being destroyed or damaged in the states of Tabasco, Veracruz, Chiapas, and Oaxaca, resulting in over 600,000 people being displaced from their homes.
	Meteorological	Aug to Sep 2007	Hurricane Karl, Dean and Henriette	3 900	The impact of Hurricane Karl (Category 3) was observed in 114 cities in the state of Veracruz, with strong winds and heavy rainfall. Similar events include Hurricanes Dean (13–23 August 2007) and Lorenzo (25–28 September 2007), which formed in the Atlantic Ocean, and Hurricane Henriette (30 August–6 September 2007), which formed in the Pacific Ocean.
	Meteorological	Sep 2010	Tropical Storm Matthew	167	NA
Central America:					
Costa Rica					
The Atlantic slope	Meteorological	Sep 2010	Tropical Storm Nicole	13	Tropical Storm Nicole has resulted in significant damage to electric and transportation infrastructures, housing, and agriculture.
The Atlantic slope	Meteorological	Nov 2010	Hurricane Tomas	330	Hurricane Tomas impacted Costa Rica, bringing about strong winds and heavy rainfall, which led to numerous landslides, power outages, road closures, and unfortunately resulted in 28 fatalities.
Guatemala					
	Meteorological	Sep 4 2007	Storm Felix	NA	Puerto Barrios, Morales districts (Izabal province).
	Hydrological	Sep Oct 2007	Riverine flood	NA	Guatemala district (Guatemala province) Total Deaths 11
	Meteorological	Sep 25 2010	Tropical storm Matthew	NA	Peten, Isabel, Suchitepequez, Huehuetenango, El Progreso provinces
	Hydrological	Sep 4 2007	Riverine flood and Landslide	671	Chimaltenango, Quezaltenango, Escuintla, Retalhuleu, Suchitepequez, Solola, Totonicapan Total Deaths provinces 53
Caribbean					
Dominican Republic					
	Meteorological	Oct 28 to Dec 2007	Storm Noel, Olga and Dean	110	Noel 110, Olga 64, Dean 56
	Hydrological	Jun 2007	Riverine flood	NA	Azua, Barahona, Distrito Nacional, La Altagracia, La Romana, Pedernales, Peravia, San Cristobal, San Pedro de Macoris, Santiago, Santo Domingo provinces
	Meteorological	Oct 29 2010	Hurricane Tomas	NA	Azua, Baoruco, Barahona, Dajabon, Distrito Nacional, Duarte, El Seibo, Elias Pina, Espaillat, Hato Mayor, Independencia, La Altagracia, La Romana, La Vega, Maria Trinidad Sanches, Monsenor Nouel, Monte Cristi, Monte Plata, Pedernales, Peravia, Puerto Plata, Salcedo, Samana, San Cristobal, San José de Ocoa, San Juan, San Pedro de Macoris, Sanchez Ramirez, Santiago, Santiago Rodriguez, Santo Domingo, Valverde provinces
	Hydrological	Jul 2010	Riverine flood	NA	Azua, Baoruco, Barahona, Dajabon, Distrito Nacional, Duarte, El Seibo, Elias Pina, Espaillat, Hato Mayor, Independencia, La Altagracia, La Romana, La Vega, Maria Trinidad Sanches, Monsenor Nouel, Monte Cristi, Monte Plata, Pedernales, Peravia, Puerto Plata, Salcedo, Samana, San Cristobal, San José de Ocoa, San Juan, San Pedro de Macoris, Sanchez Ramirez, Santiago, Santiago Rodriguez, Santo Domingo, Valverde provinces
Jamaica					
	Meteorological	Oct 28 to Dec 2007	Storm Noel and Dean	423	Dean 423 Clarendon, Saint Thomas, Saint James, Saint Andrew And Kingston provinces
	Meteorological	Sept 29 2010	Storm Nicole	201	Clarendon, Hanover, Manchester, Portland, Saint Andrew And Kingston, Saint Ann, Saint Catherine, Saint Elizabeth, Saint James, Saint Mary, Saint Thomas, Trelawny, Westmoreland provinces

Note: compiled by authors with data from IMF's "State of the climate" reports from 2007 to 2019, OECD and the World Bank reports, Aon Benfield's "Annual Global Climate and Catastrophe" reports from 2010 to 2017, EM-DAT database and national government reports. Natural Disasters classification follows the EM-DATA guidelines. The EM-DAT was created by the Center for Research on the Epidemiology of Disasters (CRED). Total affected corresponds to the sum of injured, affected and homeless.

Table A2.2. Latin American natural disasters associated with the strong *La Niña* events from 2007-2008 and 2010-2011 (continued)

Location	Disaster type	Date	Notable event	Estimated Damage	Additional information
South of America					
Argentina					
	Hydrological	Jan to Mar 2008	Riverine flood	NA	Salta city (Capital district, Salta province), General San Martin, Oran, Rivadavia districts (Salta province)
	Meteorological	Jul 2010	Cold wave	NA	Buenos Aires, Buenos Aires D.f., Catamarca, Chaco, Chubut, Cordoba, Corrientes, Entre Rios, Formosa, Jujuy, La Pampa, La Rioja, Mendoza, Misiones, Neuquen, Rio Negro, Salta, San Juan, San Luis, Santa Cruz, Santa Fe, Santiago Del Estero, Tierra Del Fuego, Tucuman provinces Total Deaths 42
Brazil					
Northeast	Hydrological	June 2010	Flood and mudslides	860	The heavy rains, intensified by the influence of La Niña, have led to widespread flooding and mudslides. These events have resulted in the destruction and damage of at least 115,000 homes and a loss of 72 lives.
Amazon	Climatological	2010	Drought	NA	The onset of the drought occurred during the El Niño event in 2009 and subsequently intensified during La Niña. In the Amazon region, these prolonged dry spells have had adverse effects on water availability, transportation infrastructure, and fishing activities, primarily caused by exceptionally low river levels.
Southeastern and West central	Hydrological	April 2010	Flood and mudslides	14 200	A total of 25 000 local homes have been destroyed, and 256 people have been killed or injured as a result of floods and mudslides associated with La Niña.
Southern	Meteorological	April to Sep 2010	Cold wave and drought	NA	The combination of reduced precipitation and lower temperatures, exacerbated by the presence of La Niña, has resulted in drought conditions and significant damage to agricultural and livestock sectors. These circumstances have further aggravated water scarcity issues for summer crops such as soybean, maize, and rice, as well as pastureland.
Chile:					
Andes	Meteorological	July and August	Cold wave	NA	The severe drought associated with La Niña has resulted in the death of thousands of livestock. The Chilean government has declared an agricultural emergency in response.
	Climatological	second half of 2010	Drought	NA	The sectors most affected include agriculture, livestock, timber industries, energy, and industrial sectors.
Southern region	Meteorological	July 2010	White earthquake	NA	On July 10th, an unprecedented drop in temperatures and a significant white earthquake prompted the Chilean government to declare an agricultural emergency. The accumulation of over one meter of snow resulted in severe damage to crops and livestock. This weather event, known as a "white earthquake," had not been witnessed since 1995 prior to 2010.
Colombia:					
Country (Global)	Hydrological	2010/2011	Floods and landslides	6300	The floods triggered by the La Niña event of 2010/2011 resulted in an approximate cumulative damage cost of USD 6.3 billion. The total government expenditure, encompassing both immediate response and recovery efforts, was estimated at USD 1.5 billion.
Central region	Hydrological	Nov to Dec 2010	Flood	+ 300	The flash floods and landslides associated with La Niña have submerged 250,000 homes and a significant portion of Colombia's agricultural regions. The event resulted in a minimum of 176 fatalities and left 225 individuals injured.
Northwest	Hydrological	Sep 2010	Floods and landslides	+ 400	The landslides and floods, exacerbated by La Niña, have resulted in extensive damage. According to government authorities, over 552 municipalities in 28 out of the country's 32 departments have been affected, and more than 201 700 homes have been destroyed.
Peru:					
Country (Global)	Climatological	Jul to Sep 2010	Drought	NA	Precipitation levels experienced a notable decline, with observed deficits reaching up to 100%.
Low-lying Amazon rainforest	Hydrological	Nov 2010	Flood	230	The torrential rains associated with La Niña resulted in substantial landslides, resulting in the loss of life of a minimum of two individuals and causing injuries to 100 others.
Peruvian Altiplano	Meteorological	July 2010	Cold wave	NA	The Peruvian Altiplano, densely populated by impoverished farmers, experienced record-low temperatures of -20 degrees. Government reports indicate that at least 409 individuals lost their lives as a result of hypothermia, pneumonia, and carbon monoxide poisoning.
Ecuador					
	Hydrological	Jan 2008	Riverine flood	1 359	Azuay, Bolivar, Canar, Carchi, Chimborazo, Cotopaxi, El Oro, Esmeraldas, Imbabura, Loja, Pichincha, Santa Elena (Adm1). Alfredo Baquerizo Moreno, Baba, Babahoyo, Chone, Daule, Montalvo, Salitre, Samborondon, San Jacinto de Yaguachi, Santa Lucia, Tosagua, Urdaneta, Vinces (Adm2). Total Deaths 41
	Hydrological	Fev 2011	Riverine flood	NA	Vinces district (Los Rios province), Bolivar, Carchi, Chimborazo, Cotopaxi, El Oro, Guayas, Imabura, Manabi, Zamora Chinchipe provinces
Paraguay					
	Climatological	Sep 2007	Wildfire	NA	Tradition of burning crop fields, drought and lack of rain
	Meteorological	Jul 2010	Cold wave	NA	Alto Paraguay, Alto Parana, Amambay, Boqueron, Caaguazu, Caazapa, Canindeyu, Central, Concepcion, Cordillera, Guaira, Itapua, Misiones, Neembucu, Paraguari, Presidente Hayes, San Pedro provinces
Uruguay					
	Meteorological	Jul 2007 and Jul 2010	Cold wave	NA	Artigas, Canelones, Cerro Largo, Colonia, Durazno, Flores, Florida, Lavalleja, Maldonado, Montevideo, Paysandu, Rio Negro, Rivera, Rocha, Salto, San Jose, Soriano, Tacuarembo, Treinta Y Tres provinces

Note: compiled by authors with data from IMF's "State of the climate" reports from 2007 to 2019, OECD and the World Bank reports, Aon Benfield's "Annual Global Climate and Catastrophe" reports from 2010 to 2017, EM-DAT database and national government reports. Natural Disasters classification follows the EM-DATA guidelines. The EM-DAT was created by the Center for Research on the Epidemiology of Disasters (CRED). Total affected corresponds to the sum of injured, affected and homeless.

Appendix 3. Data description, sources and descriptive statistics

Table A3.1. Data description and sources

Variable	Description	Source	BankFocus
Climate indice			
ONI	Monthly Oceanic Niño Index (ONI)	National Oceanic and Atmospheric Administration (NOAA)	
Dependent variables			
Stability			
Z-score	Z-score computed as the sum of aggregate profits the return of total assets and aggregate capital ratio divided by the volatility of aggregate profits before tax, multiplied by 100.	BankFocus, own calculation	63300, 52600, 73400, 63300
Performances			
ROE	The ratio of profit(loss) before tax to total equity multiplied by 100.	BankFocus	73400, 63300
ROA	The ratio of profit(loss) before tax to total assets multiplied by 100.	BankFocus	73400, 52600
Credit risk			
Non-performing loans	The ratio of non-performing loans to gross customer loans multiplied by 100.	BankFocus	99280
Liquidity risk			
Total Deposits to total assets	The ratio of total customer and Bank deposits to total assets multiplied by 100.	BankFocus	60300, 60400, 52600
Customer Deposits to total assets	The ratio of total customer deposits to total assets multiplied by 100.	BankFocus	60300, 52600
Bank Deposits to total assets	The ratio of total bank deposits to total assets multiplied by 100.	BankFocus	60400, 52600
Bank-specific controls			
Size	The nature logarithm of total assets (in billions of US dollars).	BankFocus	52600
Growth rate of assets	The growth rate of total bank assets multiplied by 100.	BankFocus	52600
Capital ratio	The ratio of total equity to total assets multiplied by 100.	BankFocus	63300, 52600
Cost to income	The ratio of total operating expenses to total operating revenues multiplied by 100.Total operating expenses is the sum of Staff expenses and other administrative and operating expenses.	BankFocus	72100, 72800
Net interest margin	The net interest income as a pourcentage of interest earning assets multiplied by 100.	BankFocus	99530
Loans to total assets	The ratio of total gross loans and advances to customers to total assets multiplied by 100.	BankFocus	51500, 52600
Noninterest income	The noninterest income to total assets ratio, expressed as a percentage, is calculated by multiplying by 100. Total noninterest income is the sum of the net fee commission income and the total net trading income and the fair value.	BankFocus	71300, 71700, 52600

Variable	Description	Source	BankFocus
Bank Failures	Binary variable, taking the value 1 for banks considered "non-active" according to the "BankFocus" database, and 0 otherwise.	BankFocus	own calculation
Bank Mergers and Acquisitions	Binary variable, taking the value of 1 for the year in which a financial institution potentially undergoes or engages in a merger and acquisition, and 0 otherwise. The selection is based on historical data obtained from BankFocus for each bank, and with a threshold of a 15% or higher variation rate in total assets.	BankFocus	own calculation
Consolidation codes			
C1	Binary variable, taking the value of 1 for statement of a mother company integrating the statements of its controlled subsidiaries or branches with no unconsolidated companion, and 0 otherwise.	BankFocus	own calculation
C2	Binary variable, taking the value of 1 for statement of a mother company integrating the statements of its controlled subsidiaries or branches with an unconsolidated companion, and 0 otherwise.	BankFocus	own calculation
U1	Binary variable, taking the value of 1 for statement not integrating the statements of the possible controlled subsidiaries or branches of the concerned company with no consolidated companion, and 0 otherwise.	BankFocus	own calculation
U2	Binary variable, taking the value of 1 for statement not integrating the statements of the possible controlled subsidiaries or branches of the concerned company with an consolidated companion, and 0 otherwise.	BankFocus	own calculation
U*	Binary variable, taking the value of 1 for additional unconsolidated statement, and 0 otherwise.	BankFocus	own calculation
Country-specific macro-financial controls			
Banks' total assets to GDP	The ratio of total assets held by deposit money banks as a share of GDP, expressed in percentages.	World Bank, GFDD	GFDD.DI.02
Credits to deposits	The ratio of credit provided to the private sector by domestic deposits money banks as a share of total deposits, expressed in percentages.	World Bank, GFDD	GFDD.SI.04
Concentration Bank	The ratio of assets held by the five largest banks as a share of total commercial banking assets by country, expressed in percentages.	World Bank, GFDD	GFDD.OI.06
Real bank lending rate	The difference between the average annual bank lending rate and the inflation rate, expressed in percentages.	Latin Macro Watch	
Private credit	The ratio of private credit by deposit money banks and other financial institutions to GDP, expressed in percentages.	World Bank, GFDD	GFDD.DI.12
Growth private credit	Growth rate of private credit by deposit money banks and other financial institutions to GDP, expressed in percentages.	World Bank, GFDD	GFDD.DI.12
Subprimes crisis	Binary variables, taking the value of 1 for the year t of occurrence of a Subprimes crisis (between 2007 and 2009), and 0 otherwise.		own calculation
VIX	The annual $S\&P$ 500 Volatility Index (VIX), daily average.	CBOE	
FED funds rate	The nominal of effective Federal funds rate, expressed in percentages.	CBOE	

Variable	Description	Source	Code Source
Country-specific macroeconomics controls			
Real GDP	Annual real GDP in a constant 2015-US dollar.	World Bank, WDI	
Real GDP growth	Growth rate of Annual real GDP in a constant 2015 dollar US , expressed in percentages.	World Bank, WDI	
Real GDP per capita	annual real GDP per Capita in US dollar at constant 2015 prices.	World Bank, WDI	
Inflation	Annual growth rate of the CPI index (base 2015) multiplied by 100, expressed in percentages.	World Bank, WDI	
Growth nominal exchange rate	Growth rate of annual exchange rate multiplied by 100, from the currency unit to US dollars, end of period, expressed in percentages.	Latin Macro Watch	
Growth of current account balance	Growth rate of annual current account balanced multiplied by 100, net (Excluding Exceptional Financing).	IMF IFS	
Growth of terms of trade	Growth rate of annual Net Barter Terms of Trade Index (base 2015) multiplied by 100.	World Bank, WDI	
Sovereign debt crisis	Binary variables, taking the value of 1 for the year t of occurrence of a sovereign debt crisis in country i, and 0 otherwise.	Laeven, L. and Valencia, F. (2020)	
Currency crisis	Binary variables, taking the value of 1 for the year t of occurrence of a currency crisis in country i, and 0 otherwise.	Laeven, L. and Valencia, F. (2020)	

Note: to address potential outlier values, a logarithmic transformation was applied to all dependent and control variables. For variables expressed as a growth rate, we applied the following transformation: $\bar{x}=\text{sign}(x)\cdot\log(1+|x|)$. The use of $\bar{x}$ mitigates potential extreme values of x, while preserving its negative values and thus the size of our sample.

Table A3.2. Descriptive statistics

	Obs	Mean	Min	25%	Median	75%	Max	Std. dev.	Skewness	Kurtosis
Dependent variables										
Z-score	8 290	2.99	0.37	2.65	2.95	3.27	4.60	0.52	0.31	3.82
ROE	8 290	2.26	-5.89	2.14	2.69	3.03	5.46	1.48	-2.60	9.96
ROA	8 290	1.04	-4.01	0.74	1.17	1.52	3.33	0.80	-1.74	7.95
Non-performing loans	8 290	1.87	0.01	1.30	1.87	2.42	4.55	0.77	0.06	2.64
Total Deposits to total assets	8 290	4.06	0.10	3.92	4.23	4.38	4.58	0.51	-2.63	13.13
Customers deposits to total assets	8 290	3.97	0	0	4.16	4.33	4.58	0.59	-2.87	14.86
Banks deposits to total assets	8 290	0.795	0	0	0	1.59	4.45	1.13	1.16	3.03
Bank-specific controls										
Size	8 290	0.59	0.00	0.01	0.07	0.60	6.32	1.07	2.38	8.66
Growth rate of assets	7 082	1.17	-4.35	-1.45	2.22	3.08	7.62	2.49	-0.64	1.93
Capital ratio	8 290	2.88	1.15	2.54	2.83	3.14	4.57	0.52	0.63	3.70
Cost to income	8 290	4.14	2.21	3.99	4.17	4.32	5.30	0.28	-0.77	6.25
Net interest margin	8 290	2.48	-4.27	2.09	2.50	2.93	4.94	0.69	-1.00	8.36
Loans to total assets	8 290	4.03	0.12	3.88	4.13	4.28	4.60	0.38	-2.22	12.22
Non-interest income	8 290	2.26	-5.27	1.68	2.71	3.14	5.35	1.35	-1.46	5.61
Country-specific macro-financial controls										
Banks' total assets to GDP	8 290	4.24	2.53	3.74	4.60	4.68	4.75	0.54	-0.69	1.95
Credits to deposits	8 290	4.61	3.90	4.48	4.52	4.76	5.42	0.25	1.01	4.52
Concentration Bank	8 290	4.35	3.92	4.31	4.40	4.41	4.61	0.12	-1.24	5.18
Real bank lending rate	8 290	2.71	-2.84	2.12	3.30	3.63	3.88	1.25	-1.81	6.76
Private credit	8 290	4.00	2.37	3.54	4.26	4.36	4.82	0.50	-0.92	2.74
Growth private credit	8 290	0.94	-3.31	-0.88	1.19	2.06	3.64	1.50	-0.59	2.12
VIX	8 290	2.73	2.41	2.65	2.76	2.81	3.49	0.20	1.02	6.38
FED funds rate	8 290	0.57	0.07	0.15	0.43	0.94	1.83	0.44	0.58	2.30
Country-specific macroeconomics controls										
Real GDP	8 290	27.35	23.34	26.41	28.19	28.22	28.26	1.32	-1.26	3.06
Real GDP growth	8 290	0.52	-2.14	0.15	0.84	1.25	2.65	1.15	-0.77	2.39
Real GDP per capita	8 290	9.07	7.70	9.04	9.06	9.19	9.84	0.26	-0.82	5.97
Inflation	8 290	1.74	-0.34	1.49	1.57	2.00	4.00	0.56	0.331	6.13
Growth nominal exchange rate	8 290	1.11	-3.28	-0.20	1.61	2.89	4.64	2.12	-0.57	2.14
Growth of current account balance	8 290	-0.16	-8.33	-3.78	-2.75	3.26	8.67	3.82	0.21	1.37
Growth of terms of trade	8 290	-0.20	-3.26	-1.47	-0.31	1.21	3.43	1.65	0.09	1.73

Note: to address potential outlier values, a logarithmic transformation was applied to all dependent and control variables. For variables expressed as a growth rate, we applied the following transformation: $\bar{x}=\mathrm{sign}(x)\cdot\log(1+|x|)$. The use of $\bar{x}$ mitigates potential extreme values of x, while preserving its negative values and thus the size of our sample.

Table A3.3. Distribution of banks by country from 2005 to 2019

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	(Percent)
Argentina	4	6	7	7	10	10	13	13	30	30	30	31	30	30	26	277	(3.34%)
Bolivia	0	2	2	2	2	2	2	2	6	6	6	6	6	5	5	54	0.65%
Brazil	4	7	7	7	12	12	23	25	35	783	783	784	753	715	678	4628	(55.83%)
Chile	1	1	3	3	13	13	13	14	15	16	16	15	15	14	13	165	(2.00%)
Colombia	2	5	6	6	17	17	20	20	21	22	20	20	20	19	19	234	(2.82%)
Costa Rica	1	2	2	2	5	5	28	29	31	32	32	33	32	30	30	294	(3.55%)
Dominican Republic	0	3	3	3	4	4	4	4	26	26	26	26	26	24	24	203	(2.45%)
Ecuador	0	0	0	0	1	1	3	4	35	38	38	38	38	38	37	271	(3.27%)
Guatemala	0	0	0	0	3	3	3	3	8	8	8	8	8	7	7	66	(0.80%)
Jamaica	1	1	2	2	2	2	2	2	3	4	4	4	4	4	4	41	(0.49%)
Mexico	11	16	16	16	21	21	23	26	131	156	156	156	158	154	154	1215	(14.66%)
Panama	0	2	2	2	7	7	7	7	14	16	16	16	16	16	16	144	(1.74%)
Paraguay	0	1	1	1	1	1	1	1	12	12	12	12	12	12	12	91	(1.10%)
Peru	28	29	29	29	33	33	34	34	34	32	31	31	29	29	29	464	(5.60%)
Trinidad and Tobago	2	2	2	2	2	2	2	3	4	5	5	5	4	4	4	48	(0.58%)
Uruguay	0	4	4	4	5	5	5	6	10	10	10	10	8	7	7	95	(1.15%)
Total	54	81	86	86	138	138	183	193	415	1196	1193	1195	1159	1108	1065	8290	(100%)
(Percent)	(0.65%)	(0.98%)	(1.04%)	(1.04%)	(1.66%)	(1.66%)	(2.21%)	(2.33%)	(5.01%)	(14.43%)	(14.39%)	(14.41%)	(13.98%)	(13.37%)	(12.85%)	(100%)	

Table A3.4. Distribution of banks by business model from 2005 to 2019

Business model	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total	(Percent)
Bank holding company	6	8	9	9	16	16	18	19	22	23	23	24	22	21	20	256	(3.06%)
Commercial bank	29	53	57	57	99	99	128	136	223	265	264	263	260	247	242	2422	(29.22%)
Cooperative bank	2	3	3	3	6	6	19	20	63	785	784	786	755	720	683	4638	(56.00%)
Savings bank	17	17	17	17	17	17	18	18	107	123	122	122	122	120	120	974	(11.75%)
Total	54	81	86	86	138	138	183	193	415	1196	1193	1195	1159	1108	1065	8290	(100%)
(Percent)	(0.65%)	(0.98%)	(1.04%)	(1.04%)	(1.66%)	(1.66%)	(2.21%)	(2.33%)	(5.01%)	(14.43%)	(14.39%)	(14.41%)	(13.98%)	(13.37%)	(12.85%)	(100%)	

Table A3.5. Cross-sectional dependence test

	Stability	Performances		Credit risk	Liquidity risk		
	Zscore	ROE	ROA	NPL	Total Deposits to total assets	Customer Deposits to total assets	Bank Deposits to total assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Statistic	24.94	175.44	35.12	72.10	202.28	196.74	333.39
P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Appendix 4. Robustness

Alternative classification of ENSO events

Table A4.1. Banking stability and moderate ENSO events

	Stability	Performances		Credit risk	Liquidity risk		
	Zscore	ROE	ROA	NPL	Total Deposits to total assets	Customer Deposits to total assets	Bank Deposits to total assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Moderate El Niño	0.005	-0.002	0.017	**0.075***	0.014	0.018	-0.008
	(0.022)	(0.110)	(0.046)	(0.041)	(0.015)	(0.019)	(0.064)
Moderate El Niño (t-1)	-0.009	0.115	0.044	**-0.068***	**0.031****	**0.047*****	-0.091
	(0.024)	(0.086)	(0.039)	(0.039)	(0.014)	(0.017)	(0.058)
Moderate La Niña	-0.004	0.069	0.034	0.008	0.016	-0.003	0.014
	(0.020)	(0.087)	(0.037)	(0.042)	(0.017)	(0.024)	(0.049)
Moderate La Niña (t-1)	-0.000	0.045	0.023	-0.017	0.001	-0.021	-0.002
	(0.018)	(0.083)	(0.035)	(0.041)	(0.013)	(0.019)	(0.048)
N	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.86	0.43	0.48	0.67	0.87	0.89	0.71
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Accounting for additional control variables: bank-specific controls

Table A4.2.a Adding bank-specific controls: z-score

	Stability (Zscore)																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Strong El Niño	0.000	-0.000	-0.008***	0.004	-0.003	-0.001	0.005	0.004	0.003	-0.012**	-0.005	-0.000	0.004	0.004	-0.002	0.004	-0.002	-0.003
	(0.006)	(0.008)	(0.002)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)
Strong El Niño (t-1)	-0.015***	0.010	-0.009***	-0.017***	-0.024***	-0.011*	-0.014**	-0.015***	-0.016***	-0.022***	-0.012**	-0.025***	-0.015***	-0.016***	-0.018***	-0.016***	-0.018***	-0.018***
	(0.005)	(0.006)	(0.002)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.002)
Strong La Niña	-0.059***	-0.004	0.017***	-0.027	-0.021	-0.012	-0.018	-0.018	-0.018	-0.029	-0.036*	-0.021	-0.019	-0.016	-0.025	-0.018	-0.027	-0.004
	(0.020)	(0.021)	(0.006)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.006)
Strong La Niña (t-1)	-0.035*	-0.000	0.007	-0.006	-0.006	0.003	-0.003	-0.003	-0.003	-0.019	-0.009	-0.009	-0.004	-0.002	-0.011	-0.004	-0.013	-0.001
	(0.019)	(0.020)	(0.006)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.005)
Bank-specific controls																		
Size	-0.206***																	-0.055***
	(0.043)																	(0.010)
Growth rate of assets		-0.007***																0.004***
		(0.002)																(0.000)
Capital ratio			1.102***															1.073***
			(0.014)															(0.012)
Cost to income				-0.370***														-0.165***
				(0.030)														(0.011)
Net interest margin					0.097***													0.007*
					(0.015)													(0.004)
Loans to total assets						0.200***												0.016**
						(0.030)												(0.007)
Noninterest income							0.007											
							(0.005)											
Bank Failures (t-1)								-0.141										
								(0.260)										
Bank Failures (t-2)									-0.131**									-0.008
									(0.061)									(0.011)
Bank Mergers and Acquisitions										0.043***								0.006***
										(0.006)								(0.002)
Bank Mergers and Acquisitions(t-1)											0.054***							0.000
											(0.006)							(0.002)
Bank Mergers and Acquisitions(t-2)												0.051***						0.001
												(0.008)						(0.002)
C1													-0.092***					-0.031
													(0.022)					(0.021)
C2														0.035				
														(0.040)				
U1															-0.066***			-0.024
															(0.014)			(0.016)
U2																-0.111**		-0.032***
																(0.048)		(0.010)
U*																	0.067***	-0.025
																	(0.014)	(0.016)
N	8290	7082	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	7082
R-squared adj.	0.86	0.87	0.99	0.87	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.99
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.2.b Adding bank-specific controls: ROE

	Performance (ROE)																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Strong El Niño	-0.083**	0.181***	-0.097***	-0.083***	-0.099***	-0.087**	-0.081**	-0.086**	-0.087**	-0.135***	-0.095***	-0.085**	-0.084**	-0.084**	-0.100***	-0.082**	-0.099***	0.056
	(0.036)	(0.051)	(0.034)	(0.032)	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)	(0.037)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.046)
Strong El Niño (t-1)	-0.089**	-0.134***	-0.083**	-0.105***	-0.107***	-0.087**	-0.084**	-0.088**	-0.091***	-0.109***	-0.085**	-0.093**	-0.089**	-0.089**	-0.096***	-0.089**	-0.096***	-0.198***
	(0.035)	(0.034)	(0.035)	(0.032)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)
Strong La Niña	0.174**	0.125	0.199***	0.084	0.155**	0.167**	0.163**	0.161**	0.160**	0.127*	0.139*	0.162**	0.162**	0.160**	0.144*	0.162**	0.138*	0.044
	(0.079)	(0.078)	(0.074)	(0.070)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.074)	(0.075)	(0.075)	(0.075)	(0.076)	(0.075)	(0.075)	(0.076)	(0.074)
Strong La Niña (t-1)	0.038	0.083	0.040	0.003	0.022	0.033	0.028	0.027	0.027	-0.023	0.022	0.028	0.029	0.028	0.008	0.026	0.002	0.041
	(0.079)	(0.075)	(0.073)	(0.057)	(0.073)	(0.073)	(0.073)	(0.074)	(0.074)	(0.074)	(0.073)	(0.073)	(0.074)	(0.074)	(0.073)	(0.073)	(0.073)	(0.063)
Bank-specific controls																		
Size	0.053																	
	(0.126)																	
Growth rate of assets		**0.072*** **																**0.063*** **
		(0.009)																(0.009)
Capital ratio			**1.146*** **															**0.818*** **
			(0.186)															(0.164)
Cost to income				**-3.353*** **														**-3.039*** **
				(0.191)														(0.209)
Net interest margin					**0.215*** **													-0.021
					(0.060)													(0.051)
Loans to total assets						0.110												
						(0.137)												
Noninterest income							0.027											
							(0.024)											
Bank Failures (t-1)								**-2.378*** **										**-1.883*** **
								(0.755)										(0.569)
Bank Failures (t-2)									**-1.206*** **									**-0.711** **
									(0.408)									(0.319)
Bank Mergers and Acquisitions										**0.137*** **								**0.094*** **
										(0.033)								(0.033)
Bank Mergers and Acquisitions (t-1)											**0.071** **							0.027
											(0.031)							(0.036)
Bank Mergers and Acquisitions (t-2)												0.018						
												(0.038)						
C1													-0.099					
													(0.066)					
C2														-0.055				
														(0.140)				
U1															**-0.179** **			-0.047
															(0.075)			(0.144)
U2																**-0.339*** **		-0.101
																(0.118)		(0.109)
U*																	**0.179** **	-0.077
																	(0.070)	(0.118)
N	8290	7082	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	7082
R-squared adj.	0.43	0.48	0.44	0.54	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.58
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.2.c Adding bank-specific controls: ROA

	Performance (ROA)																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Strong El Niño	-0.018	0.128***	-0.026	-0.015	-0.026	-0.018	-0.014	-0.017	-0.017	-0.057***	-0.028	-0.019	-0.015	-0.015	-0.029	-0.014	-0.028	0.049**
	(0.018)	(0.026)	(0.017)	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.022)
Strong El Niño (t-1)	-0.047**	-0.050***	-0.042**	-0.057***	-0.061***	-0.044**	-0.045**	-0.046**	-0.049***	-0.063***	-0.043**	-0.057***	-0.047**	-0.047**	-0.053***	-0.047**	-0.053***	-0.105***
	(0.019)	(0.018)	(0.018)	(0.017)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Strong La Niña	0.046	0.061*	0.100***	0.024	0.063*	0.073**	0.069**	0.068**	0.067**	0.039	0.043	0.066*	0.068**	0.069**	0.053	0.068**	0.048	-0.023
	(0.035)	(0.036)	(0.031)	(0.030)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.031)
Strong La Niña (t-1)	0.006	0.050	0.033	0.009	0.018	0.027	0.023	0.023	0.022	-0.019	0.015	0.018	0.023	0.024	0.005	0.022	0.000	-0.003
	(0.033)	(0.035)	(0.029)	(0.025)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.028)
Bank-specific controls																		
Size	**-0.118****																	**-0.122****
	(0.057)																	(0.054)
Growth rate of assets		**0.034*****																**0.033*****
		(0.005)																(0.004)
Capital ratio			**0.973*****															**0.764*****
			(0.090)															(0.076)
Cost to income				**-1.911*****														**-1.716*****
				(0.099)														(0.107)
Net interest margin					**0.160*****													0.007
					(0.031)													(0.023)
Loans to total assets						**0.123***												-0.105
						(0.069)												(0.067)
Noninterest income							0.011											
							(0.012)											
Bank Failures (t-1)								**-1.281*****										**-0.888*****
								(0.485)										(0.204)
Bank Failures (t-2)									**-0.726*****									**-0.370***
									(0.250)									(0.220)
Bank Mergers and Acquisitions										**0.112*****								**0.067*****
										(0.018)								(0.017)
Bank Mergers and Acquisitions(t-1)											**0.076*****							0.023
											(0.017)							(0.017)
Bank Mergers and Acquisitions(t-2)												**0.052*****						0.017
												(0.020)						(0.021)
C1													**-0.091****					-0.086
													(0.037)					(0.065)
C2														0.004				
														(0.062)				
U1															**-0.155*****			-0.074
															(0.041)			(0.076)
U2																**-0.199*****		**-0.111***
																(0.052)		(0.057)
U*																	**0.151*****	-0.087
																	(0.038)	(0.063)
N	8290	7082	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	7082
R-squared adj.	0.48	0.53	0.52	0.60	0.49	0.48	0.48	0.48	0.48	0.49	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.66
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.2.d Adding bank-specific controls: non-performing loans

	Credit risk (NPL)																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Strong El Niño	-0.084***	-0.239***	-0.082***	-0.085***	-0.087***	-0.076***	-0.083***	-0.084***	-0.084***	-0.035***	-0.062***	-0.077***	-0.085***	-0.085***	-0.069***	-0.084***	-0.071***	-0.172***
	(0.013)	(0.018)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)	(0.019)
Strong El Niño (t-1)	0.037***	-0.006	0.036***	0.038***	0.033***	0.028**	0.039***	0.036***	0.037***	0.056***	0.029**	0.055***	0.037***	0.036***	0.044***	0.037***	0.043***	0.027*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)
Strong La Niña	-0.091**	-0.105***	-0.104***	-0.093**	-0.098***	-0.109***	-0.097**	-0.096**	-0.096**	-0.061*	-0.048	-0.090**	-0.093**	-0.092**	-0.078**	-0.097***	-0.074**	-0.060
	(0.038)	(0.039)	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)	(0.036)	(0.037)	(0.037)	(0.037)	(0.038)
Strong La Niña (t-1)	0.031	-0.074**	0.025	0.028	0.025	0.016	0.026	0.027	0.027	0.078**	0.043	0.038	0.029	0.029	0.048	0.025	0.052*	-0.031
	(0.032)	(0.031)	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)	(0.030)	(0.031)
Bank-specific controls																		
Size	0.031																	
	(0.051)																	
Growth rate of assets		-0.025***																-0.030***
		(0.003)																(0.003)
Capital ratio			-0.226***															-0.106
			(0.067)															(0.066)
Cost to income				0.155***														0.003
				(0.059)														(0.061)
Net interest margin					0.041*													0.083***
					(0.024)													(0.028)
Loans to total assets						-0.386***												-0.324***
						(0.056)												(0.060)
Noninterest income							0.009											
							(0.010)											
Bank Failures (t-1)								0.739***										0.560**
								(0.259)										(0.282)
Bank Failures (t-2)									0.306***									0.177
									(0.104)									(0.118)
Bank Mergers and Acquisitions										-0.134***								-0.098***
										(0.013)								(0.014)
Bank Mergers and Acquisitions(t-1)											-0.142***							-0.039***
											(0.014)							(0.014)
Bank Mergers and Acquisitions(t-2)												-0.097***						-0.014
												(0.016)						(0.018)
C1													0.231					
													(0.474)					
C2														0.086				
														(0.105)				
U1															0.177***			0.204
															(0.045)			(0.134)
U2																-0.171		
																(0.121)		
U*																	-0.160***	0.105
																	(0.044)	(0.125)
N	8290	7082	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	7082
R-squared adj.	0.671	0.723	0.673	0.671	0.671	0.678	0.671	0.671	0.671	0.677	0.678	0.673	0.671	0.671	0.673	0.671	0.673	0.734
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.2.e Adding bank-specific controls: deposits to total assets

	Liquidity risk (Total Deposits to total assets)																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Strong El Niño	-0.054***	-0.076***	-0.051***	-0.053***	-0.052***	-0.052***	-0.051***	-0.053***	-0.053***	-0.041***	-0.047***	-0.051***	-0.053***	-0.053***	-0.041***	-0.053***	-0.042***	-0.031***
	(0.006)	(0.009)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Strong El Niño (t-1)	-0.006	-0.029***	-0.008	-0.006	-0.006	-0.008	-0.003	-0.006	-0.007	-0.002	-0.009*	-0.001	-0.006	-0.006	-0.001	-0.007	-0.002	0.005
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Strong La Niña	0.000	0.017	0.011	0.021	0.017	0.015	0.017	0.017	0.017	0.025*	0.030**	0.019	0.013	0.014	0.031**	0.017	0.035**	0.015
	(0.014)	(0.016)	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.016)
Strong La Niña (t-1)	-0.004	0.010	0.007	0.010	0.009	0.007	0.007	0.008	0.009	0.021	0.013	0.012	0.006	0.007	0.025*	0.009	0.029**	0.014
	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)
Bank-specific controls																		
Size	-0.081***																	-0.137***
	(0.028)																	(0.032)
Growth rate of assets		-0.000																
		(0.001)																
Capital ratio			-0.183***															-0.162***
			(0.035)															(0.033)
Cost to income				0.167***														0.101***
				(0.026)														(0.027)
Net interest margin					-0.011													
					(0.010)													
Loans to total assets						-0.044												
						(0.039)												
Noninterest income							0.017***											0.015***
							(0.006)											(0.006)
Bank Failures (t-1)								-0.238										
								(0.153)										
Bank Failures (t-2)									0.053									
									(0.099)									
Bank Mergers and Acquisitions										-0.032***								-0.019***
										(0.005)								(0.005)
Bank Mergers and Acquisitions(t-1)											-0.039***							-0.021***
											(0.006)							(0.005)
Bank Mergers and Acquisitions(t-2)												-0.030***						-0.017**
												(0.007)						(0.007)
C1													-0.237					
													(0.235)					
C2														-0.050				
														(0.045)				
U1															0.134***			-0.015
															(0.015)			(0.068)
U2																0.053		
																(0.045)		
U*																	-0.133***	-0.117*
																	(0.015)	(0.067)
N	8290	7082	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	7082
R-squared adj.	0.88	0.89	0.88	0.88	0.87	0.87	0.88	0.87	0.87	0.88	0.88	0.88	0.87	0.87	0.88	0.87	0.88	0.88
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.2.f Adding bank-specific controls: customer deposits to total assets

	Liquidity risk (Customer Deposits to total assets)																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Strong El Niño	-0.036***	-0.060***	-0.033***	-0.035***	-0.036***	-0.034***	-0.032***	-0.035***	-0.035***	-0.028***	-0.031***	-0.033***	-0.034***	-0.035***	-0.033***	-0.035***	-0.032***	-0.025***
	(0.006)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Strong El Niño (t-1)	0.008	-0.008	0.006	0.008	0.006	0.007	0.011**	0.008	0.007	0.010*	0.006	0.012**	0.008	0.008	0.008	0.007	0.009	0.012**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Strong La Niña	0.001	0.024	0.014	0.022	0.019	0.019	0.020	0.020	0.020	0.024	0.028*	0.021	0.015	0.014	0.022	0.020	0.024	0.000
	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)
Strong La Niña (t-1)	-0.010	0.017	0.002	0.005	0.003	0.003	0.003	0.004	0.004	0.011	0.007	0.007	0.001	0.001	0.007	0.005	0.009	-0.008
	(0.018)	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Bank-specific controls																		
Size	-0.092***																	-0.140***
	(0.030)																	(0.034)
Growth rate of assets		-0.002																
		(0.002)																
Capital ratio			-0.195***															-0.205***
			(0.037)															(0.036)
Cost to income				0.103***														0.060**
				(0.030)														(0.031)
Net interest margin					0.022**													0.056***
					(0.011)													(0.014)
Loans to total assets						-0.035												
						(0.035)												
Noninterest income							0.018**											0.021***
							(0.007)											(0.007)
Bank Failures (t-1)								-0.190										
								(0.167)										
Bank Failures (t-2)									0.020									
									(0.097)									
Bank Mergers and Acquisitions										-0.017***								-0.012**
										(0.006)								(0.005)
Bank Mergers and Acquisitions(t-1)											-0.024***							-0.016***
											(0.007)							(0.006)
Bank Mergers and Acquisitions(t-2)												-0.023***						-0.021**
												(0.009)						(0.009)
C1													-0.327					
													(0.208)					
C2														-0.093				
														(0.066)				
U1															0.025*			-0.054
															(0.015)			(0.060)
U2																0.082		
																(0.060)		
U*																	-0.030**	-0.080
																	(0.014)	(0.057)
N	8290	7082	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	7082
R-squared adj.	0.89	0.91	0.90	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.90
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.2.g Adding bank-specific controls: bank deposits to total assets

	Liquidity risk (Bank Deposits to total assets)																	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Strong El Niño	-0.171***	-0.177***	-0.172***	-0.173***	-0.153***	-0.177***	-0.175***	-0.174***	-0.173***	-0.121***	-0.150***	-0.168***	-0.173***	-0.173***	-0.076***	-0.174***	-0.084***	-0.056**
	(0.020)	(0.027)	(0.020)	(0.020)	(0.018)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)	(0.016)	(0.020)	(0.016)	(0.024)
Strong El Niño (t-1)	-0.112***	-0.185***	-0.112***	-0.110***	-0.086***	-0.107***	-0.113***	-0.111***	-0.111***	-0.091***	-0.120***	-0.099***	-0.111***	-0.112***	-0.068***	-0.111***	-0.072***	-0.123***
	(0.017)	(0.021)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.015)	(0.017)	(0.015)	(0.021)
Strong La Niña	0.024	-0.009	-0.002	0.010	0.014	0.008	0.002	0.002	0.003	0.040	0.053	0.007	0.002	0.009	0.120**	0.003	0.153***	0.148**
	(0.052)	(0.059)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.053)	(0.054)	(0.054)	(0.055)	(0.054)	(0.059)	(0.055)	(0.056)	(0.057)
Strong La Niña (t-1)	0.003	0.018	-0.015	-0.011	-0.002	-0.009	-0.013	-0.014	-0.014	0.040	0.003	-0.006	-0.014	-0.011	0.122***	-0.012	0.154***	0.150***
	(0.042)	(0.051)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)	(0.047)	(0.043)	(0.046)	(0.051)
Bank-specific controls																		
Size	0.107																	
	(0.089)																	
Growth rate of assets		0.016***																0.018***
		(0.004)																(0.004)
Capital ratio			-0.136															
			(0.094)															
Cost to income				0.334***														0.100
				(0.072)														(0.069)
Net interest margin					-0.302***													-0.084**
					(0.055)													(0.039)
Loans to total assets						0.165**												0.328***
						(0.065)												(0.071)
Noninterest income							-0.010											
							(0.013)											
Bank Failures (t-1)								-0.459**										-0.287
								(0.226)										(0.347)
Bank Failures (t-2)									0.134									
									(0.187)									
Bank Mergers and Acquisitions										-0.140***								-0.028
										(0.019)								(0.019)
Bank Mergers and Acquisitions(t-1)											-0.148***							-0.013
											(0.020)							(0.021)
Bank Mergers and Acquisitions(t-2)												-0.063***						0.106***
												(0.023)						(0.025)
C1													-0.009					
													(0.238)					
C2														0.105				
														(0.134)				
U1															1.124***			0.376
															(0.097)			(0.306)
U2																0.136		
																(0.147)		
U*																	-1.076***	-0.644**
																	(0.091)	(0.288)
N	8290	7082	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290	7082
R-squared adj.	0.71	0.74	0.71	0.72	0.72	0.71	0.71	0.71	0.71	0.72	0.72	0.71	0.71	0.71	0.76	0.71	0.76	0.78
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Accounting for additional control variables: country-specific macro-financial controls

Table A4.3.a Adding country-specific macro-financial controls: z-score

	Stability (Zscore)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	0.004	-0.018***	0.005	0.001	0.010*	0.011*	0.004	0.009	-0.007	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Strong El Niño (t-1)	-0.014**	-0.015***	-0.014**	-0.020***	-0.012**	-0.023***	-0.015***	-0.012**	-0.021***	-0.015*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Strong La Niña	-0.059***	-0.006	-0.017	-0.015	-0.049***	-0.020	-0.027	0.003	-0.031	-0.027
	(0.018)	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.018)	(0.020)	(0.020)	(0.022)
Strong La Niña (t-1)	-0.038**	0.006	-0.002	-0.001	-0.030*	-0.003	-0.015	0.019	-0.016	-0.009
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)	(0.018)	(0.017)	(0.020)
Country-specific macro-financial controls										
Banks' total assets to GDP	-0.260***									-0.213*
	(0.040)									(0.124)
Credits to deposits		0.199***								0.261***
		(0.038)								(0.046)
Concentration Bank			-0.035							
			(0.054)							
Real bank lending rate				0.016***						0.021***
				(0.006)						(0.006)
Private credit					-0.195***					-0.087
					(0.035)					(0.111)
Growth private credit						-0.005***				-0.003
						(0.001)				(0.002)
Subprimes crisis							0.033*			0.011
							(0.019)			(0.018)
VIX								-0.036**		-0.027
								(0.015)		(0.019)
FED funds rate									-0.021**	0.012
									(0.010)	(0.013)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.3.b Adding country-specific macro-financial controls: ROE

	Performance (ROE)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.083**	-0.106***	-0.115***	-0.099***	-0.061*	-0.073*	-0.083**	-0.085**	-0.046	-0.154***
	(0.035)	(0.037)	(0.037)	(0.036)	(0.036)	(0.038)	(0.035)	(0.039)	(0.037)	(0.039)
Strong El Niño (t-1)	-0.083**	-0.089**	-0.124***	-0.114***	-0.075**	-0.102***	-0.088**	-0.090**	-0.068*	-0.137***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)	(0.036)	(0.035)	(0.037)	(0.038)	(0.035)
Strong La Niña	-0.028	0.176**	0.134*	0.178**	0.049	0.160**	0.111	0.160*	0.212**	-0.072
	(0.068)	(0.073)	(0.076)	(0.076)	(0.070)	(0.075)	(0.069)	(0.083)	(0.084)	(0.071)
Strong La Niña (t-1)	-0.134*	0.039	0.019	0.040	-0.068	0.030	-0.037	0.026	0.080	-0.176**
	(0.071)	(0.074)	(0.073)	(0.074)	(0.074)	(0.073)	(0.081)	(0.083)	(0.075)	(0.082)
Country-specific macro-financial controls										
Banks' total assets to GDP	-1.213***									-2.810***
	(0.245)									(0.670)
Credits to deposits		0.202								
		(0.193)								
Concentration Bank			0.899***							0.439
			(0.255)							(0.281)
Real bank lending rate				0.102***						0.072**
				(0.032)						(0.031)
Private credit					-0.704***					1.426**
					(0.213)					(0.572)
Growth private credit						-0.008				
						(0.010)				
Subprimes crisis							0.181*			0.070
							(0.105)			(0.088)
VIX								0.006		
								(0.085)		
FED funds rate									0.078	
									(0.051)	
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.44
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.3.c Adding country-specific macro-financial controls: ROA

	Performance (ROA)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.014	**-0.042****	-0.027	-0.024	0.002	-0.005	**-0.083****	-0.013	-0.009	**-0.084*****
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)	(0.035)	(0.020)	(0.018)	(0.019)
Strong El Niño (t-1)	**-0.043****	**-0.047****	**-0.060*****	**-0.061*****	**-0.037****	**-0.059*****	**-0.088****	**-0.046****	**-0.044****	**-0.071*****
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.035)	(0.020)	(0.020)	(0.019)
Strong La Niña	**-0.059***	**0.084****	**0.059***	**0.077****	-0.017	**0.066***	0.111	**0.077***	**0.077****	**-0.068****
	(0.031)	(0.033)	(0.034)	(0.034)	(0.032)	(0.034)	(0.069)	(0.040)	(0.039)	(0.032)
Strong La Niña (t-1)	**-0.086*****	0.036	0.020	0.029	-0.050	0.024	-0.037	0.033	0.032	**-0.097*****
	(0.031)	(0.031)	(0.031)	(0.031)	(0.033)	(0.031)	(0.081)	(0.039)	(0.033)	(0.036)
Country-specific macro-financial controls										
Banks' total assets to GDP	**-0.815*****									**-1.291*****
	(0.115)									(0.295)
Credits to deposits		**0.249****								**0.380*****
		(0.101)								(0.099)
Concentration Bank			**0.322****							**0.337****
			(0.127)							(0.148)
Real bank lending rate				**0.054*****						**0.044*****
				(0.016)						(0.016)
Private credit					**-0.529*****					0.359
					(0.102)					(0.248)
Growth private credit						-0.008				
						(0.005)				
Subprimes crisis							**0.181***			0.038
							(0.105)			(0.039)
VIX								-0.014		
								(0.045)		
FED funds rate									0.012	
									(0.026)	
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.49	0.48	0.48	0.48	0.49	0.48	0.43	0.48	0.48	0.50
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.3.d Adding country-specific macro-financial controls: non-performing loans

	Credit risk (NPL)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.086***	0.005	-0.098***	-0.086***	-0.101***	-0.085***	-0.085***	-0.098***	0.006	0.039*
	(0.013)	(0.013)	(0.015)	(0.014)	(0.014)	(0.015)	(0.013)	(0.016)	(0.013)	(0.020)
Strong El Niño (t-1)	0.033***	0.036***	0.022*	0.034***	0.027**	0.038***	0.036***	0.027*	0.088***	0.054***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)	(0.018)
Strong La Niña	0.013	-0.148***	-0.109***	-0.095**	-0.018	-0.097**	-0.084***	-0.146***	0.019	-0.004
	(0.038)	(0.039)	(0.038)	(0.038)	(0.037)	(0.038)	(0.033)	(0.037)	(0.041)	(0.045)
Strong La Niña (t-1)	0.121***	-0.012	0.022	0.028	0.094***	0.027	0.043	-0.027	0.145***	0.110***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.033)	(0.034)	(0.032)	(0.036)
Country-specific macro-financial controls										
Banks' total assets to GDP	**0.699*****									**0.729*****
	(0.084)									(0.210)
Credits to deposits		**-0.842*****								**-0.864*****
		(0.081)								(0.086)
Concentration Bank			**0.390*****							**-0.267***
			(0.112)							(0.139)
Real bank lending rate				0.011						
				(0.010)						
Private credit					**0.485*****					0.026
					(0.071)					(0.179)
Growth private credit						0.001				
						(0.004)				
Subprimes crisis							-0.044			-0.030
							(0.040)			(0.040)
VIX								**0.086****		0.058
								(0.034)		(0.038)
FED funds rate									**0.183*****	**0.067*****
									(0.020)	(0.023)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.68	0.68	0.67	0.67	0.68	0.67	0.67	0.67	0.68	0.70
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.3.e Adding country-specific macro-financial controls: deposits to total assets

	Liquidity risk (Total Deposits to total assets)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	**-0.053*****	**-0.020*****	**-0.063*****	**-0.056*****	**-0.056*****	**-0.058*****	**-0.053*****	**-0.057*****	**-0.012****	**-0.014***
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)
Strong El Niño (t-1)	-0.007	-0.007	**-0.018*****	**-0.011****	-0.008	-0.001	-0.007	-0.009	**0.016*****	0.009
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)	(0.007)
Strong La Niña	**0.037*****	-0.002	0.007	0.019	**0.029****	0.018	0.013	0.002	**0.069*****	**0.045*****
	(0.013)	(0.014)	(0.015)	(0.015)	(0.012)	(0.015)	(0.013)	(0.014)	(0.017)	(0.016)
Strong La Niña (t-1)	**0.026****	-0.006	0.005	0.010	0.019	0.009	0.004	-0.007	**0.062*****	**0.038*****
	(0.012)	(0.014)	(0.014)	(0.014)	(0.012)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)
Country-specific macro-financial controls										
Banks' total assets to GDP	**0.126*****									**0.237****
	(0.040)									(0.119)
Credits to deposits		**-0.310*****								**-0.222*****
		(0.038)								(0.044)
Concentration Bank			**0.297*****							**0.101***
			(0.046)							(0.055)
Real bank lending rate				**0.017*****						-0.000
				(0.004)						(0.005)
Private credit					**0.077***					-0.124
					(0.040)					(0.118)
Growth private credit						**0.003****				**0.004****
						(0.002)				(0.002)
Subprimes crisis							0.012			
							(0.013)			
VIX								**0.025****		0.003
								(0.012)		(0.011)
FED funds rate									**0.083*****	**0.043*****
									(0.009)	(0.010)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.88	0.88	0.88	0.88	0.87	0.87	0.87	0.87	0.88	0.88
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.3.f Adding country-specific macro-financial controls: customer deposits to total assets

	Liquidity risk (Customer Deposits to total assets)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	**-0.035*****	**-0.014*****	**-0.045*****	**-0.038*****	**-0.037*****	**-0.039*****	**-0.035*****	**-0.035*****	-0.002	-0.013
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)
Strong El Niño (t-1)	0.007	0.007	-0.004	0.003	0.006	**0.013*****	0.007	0.007	**0.026*****	**0.020*****
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
Strong La Niña	**0.036****	0.008	0.010	0.023	**0.033****	0.021	0.018	0.019	**0.062*****	**0.047****
	(0.015)	(0.017)	(0.018)	(0.018)	(0.014)	(0.018)	(0.015)	(0.017)	(0.020)	(0.018)
Strong La Niña (t-1)	0.018	-0.005	0.001	0.006	0.015	0.004	0.002	0.003	**0.047****	**0.033****
	(0.016)	(0.018)	(0.018)	(0.018)	(0.016)	(0.018)	(0.018)	(0.018)	(0.019)	(0.015)
Country-specific macro-financial controls										
Banks' total assets to GDP	**0.106****									0.142
	(0.044)									(0.160)
Credits to deposits		**-0.193*****								**-0.100***
		(0.041)								(0.051)
Concentration Bank			**0.291*****							**0.158****
			(0.069)							(0.076)
Real bank lending rate				**0.019*****						-0.002
				(0.006)						(0.006)
Private credit					**0.080***					-0.066
					(0.046)					(0.156)
Growth private credit						**0.003***				**0.004***
						(0.002)				(0.002)
Subprimes crisis							0.005			
							(0.016)			
VIX								0.002		
								(0.012)		
FED funds rate									**0.066*****	**0.040*****
									(0.010)	(0.011)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.89	0.90	0.90	0.89	0.89	0.89	0.89	0.89	0.90	0.90
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.3.g Adding country-specific macro-financial controls: bank deposits to total assets

	Liquidity risk (Bank Deposits to total assets)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.173***	-0.053***	-0.186***	-0.173***	-0.174***	-0.178***	-0.172***	-0.197***	-0.075***	-0.015
	(0.020)	(0.017)	(0.023)	(0.021)	(0.021)	(0.022)	(0.020)	(0.022)	(0.016)	(0.025)
Strong El Niño (t-1)	-0.112***	-0.112***	-0.125***	-0.111***	-0.111***	-0.105***	-0.110***	-0.127***	-0.056***	-0.078***
	(0.017)	(0.017)	(0.019)	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.016)	(0.023)
Strong La Niña	0.032	-0.067	-0.009	0.002	0.004	0.004	-0.036	-0.081	0.129**	-0.047
	(0.048)	(0.055)	(0.055)	(0.055)	(0.048)	(0.055)	(0.047)	(0.053)	(0.062)	(0.066)
Strong La Niña (t-1)	0.011	-0.066	-0.018	-0.014	-0.013	-0.014	-0.063	-0.104**	0.116**	-0.061
	(0.038)	(0.043)	(0.043)	(0.043)	(0.039)	(0.043)	(0.042)	(0.044)	(0.047)	(0.050)
Country-specific macro-financial controls										
Banks' total assets to GDP	0.187									
	(0.153)									
Credits to deposits		-1.129***								-1.019***
		(0.116)								(0.130)
Concentration Bank			0.356**							-0.372**
			(0.153)							(0.173)
Real bank lending rate				-0.002						
				(0.019)						
Private credit					0.009					
					(0.123)					
Growth private credit						0.004				
						(0.005)				
Subprimes crisis							0.133**			0.039
							(0.058)			(0.061)
VIX								0.146***		0.092*
								(0.041)		(0.049)
FED funds rate									0.200***	0.103***
									(0.028)	(0.033)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.71	0.72	0.71	0.71	0.71	0.71	0.71	0.71	0.72	0.73
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.3.h Adding country-specific macro-financial controls: country-specific effect of the *subprime* crisis

	Stability	Performances		Credit risk	Liquidity risk		
	Zscore	ROE	ROA	NPL	Total Deposits to total assets	Customer Deposits to total assets	Bank Deposits to total assets
	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strong El Niño	0.004	-0.083**	-0.015	-0.085***	-0.053***	-0.035***	-0.172***
	(0.006)	(0.035)	(0.018)	(0.013)	(0.006)	(0.006)	(0.020)
Strong El Niño (t-1)	-0.015***	-0.088**	-0.047**	0.037***	-0.006	0.008	-0.110***
	(0.006)	(0.035)	(0.019)	(0.013)	(0.005)	(0.005)	(0.017)
Strong La Niña	-0.027	0.103	0.031	-0.081**	0.013	0.020	-0.044
	(0.018)	(0.068)	(0.031)	(0.033)	(0.013)	(0.015)	(0.047)
Strong La Niña (t-1)	-0.015	-0.014	-0.008	0.035	0.002	-0.002	-0.048
	(0.019)	(0.082)	(0.035)	(0.033)	(0.014)	(0.018)	(0.042)
N	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.86	0.43	0.49	0.67	0.88	0.89	0.72
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects. To control for the country-specific impact of the subprime crisis on banking stability, we also estimate equation (1) with the inclusion of a set of dummy variables corresponding to the interaction between the subprime crisis dummy and country fixed-effects.

Accounting for additional control variables: country-specific macroeconomic controls

Table A4.4.a Adding country-specific macroeconomic controls: z-score

	Stability (Zscore)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	0.004	**-0.032*****	0.005	**-0.016*****	**0.015*****	-0.005	0.003	0.004	**-0.033*****	**-0.029*****
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Strong El Niño (t-1)	**-0.018*****	**-0.053*****	**-0.017*****	**-0.034*****	**-0.032*****	**-0.058*****	**-0.015*****	**-0.015*****	**-0.014*****	**-0.047*****
	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Strong La Niña	**-0.039****	-0.010	-0.026	-0.030	-0.021	-0.017	-0.018	-0.018	-0.020	**-0.041****
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Strong La Niña (t-1)	-0.023	-0.018	-0.011	-0.014	-0.008	-0.007	-0.003	-0.002	-0.005	**-0.040****
	(0.019)	(0.017)	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)
Country-specific macroeconomics controls										
Real GDP	**-0.160****									**-0.147*****
	(0.065)									(0.067)
Real GDP growth		**-0.026*****								**-0.015*****
		(0.004)								(0.005)
Real GDP per capita			-0.097							
			(0.086)							
Inflation				**0.056*****						**0.036*****
				(0.008)						(0.008)
Growth nominal exchange rate					**-0.006*****					-0.001
					(0.002)					(0.002)
Growth of current account balance						**-0.003*****				-0.001
						(0.001)				(0.001)
Growth of terms of trade							-0.000			
							(0.002)			
Sovereign debt crisis								**0.092*****		0.041
								(0.025)		(0.027)
Currency crisis									**0.055*****	0.005
									(0.010)	(0.014)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.4.b Adding country-specific macroeconomic controls: ROE

	Performance (ROE)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.083**	-0.107***	-0.068*	-0.114***	-0.061	-0.095***	-0.042	-0.082**	-0.135**	-0.077**
	(0.035)	(0.040)	(0.035)	(0.035)	(0.038)	(0.037)	(0.037)	(0.035)	(0.054)	(0.037)
Strong El Niño (t-1)	-0.107***	-0.113***	-0.109***	-0.118***	-0.124***	-0.106***	-0.102***	-0.087**	-0.088**	-0.149***
	(0.036)	(0.043)	(0.036)	(0.036)	(0.041)	(0.037)	(0.035)	(0.035)	(0.035)	(0.038)
Strong La Niña	0.003	0.168**	0.036	0.144*	0.157**	0.164**	0.141*	0.163**	0.160**	0.003
	(0.076)	(0.075)	(0.073)	(0.075)	(0.074)	(0.075)	(0.074)	(0.075)	(0.075)	(0.076)
Strong La Niña (t-1)	-0.123	0.020	-0.094	0.012	0.018	0.024	0.020	0.034	0.026	-0.115
	(0.084)	(0.075)	(0.081)	(0.073)	(0.073)	(0.074)	(0.074)	(0.074)	(0.074)	(0.083)
Country-specific macroeconomics controls										
Real GDP	**-1.193***									-0.014
	(0.377)									(0.851)
Real GDP growth		-0.016								
		(0.018)								
Real GDP per capita			**-1.496***							-1.435
			(0.476)							(1.105)
Inflation				**0.088**						**0.107**
				(0.036)						(0.045)
Growth nominal exchange rate					-0.012					
					(0.009)					
Growth of current account balance						-0.003				
						(0.003)				
Growth of terms of trade							**0.020**			0.012
							(0.009)			(0.009)
Sovereign debt crisis								**0.456***		**0.426***
								(0.133)		(0.136)
Currency crisis									0.079	
									(0.069)	
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.4.c Adding country-specific macroeconomic controls: ROA

	Performance (ROA)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.015	**-0.051*****	-0.006	**-0.043****	-0.000	**-0.095*****	-0.001	-0.014	**-0.068*****	**-0.069*****
	(0.018)	(0.019)	(0.018)	(0.017)	(0.019)	(0.037)	(0.018)	(0.018)	(0.024)	(0.025)
Strong El Niño (t-1)	**-0.058*****	**-0.085*****	**-0.059*****	**-0.074*****	**-0.070*****	**-0.106*****	**-0.052*****	**-0.046****	**-0.046****	**-0.086*****
	(0.019)	(0.022)	(0.019)	(0.019)	(0.021)	(0.037)	(0.019)	(0.019)	(0.019)	(0.023)
Strong La Niña	-0.032	**0.077****	-0.002	0.052	**0.065***	**0.164****	**0.062***	**0.069****	**0.065***	-0.042
	(0.034)	(0.034)	(0.033)	(0.034)	(0.034)	(0.075)	(0.034)	(0.034)	(0.034)	(0.034)
Strong La Niña (t-1)	**-0.073***	0.009	-0.045	0.007	0.016	0.024	0.021	0.026	0.020	**-0.089****
	(0.037)	(0.032)	(0.035)	(0.031)	(0.031)	(0.074)	(0.031)	(0.031)	(0.031)	(0.037)
Country-specific macroeconomics controls										
Real GDP	**-0.752*****									**-0.914****
	(0.180)									(0.449)
Real GDP growth		**-0.026*****								-0.011
		(0.009)								(0.012)
Real GDP per capita			**-0.836*****							0.230
			(0.232)							(0.582)
Inflation				**0.081*****						**0.046****
				(0.019)						(0.023)
Growth nominal exchange rate					**-0.008***					0.000
					(0.004)					(0.005)
Growth of current account balance						-0.003				
						(0.003)				
Growth of terms of trade							0.007			
							(0.005)			
Sovereign debt crisis								**0.268*****		**0.219****
								(0.086)		(0.094)
Currency crisis									**0.083*****	0.034
									(0.031)	(0.038)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.49	0.48	0.49	0.48	0.48	0.43	0.48	0.48	0.48	0.49
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.4.d Adding country-specific macroeconomic controls: non-performing loans

	Credit risk (NPL)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	**-0.085*****	**-0.078*****	**-0.080*****	**-0.041*****	**-0.069*****	**-0.088*****	**-0.051*****	**-0.085*****	-0.014	-0.005
	(0.013)	(0.016)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.017)	(0.017)
Strong El Niño (t-1)	**0.037*****	**0.044*****	**0.031****	**0.078*****	0.014	**0.032****	**0.027****	**0.036*****	**0.035*****	**0.044*****
	(0.013)	(0.016)	(0.013)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)
Strong La Niña	**-0.092*****	**-0.098*****	**-0.132*****	**-0.070***	**-0.101*****	**-0.097****	**-0.114*****	**-0.097****	**-0.092****	**-0.098*****
	(0.032)	(0.038)	(0.032)	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.035)
Strong La Niña (t-1)	0.031	0.029	-0.008	**0.053***	0.019	0.025	0.019	0.026	0.032	0.018
	(0.030)	(0.032)	(0.029)	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)	(0.031)	(0.029)
Country-specific macroeconomics controls										
Real GDP	0.035									
	(0.140)									
Real GDP growth		0.005								
		(0.008)								
Real GDP per capita			**-0.416****							-0.324
			(0.200)							(0.205)
Inflation				**-0.126*****						**-0.130*****
				(0.022)						(0.025)
Growth nominal exchange rate					**-0.008*****					**-0.011*****
					(0.003)					(0.004)
Growth of current account balance						-0.001				
						(0.001)				
Growth of terms of trade							**0.015*****			-0.003
							(0.004)			(0.005)
Sovereign debt crisis								**-0.104*****		-0.054
								(0.040)		(0.041)
Currency crisis									**-0.111*****	-0.025
									(0.022)	(0.025)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.67	0.68
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.4.e Adding country-specific macroeconomic controls: deposits to total assets

	Liquidity risk (Total Deposits to total assets)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	**-0.053*****	**-0.019*****	**-0.052*****	**-0.032*****	**-0.042*****	**-0.053*****	**-0.027*****	**-0.053*****	**-0.010***	0.009
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)
Strong El Niño (t-1)	-0.007	**0.029*****	-0.008	**0.013****	**-0.023*****	-0.007	**-0.014*****	-0.007	-0.008	**0.012****
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Strong La Niña	0.012	0.009	0.006	**0.030****	0.014	0.017	0.003	0.017	0.020	0.008
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Strong La Niña (t-1)	0.004	0.023	-0.002	0.021	0.003	0.008	0.003	0.009	0.012	0.017
	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
Country-specific macroeconomics controls										
Real GDP	-0.034									
	(0.049)									
Real GDP growth		**0.024*****								**0.020*****
		(0.003)								(0.004)
Real GDP per capita			**-0.123***							-0.036
			(0.064)							(0.063)
Inflation				**-0.060*****						**-0.043*****
				(0.007)						(0.007)
Growth nominal exchange rate					**-0.006*****					**-0.007*****
					(0.001)					(0.002)
Growth of current account balance						-0.000				
						(0.000)				
Growth of terms of trade							**0.012*****			**0.004*****
							(0.001)			(0.001)
Sovereign debt crisis								-0.008		
								(0.020)		
Currency crisis									**-0.068*****	0.005
									(0.009)	(0.009)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.87	0.88	0.87	0.88	0.88	0.87	0.88	0.87	0.88	0.88
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.4.f Adding country-specific macroeconomic controls: customer deposits to total assets

	Liquidity risk (Customer Deposits to total assets)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.035***	-0.010*	-0.035***	-0.022***	-0.027***	-0.038***	-0.015**	-0.035***	-0.009	0.007
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Strong El Niño (t-1)	0.008	0.033***	0.007	0.019***	-0.005	0.003	0.001	0.007	0.007	0.019***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Strong La Niña	0.024	0.014	0.019	0.028	0.018	0.020	0.009	0.020	0.022	0.011
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Strong La Niña (t-1)	0.008	0.014	0.004	0.012	0.000	0.003	-0.000	0.004	0.006	0.010
	(0.016)	(0.019)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Country-specific macroeconomics controls										
Real GDP	0.032									
	(0.056)									
Real GDP growth		0.018***								0.019***
		(0.003)								(0.005)
Real GDP per capita			-0.008							
			(0.067)							
Inflation				-0.036***						-0.020**
				(0.007)						(0.009)
Growth nominal exchange rate					-0.004***					-0.005**
					(0.001)					(0.002)
Growth of current account balance						-0.001*				-0.001**
						(0.001)				(0.001)
Growth of terms of trade							0.009***			0.004**
							(0.001)			(0.002)
Sovereign debt crisis								-0.014		
								(0.014)		
Currency crisis									-0.041***	0.008
									(0.009)	(0.011)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Table A4.4.g Adding country-specific macroeconomic controls: bank deposits to total assets

	Liquidity risk (Bank Deposits to total assets)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Strong El Niño	-0.173***	-0.045*	-0.162***	-0.085***	-0.168***	-0.156***	-0.122***	-0.173***	0.005	0.029
	(0.020)	(0.023)	(0.020)	(0.018)	(0.020)	(0.021)	(0.018)	(0.020)	(0.028)	(0.029)
Strong El Niño (t-1)	-0.119***	0.026	-0.125***	-0.029	-0.119***	-0.086***	-0.127***	-0.112***	-0.117***	-0.003
	(0.018)	(0.023)	(0.018)	(0.018)	(0.022)	(0.018)	(0.018)	(0.017)	(0.017)	(0.024)
Strong La Niña	-0.072	-0.027	-0.087*	0.057	0.001	0.002	-0.024	0.003	0.015	0.003
	(0.048)	(0.056)	(0.050)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.049)
Strong La Niña (t-1)	-0.085**	0.040	-0.101**	0.039	-0.017	-0.005	-0.026	-0.014	-0.001	0.028
	(0.042)	(0.043)	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)	(0.043)	(0.043)	(0.041)
Country-specific macroeconomics controls										
Real GDP	-0.557**									2.053***
	(0.217)									(0.672)
Real GDP growth		0.093***								0.058***
		(0.012)								(0.015)
Real GDP per capita			-1.053***							-3.476***
			(0.270)							(0.848)
Inflation				-0.255***						-0.129***
				(0.027)						(0.035)
Growth nominal exchange rate					-0.003					
					(0.004)					
Growth of current account balance						0.005***				-0.001
						(0.002)				(0.002)
Growth of terms of trade							0.024***			-0.006
							(0.005)			(0.006)
Sovereign debt crisis								-0.054		
								(0.110)		
Currency crisis									-0.280***	-0.089**
									(0.034)	(0.035)
N	8290	8290	8290	8290	8290	8290	8290	8290	8290	8290
R-squared adj.	0.71	0.72	0.72	0.72	0.71	0.71	0.71	0.71	0.72	0.73
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Banking business model FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: coefficients displayed are marginal effects. OLS columns stand for fixed-effects OLS regressions with standard errors clustered at the bank level in brackets. All regressions include bank, country, and banking business model fixed-effects.

Appendix 5. Heterogeneity: strong ENSO events and banking resilience indicators

Table A5.1. Descriptive statistics of the banking dependent variables according to residence indicators

	Dependent variables (%)						
	Stability	Performances		Credit risk	Liquidity risk		
	Zscore	ROE	ROA	NPL	Total Deposits to assets	Customer deposits to assets	Bank deposits to assets
Large size (Total assets ≥ 1bn US dollars)							
Mean	2.63	2.72	1.01	1.37	4.08	3.90	1.70
Std	0.41	1.09	0.53	0.64	0.49	0.67	0.97
Max	4.43	5.46	2.95	4.43	4.58	0	0
Min	1.03	-4.24	-2.75	0.01	0.13	4.54	4.45
Small size (Total assets < 1bn US dollars)							
Mean	3.10	2.12	1.05	2.02	4.05	3.99	0.51
Std	0.50	1.56	0.86	0.74	0.51	0.56	1.01
Max	4.60	4.42	3.33	4.55	4.58	0	0
Min	0.37	-5.89	-4.01	0.01	0.10	4.58	4.35
High Capital ratio (≥ Median)							
Mean	3.35	2.22	1.23	2.07	3.95	3.87	0.50
Std	0.42	1.39	0.85	0.76	0.56	0.65	1.04
Max	4.60	5.46	3.33	4.55	4.55	0	0
Min	1.26	-5.52	-4.01	0.01	0.10	4.55	4.35
Low Capital ratio (< Median)							
Mean	2.63	2.31	0.85	1.66	4.17	4.07	1.09
Std	0.33	1.56	0.69	0.71	0.42	0.51	1.14
Max	4.03	4.18	2.54	4.43	4.58	0	0
Min	0.37	-5.89	-3.47	0.01	0.13	4.58	4.45
High Non-interest income (≥ Median)							
Mean	2.89	2.41	1.04	1.90	4.07	4.00	0.85
Std	0.45	1.41	0.74	0.76	0.43	0.47	1.10
Max	4.53	4.44	3.33	4.55	4.58	0.03	0
Min	0.37	-5.89	-4.01	0.01	0.13	4.54	4.28
Low Non-interest income (< Median)							
Mean	3.09	2.11	1.04	1.83	4.05	3.94	0.74
Std	0.57	1.54	0.85	0.77	0.58	0.69	1.15
Max	4.60	5.46	3.03	4.53	4.58	0	0
Min	0.79	-5.52	-3.74	0.01	0.10	4.58	4.45

Note: A bank is considered large if the averaged value of its total assets over the period 2005-2019 is equal to or above 1 billion US dollars. A bank is considered as having a high level of capitalization if its averaged capital ratio (total equity to total assets) over the period 2005-2019 is equal to or above the sample median. A bank is considered as having a high level of market-oriented activities if its averaged non-interest income to total income ratio over the period 2005-2019 is equal to or above the sample median