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Financial Institutions and Climate Shocks: Pre-emptive vs. Reactive Lending Adjustments in the Case of El Niño*

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Abstract

Financial institutions are increasingly exposed to climate change through their balance sheets. Nonetheless, the way in which they process climate information remains poorly understood. This paper examines whether financial institutions respond reactively to natural disasters or pre-emptively to climate forecasts, using Peruvian credit registry data. Relying on revisions to El Niño probability forecasts as an exogenous climate news shock, we find that financial institutions engage in forward-looking risk management during El Niño episodes. Specifically, a 10-percentage-point revision increases credit growth by 0.5 basis points, compared to the typical 6 basis points of month-to-month credit growth changes. In addition, the same forecast revision increases bank capitalisation by over 1 percentage point, compared to the average capital position of 18%. The increased lending amounts to 54 million soles per month, equivalent to 6.5% of new loans issued nationwide each month. These pre-emptive adjustments occur in response to forecast revisions alone, independent of actual disasters.

Keywords: El Niño, banks, non-bank financial institutions, micro finance institutions, credit, forecast, natural disasters

JEL classification: G21, G23, Q54

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1 Introduction

Global damages from natural disasters are expected to increase, with damages from flooding alone projected to grow by 134% with a temperature rise of 2 °C compared to the 1976–2005 baseline (Alfieri et al., 2017). To protect their balance sheets from these damages, financial institutions are increasingly including climate shocks into their decision-making processes (Carney, 2015). To understand this mechanism, a growing body of literature examines how banks respond to actual climate shocks such as natural disasters (Blickle et al., 2021; Klomp, 2014; Mamonov et al., 2024; Noth & Schüwer, 2023). By contrast, there is a lack of information on how financial institutions process climate forecast information and adapt their lending and risk management practices. Studies have yet to examine these two types of risks together to compare their potentially different effects on lending and bank capitalisation. To address these gaps, this paper asks: Do financial institutions respond ex ante to climate forecasts, or do they react to natural disasters ex post? We answer this question using updates to probability forecasts of Peru's El Niño episodes, or "forecast revisions", to empirically compare how financial institutions respond to climate forecasts versus actual climate events.

Specifically, we focus on the El Niño Southern Oscillation (ENSO), a climate pattern that alternates between warm El Niño and cold La Niña phases. ENSO is an ideal empirical setting because, similar to climate change, it is predictable with considerable uncertainty, and during El Niño, the probability of experiencing actual disasters is higher, but never certain. We measure these "climate news shocks" through El Niño forecast revisions. In particular, we focus on the 6-month changes in El Niño probability forecasts published by climate scientists. These revisions are completely exogenous due to their scientific nature and unpredictability, thus providing a natural experiment to study the reactions of financial institutions. Peru provides a particularly appropriate setting for this analysis, as El Niño events impact the country's economy greatly through flooding, landslides and agricultural disruptions, making climate forecasts highly important for the country's financial sector (Connecting Business Initiative, 2023; International Monetary Fund. Western Hemisphere Dept., 2024).

To understand whether financial institutions adjust their lending behaviour in response to climate shocks, we implement a two-pronged empirical strategy. First, we examine how climate-related news shocks and natural disasters affect financial institutions' lending decisions to non-financial firms, with a focus on loan-level credit growth. For this analysis, we use monthly loan-level credit data from the Peruvian Credit Registry between 2011 and 2019, combined with El Niño probability forecasts and natural disaster data. Using forecast revisions as our measure of climate news shocks, we analyse lending responses both during El Niño episodes (when positive revisions correctly anticipate El Niño conditions) and outside these episodes (when negative revisions correctly anticipate non-El Niño conditions). Our identification strategy relies on the exogenous changes in forecast revisions and separates credit supply from demand effects by exploiting variation in financial institution characteristics. Specifically, we examine how financial institutions' responses to forecast revisions vary with their portfolio share (importance of provincial loans on their balance sheet) and market share (relative importance within a province). To further identify supply-side effects, we also examine how financial institutions respond to natural disasters in provinces where they operate but where the particular borrower does not, providing additional evidence that observed changes in lending reflect institutional decisions rather than shifts in borrower demand.

Second, we focus on the financial institutions' capitalisation. We examine how climate news and natural disasters affect creditors' capital positions, a direct measure of financial institutions' risk management decisions. We measure how these responses vary with financial institution characteristics, including provincial portfolio concentration, mortgage ratios, profitability measured by return on equity, asset quality reflected by delinquency ratio, and operational efficiency through operating ratio. We use portfolio and market share-weighted natural disasters to examine financial institutions' exposure to natural disasters. This approach allows to identify the characteristics of financial institutions that make them most likely to adjust their capital positions in response to climate news or natural disasters.

Using both empirical strategies, we find similar results. We observe that financial institutions engage in forward-looking climate risk management, responding primarily to forecast revisions rather than to natural disasters, with responses that depend on financial institution characteristics. First, focusing on granular credit growth, we find that financial institutions respond significantly to forecast revisions, but in different ways, depending on whether the forecast occurs during El Niño episodes or outside of these. During El Niño, positive forecast revisions of 10 percent (correctly anticipating El Niño conditions) increase credit growth by approximately 8% of average credit growth. This number aggregates to 54 million soles, which is equivalent to 0.06% of the Peruvian GDP. The effects are larger for financial institutions with higher external exposure to natural disasters, weighted by portfolio or market share. Outside El Niño, negative forecast revisions (correctly anticipating non-El Niño conditions) increase credit growth by approximately 4% of average credit growth. In contrast, natural disasters show no significant effect on credit growth regardless of financial institution characteristics or El Niño episodes.

Second, turning to bank capitalisation effects, our results show that forecast revisions significantly affect capital ratios during El Niño episodes but not outside of these episodes. A 10 percentage points increase in forecast revision during El Niño increases the capital ratio by 1.1 percentage points, representing around 6% of financial institutions' average capital ratios. This effect varies substantially with financial institution characteristics: financial institutions with higher return on equity, delinquency ratios, and operating ratios show stronger capital responses to forecast revisions. Again, disasters show no direct effects on financial institutions' capital positions.

The contribution of this paper is threefold. First, we contribute to the emerging literature on studying if weather forecasts change the effects of natural disasters and if market participants react to weather forecasts (Carleton et al., 2024; Lemoine & Kapnick, 2024). Specifically, we identify a new channel through which climate news shock influences financial institutions. By measuring these news shocks using El Niño forecast revision, we show that banks adjust their lending decisions in anticipation of potential climate impacts before any physical climate events occur. Although theoretical work has demonstrated the importance of climate uncertainty for economic decisions (Brock & Hansen, 2018; Heal & Millner, 2014; Lemoine, 2021), studies have typically relied on news-based measures rather than direct probability assessments (Engle et al., 2020; Noailly et al., 2022). Our approach takes advantage of the unique opportunity in the

El Niño context to use frequently revised probability forecasts, allowing direct measurement of changes in uncertainty. This extends Johannes et al. (2016) "learning as long-run risk" framework, in which belief updates constitute economic shocks, by applying it specifically to the climate risk management of financial institutions. By focusing on precisely quantified probability updates rather than generalised climate news, our approach provides insights into how financial institutions will respond to newly arriving climate change information in a context where uncertainty is typically very high (Giglio et al., 2021).

Second, we provide a new explanation for the limited impact of natural disasters on financial institutions that is often found in the literature (Mamonov et al., 2024). Previous studies have documented that financial systems' responses to disasters are typically short-lived and modest (Biswas et al., 2023; Gallagher & Hartley, 2017; Mamonov et al., 2024; Noth & Schüwer, 2023), albeit with variation across firm size (Azañedo et al., 2024). Existing explanations for this resilience include the pricing of expected disaster risk through higher interest rates in vulnerable areas (Nguyen et al., 2022) and increased preparedness (Chen & Chang, 2021). Our results suggest that the resilience of financial institutions to realised disasters comes from their pre-emptive responses to climate forecasts, rather than from post-disaster adjustments. This forward-looking behaviour explains why researchers often observe limited reactive adjustments after actual disasters - risk management has already taken place before the event, especially for phenomena with some predictability, such as El Niño.

Thirdly, we show that bank heterogeneity impacts responses to forecast revisions and explain why there are no reactions to realised climate events. The existing literature has established several important patterns in financial markets during disasters: community resilience is enhanced by access to credit (Rajan & Ramcharan, 2023); multi-market banks reallocate lending to affected areas (Cortés & Strahan, 2017); local bank presence buffers employment losses (Cortés, 2014); and financial integration affects adaptation to shocks (Albert et al., 2021). Building on these findings, we find supply-side responses through bank characteristics and geographic exposure patterns, similar to recent approaches in the banking literature (Cortés & Strahan, 2017; Koetter et al., 2020; Rehbein & Ongena, 2022). We also adopt insights from the identification strategy of Khwaja and Mian (2008) by focusing on firms that borrow from multiple banks, allowing us to isolate supply-side effects. Our results show that institutional characteristics, in particular return on equity, delinquency rates and operating ratios, systematically influence the magnitude of the responses to the climate news shock. This heterogeneity supports the Amiti et al. (2017) "Anna Karenina principle" in the climate risk framework: while banks respond similarly in normal times, their responses to climate information depend on financial health and operational efficiency, with implications for financial stability and climate policy.

The remainder of this paper is organised as follows. Section 2 describes the El Niño pattern and its specific importance in Peru. Section 3 outlines the data used in the paper and presents descriptive statistics. Section 4 details the empirical strategy for identifying causal effects at both the loan and institution levels. Section 5 presents our results on how financial institutions incorporate climate forecast information into their lending and capital decisions. Section 6 concludes with implications for financial regulation and climate risk management.

2 Details on El Niño: Global Climate Pattern and Peru's Coastal Phenomenon

To test whether Peruvian financial institutions react pre-emptively to potential climate shocks, we examine El Niño episodes through forecast revisions. This channel allows us to determine whether institutions make ex-ante adjustments and whether these adjustments depend on the unexpectedness of the episodes. When the economic literature examines El Niño, it usually focuses on the global weather phenomenon. However, Peru also experiences a distinct regional phenomenon, coastal El Niño, which is especially important for the country's economy. In the following sections, we describe and distinguish between these two related phenomena, focusing on the latter to highlight the regional significance of El Niño in Peru. We then introduce the probability forecasts that serve as the basis for our forecast revision analysis.

2.1 Global and Coastal El Niño

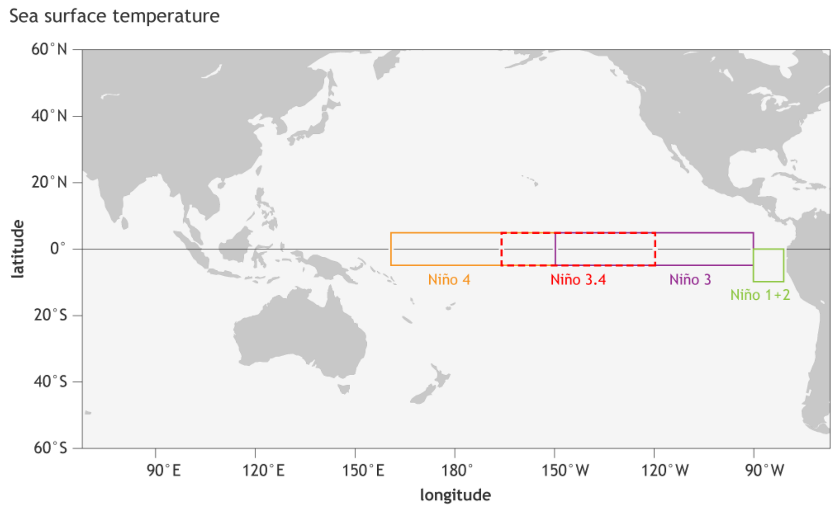
Global El Niño is the warm phase of the El Niño Southern Oscillation (ENSO) climate pattern. ENSO cycles irregularly between the warm El Niño and cold La Niña phases every 2 to 7 years, affecting several parts of the globe. Both phases cause changes in temperature, rainfall and winds (Ropelewski & Halpert, 1987). For an El Niño episode to occur, certain conditions must be met. First, the sea surface temperature (SST) in the east-central tropical Pacific, specifically within the area between 5°N and 5°S latitude and 120°W and 170°W longitude, called the Niño 3.4 region (Figure 1), must be 0.5°C above its rolling mean for a given 3-month season. Each "season" depicts a 3-month timeframe of January-February-March, February-March-April, and so on. Second, the higher temperature anomaly must persist for five consecutive overlapping seasons, with corresponding changes in the atmosphere, as defined by the US National Oceanic and Atmospheric Administration (NOAA). The opposite, i.e. a decrease by 0.5°C below the SST rolling mean, must occur during a La Niña episode (Philander, 1989).

While the global El Niño phenomenon affects weather patterns worldwide, Peru also experiences an important regional phenomenon known as coastal El Niño. To trace this regional phenomenon, the Peruvian Multisectoral Commission responsible for El Niño studies (Estudio Nacional del Fenómeno "El Niño", ENFEN) monitors not only the Niño 3.4 Pacific region, but also the Niño 1+2 regions near the Peruvian coast from 0° to 10°S latitude and 90°W to 80°W longitude (Figure 1). ENFEN defines a coastal El Niño episode when the SST in El Niño 1+2 regions is 0.5°C higher for at least three consecutive seasons.[1]

Global and coastal El Niños are connected and important for Peru due to the country's economic reliance on agriculture and its increasing exposure to extreme weather events (International Monetary Fund. Western Hemisphere Dept., 2024). During the 1972-73 global El Niño, the Peruvian anchovy fishery, one of the largest in the world at the time, collapsed, affecting the global economy (Glantz, 2001). The effects of El Niño extend beyond agriculture. In 1997-1998, global El Niño affected 0.5 mil-

[1] ENFEN, 2012: Definición operacional de los eventos El Niño y La Niña y sus magnitudes en la costa del Perú. Nota Técnica ENFEN.

Figure 1: The Niño Regions



Notes: Locations of the Pacific Ocean for monitoring sea surface temperature. The Niño 3.4 region (5°N-5°S, 120°W-170°W) is used by the US NOAA to assess global El Niño. The Niño 1+2 region (0°-10°S, 80°W-90°W) is used by the Peruvian ENFEN to assess coastal El Niño. NOAA Climate.gov image by Fiona Martin.

lion people and caused an estimated $3.5 billion in damages, with record flooding in Peru (French et al., 2020). The 2017 coastal El Niño caused other destructive floods, storms, and even vector-borne diseases such as malaria, affecting more than 2 million people (Sistema Nacional para la Respuesta y Rehabilitación, SINPAD) and causing 3.1 billion in damages (French et al., 2020).

2.2 Forecasting El Niño Episodes

El Niño episodes affect weather variability and increase the likelihood of extreme weather events, exacerbating risks to economic activity and human life. Due to the large potential impacts of El Niño episodes, accurate forecasting is important to help prepare and develop risk management strategies for different economic agents, such as governments, households, and financial institutions.

Unlike most climate phenomena, El Niño episodes can be predicted several months in advance, which provides lead time for possible preparation. Various agencies continuously monitor changes in El Niño conditions, such as sea surface warming, in order to predict its likelihood. For example, the International Research Institute for Climate and Society (IRI) at Columbia University publishes ENSO forecasts of the seasonal probability of global El Niño episodes. Specifically, in each month, they issue the probability of experiencing a global El Niño episode for a 3-month season, with forecasts extending up to 8 months ahead. For example, in January 2014, IRI published forecasts predicting the probability of El Niño conditions for nine 3-month-long seasons. First, the immediate January-March 2014 period, the February-April 2014 period, the March-May 2014 period, and so on, up to the September-November 2014 period, which is 8 months ahead.

To represent the different time dimensions of the forecasts, we define the following notation. First, $t - x$ represents the time at which the forecast was issued, where x indicates the lead time. Second, $t/(t+2)$ represents the target 3-month period being forecasted, spanning from month t to month $t + 2$. We then use the notation $\text{Probability}_{t-x}^{t/(t+2)}$ to show the probability of El Niño episodes occurring during the target period $t/(t + 2)$ as predicted by forecasts issued at time $t - x$. For example, the probability of an El Niño episode occurring during the 2014 September-November period would be estimated by the forecast issued in January 2014 and be written as $\text{Probability}_{\text{2014m1}}^{\text{2014m9/2014m11}}$.

Table 1 shows the predicted probabilities for global El Niño episodes across forecast seasons between 2014 and 2016.[2] Each row represents the predicted probabilities for different target periods, i.e. $t/(t + 2)$, where the dates in the first column indicate the first month of the season, i.e. t. The forecasts predict the probability of El Niño episodes occurring during the target 3-month seasons. Columns with different lead months indicate the time when the probabilities were issued, i.e. $t - x$. Colouring shows the probability of experiencing El Niño conditions. Green represents low probabilities, between 0 and 40%, yellow represents probabilities between 41 and 59%, and increasingly darker shades of red represent probabilities of 60% and above.

The forecasted probabilities of global El Niño episodes exhibit several patterns (Table 1). First, the earliest forecasts issued with lead time 8, in column $t - 8$, show lower average predicted probabilities, reflected by green-yellow cells. In addition, the variability of the predictions appears lower, as indicated by the similar colours of the cells. However, as the lead time of the forecast decreases and the forecasts approach

[2]The remaining periods between 2011 and 2019 are shown in Tables A.2 to A.4.

the actual date, there is more variance, as reflected by the differently coloured cells.

This visual pattern is confirmed by the summary statistics of forecasts in Table A.1. At the beginning of the forecasting period, there is little available information, and forecasters predict similar probabilities. The average probability is 37% with a standard deviation of 20% with an 8-month lead time (Table A.1, last row). As the lead time of the forecast decreases, the average probability drops to 34% and standard deviation increases to 37% (Table A.1, first row). The increase in standard deviation reflects the better information available, showing differences in actual predictions rather than relatively similar predictions for all seasons, resulting in more precise probabilities. However, this difference is not statistically significant compared to the full sample average of 38%. Although the difference is not, the predictions' accuracy increases with lead time. Specifically, Ehsan et al. (2024) shows that predictions are only accurate 30% of the time 6 months ahead, while they increase to 90% accuracy 1 month ahead.

The first two columns in Table 1 indicate El Niño episodes, with the dates of the episodes shaded in pale orange. The first column shows coastal El Niño episodes, reported by ENFEN, and the second column shows global El Niño episodes, reported by NOAA. The two sets of episodes are positively correlated ($\rho = 0.32$), but do not always coincide. While there are periods when coastal El Niño episodes occur without corresponding global episodes, Table A.2-A.4 shows that the predicted probabilities also increase during coastal El Niño events due to the geographical proximity of the considered regions (Figure 1). For example, in mid-2012, the probability of a global El Niño increased by about 40 percentage points, resulting in a coastal El Niño but not a global El Niño (Table A.2). Similar patterns emerged in mid-2014 and early 2017 (Table A.3, Table A.4). The focus on coastal El Niño is particularly important because these episodes include the catastrophic 2017 coastal El Niño, which caused large damages in Peru despite not being classified as a global El Niño. Therefore, we focus on coastal El Niño dates in our analysis and compare our results to global El Niños in a robustness test.

The last column alludes to the climate news shock variable, forecast revision, which we examine in more detail in our empirical strategy (Section 4). It shows the difference in probability between the current forecast and the forecast from six months ago. Forecast revisions are positively correlated with both global and coastal El Niño episodes ($\rho = 0.55$ and 0.44, respectively), indicating a similarity regardless of the definition of El Niño used.

3 Data

We rely on three main datasets in addition to the El Niño prediction data described in Section 2.2. First, we consider natural disasters from the Peruvian National Institute of Civil Defence (INDECI). Second, we analyse the Peruvian banking system using financial indicators from the Central Reserve Bank of Peru (BCRP), covering 61 financial institutions in five different financial entities: banks, finance companies, municipal savings and credit banks (CMACs), rural savings and credit banks (CRACs) and credit companies. Third, we examine the credit registry (Registro Crediticio Consolidado - RCC) from Peru's financial supervisory authority (Superintendencia de Banca, Seguros y Administradoras Privadas de Fondos de Pensiones - SBS), which provides monthly data on all outstanding loans from 2011-2019, with a classification of firms by size, where we focus on large, medium, small and micro firms. Additional data on firm location and economic activity come from the 2017 national census and the Tax Registry, which shows the location of firms in Peru's 196 provinces across 25 departments. This administrative structure allows us to examine heterogeneity at both the creditor and debtor levels, capturing variations in credit relationships, financial health metrics, portfolio composition and regional credit distribution patterns across different firm sizes and economic sectors.

3.1 Natural Disasters

To measure Peru's exposure to natural disasters, we focus on disasters that have caused any damage to human life and that may require humanitarian assistance between 2011 and 2019. We consider all natural disasters recorded in the National Information System for Response and Rehabilitation (Sistema Nacional para la Respuesta y Rehabilitación, SINPAD) database, which was created by the National Institute of Civil Defence (Instituto Nacional de Defensa Civil, INDECI). Specifically, we examined 35,085 natural

Table 1: Forecast Probabilities of El Niño Episodes between 2014 and 2016

El Niño Episodes		Probability of El Niño Episodes by Month									Forecast
Coastal	Global	t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$	Revision
$t/t+2$		Probability$_{t-x}^{t/(t+2)}$									
2014m1	2014m1	0	2	4	5	10	10	12	12	14	-12
2014m2	2014m2	0	3	8	11	13	16	17	18	13	-17
2014m3	2014m3	1	5	13	16	21	22	22	23	23	-21
2014m4	2014m4	25	17	21	29	29	34	35	30	32	-10
2014m5	2014m5	50	48	38	37	40	38	42	42	36	8
2014m6	2014m6	61	59	61	50	44	43	43	48	44	18
2014m7	2014m7	51	65	62	68	56	44	45	45	48	6
2014m8	2014m8	42	60	69	67	74	55	46	45	44	-4
2014m9	2014m9	56	56	68	74	69	74	60	45	44	-4
2014m10	2014m10	65	67	64	74	78	70	79	60	45	-14
2014m11	2014m11	75	66	72	70	75	78	72	78	58	3
2014m12	2014m12	83	74	67	72	73	72	74	66	75	9
2015m1	2015m1	64	76	72	67	72	68	64	67	58	0
2015m2	2015m2	47	58	70	68	67	65	62	58	57	-15
2015m3	2015m3	59	47	55	65	66	65	59	55	50	0
2015m4	2015m4	81	69	54	53	61	61	61	53	51	20
2015m5	2015m5	97	80	71	58	52	56	57	55	49	40
2015m6	2015m6	99	93	81	72	61	50	54	53	48	45
2015m7	2015m7	100	97	90	80	70	57	47	51	46	53
2015m8	2015m8	100	99	95	88	80	64	56	46	46	44
2015m9	2015m9	100	100	99	94	87	74	63	53	41	37
2015m10	2015m10	100	100	100	98	92	82	75	59	51	25
2015m11	2015m11	100	100	100	100	97	90	82	73	58	18
2015m12	2015m12	100	100	100	100	99	96	91	79	72	9
2016m1	2016m1	100	100	100	100	100	99	96	88	75	4
2016m2	2016m2	100	100	100	100	100	99	98	93	86	2
2016m3	2016m3	100	99	99	98	98	97	97	91	86	3
2016m4	2016m4	76	80	77	68	71	82	73	78	69	3
2016m5	2016m5	3	19	31	32	28	37	50	36	49	-47
2016m6	2016m6	1	3	8	14	15	14	21	31	21	-20
2016m7	2016m7	1	1	4	6	11	13	9	15	22	-8
2016m8	2016m8	0	3	3	6	8	13	14	10	14	-14
2016m9	2016m9	0	3	5	4	8	10	16	15	10	-16
2016m10	2016m10	0	1	5	6	6	10	10	18	17	-10

Notes: Predicted probabilities of global El Niño episodes. The first two columns show the start dates, t, of the 3-month seasons, $t/t+2$. They are shaded when coastal or global El Niño episodes are declared by the Peruvian ENFEN or the US NOAA agencies, respectively. The probability columns show the predicted probabilities of global El Niño episodes starting at time t. They are predicted with a lead time x in month $t-x$. Colours indicate probability ranges: green (0-40%), yellow (41-59%), and red shades (60% and above). The forecast revision, the last column, shows the difference in percentage points between the 1 and the 6-month forecast. Data provided by the International Research Institute for Climate and Society, Columbia University Climate School, Link.

disasters affecting Peruvian provinces, categorised as climatological, geophysical, hydrological, or meteorological (Table 2).

Table 2: Peru Disasters by Category and Natural Region

Category	Disaster Type	Coast		Jungle		Highlands		Total	
		Count	%	Count	%	Count	%	Count	%
Climatological		**141**	**4%**	**232**	**4%**	**2,050**	**8%**	**2,423**	**7%**
	Drought	51	1%	54	1%	1,235	5%	1,340	4%
	Forest fire	90	2%	178	3%	815	3%	1,083	3%
Geophysical		**757**	**20%**	**977**	**17%**	**2,157**	**8%**	**3,891**	**11%**
	Avalanche	11	0%	13	0%	36	0%	60	0%
	Erosion	308	8%	156	3%	83	0%	547	2%
	Mudslide	318	8%	165	3%	754	3%	1,237	4%
	Hill collapse	31	1%	81	1%	245	1%	357	1%
	Landslide	89	2%	562	10%	1,039	4%	1,690	5%
Hydrological		**2,469**	**64%**	**2,468**	**43%**	**11,636**	**46%**	**16,573**	**47%**
	Flooding	447	12%	1,087	19%	881	3%	2,415	7%
	Sea storm	82	2%	2	0%	1	0%	85	0%
	Heavy rain	1,940	51%	1,379	24%	10,754	42%	14,073	40%
Meteorological		**471**	**12%**	**2,014**	**35%**	**9,713**	**38%**	**12,198**	**35%**
	Low temperature	73	2%	191	3%	6,983	27%	7,247	21%
	Thunderstorm	4	0%	14	0%	162	1%	180	1%
	Strong winds	394	10%	1,809	32%	2,568	10%	4,771	14%
Total		**3,838**	**100%**	**5,691**	**100%**	**25,556**	**100%**	**35,085**	**100%**
	% of Total		**11%**		**16%**		**73%**		**100%**

Notes: This table shows the distribution of disaster events across Peru's natural regions, classified by disaster category and type. The percentages within each region's column represent the proportion of disasters within that region. The Jungle region combines data from both the Highland Jungle and the Lowland Jungle. Source: SINPAD, INDECI.

Table 2 shows the distribution of disasters across Peru's three main regions: the coast, the jungle, and the highlands. The Peruvian highlands are the region that suffers the most from natural disasters, as 73% of all disasters in Peru occurring there. We further detect strong relative regional heterogeneity. First, hydrological events, such as floods and rainfall, affect the coastal region the most compared to other coastal disasters, responsible for 64% of all coastal disasters. Hydrological events also affect the jungle and highlands heavily, accounting for 43% and 46% of disasters in these regions, respectively. However, meteorological events such as winds and low temperatures occur three times more frequently than in coastal regions, accounting for 35% and 38% of disasters respectively.

In addition to regional heterogeneity, we also find temporal heterogeneity in Peru. For example, the highest average number of disasters occurs in the summer and early autumn of the Southern Hemisphere, with an average of 600 disasters per month during January-March due to the rainy season (Figure B.1a). The severity of disasters, measured by the average number of people affected, also shows seasonality with some differences (Figure B.1b). The summer period still shows the highest average number of people affected at the provincial level, around 800 per province, but the winter period, between June and August, also shows an increase of around 600 people per province per month. In addition to the monthly variations in disasters, we detect changes on a year-to-year basis. On average, around 1 million Peruvians are affected by natural disasters each year. However, during the extreme 2017 coastal El Niño episode, this number increased to 2.3 million (Figure B.2). To account for geographical and temporal differences, we take several steps, which are described in more detail in Section 4.2.

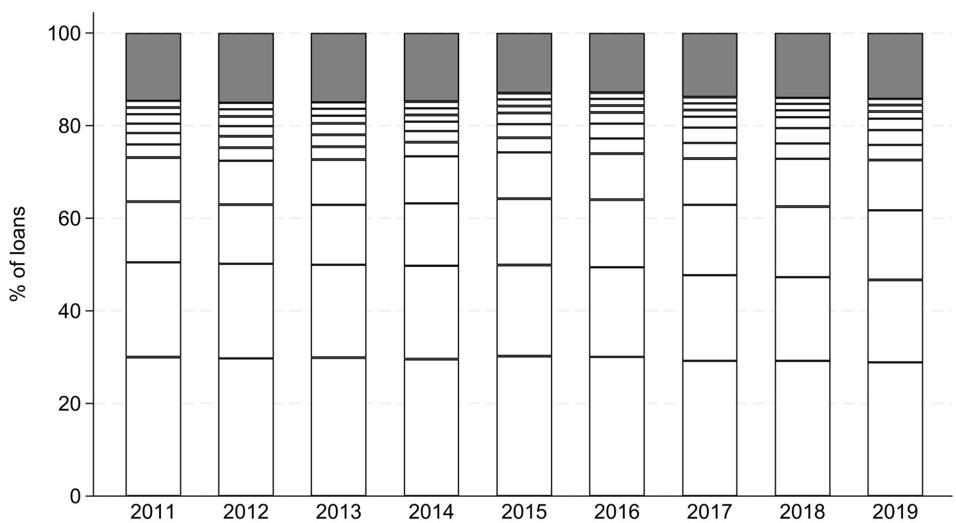
Disasters also differ in terms of number and human impact during and outside of coastal El Niño. During El Niño, disasters are more frequent and more people are affected. On average, 1.52 disasters occur per province outside El Niño months, which is significantly lower than the average of 1.95 disasters per province during El Niño months. In terms of the number of people affected, the difference is almost double. On average, 370 people per province per month are affected by disasters outside El Niño, compared to 719 people during El Niño (Table B.1).

3.2 Financial Institutions

To represent the Peruvian credit sector from the lending side, we focus on Peruvian financial institutions and their key financial indicators for the period 2011-2019 from the Central Reserve Bank of Peru (Banco Central del Reserva del Perú, BCRP). We use data from 61 financial institutions, including private banks (13), financial companies (12), municipal savings and loan banks (Cajas Municipales de Ahorro y Crédito (CMAC), (13)), rural saving and loans associations (Cajas Rurales de Ahorro y Crédito (CRAC), (12)) and credit entities (11).

The market is concentrated in Peru. The five largest financial institutions account for around 76% of outstanding credit, a share that has remained stable over time (Figure 2). The Peruvian financial system is also highly concentrated geographically. The department of Lima accounts for 71% of total outstanding credit, defined as credit to enterprises, households and mortgages, followed by Arequipa, La Libertad and Piura (Figure C.1). Although banks on average concentrate their credit portfolio in Lima (78%), other financial institutions diversify their portfolios more among departments (Figure C.2). For more information on the structure, concentration and geographical distribution of the Peruvian financial institutions, see Appendix C and Armas et al. (2024) for further description of the Peruvian financial system.

Figure 2: Financial Institutions' Concentration between 2011 and 2019



Notes: Concentration is defined as financial institutions' market share of outstanding loans. The white areas show the 10 largest financial institutions. The shaded area represents the combined market share of the remaining financial institutions. The market share is the average market share of a financial institution in one year. Figure based on calculation by Amiti and Weinstein (2018). Source: Central Reserve Bank of Peru.

Financial institutions also differ in their financial indicators (Table 3). In particular, the global capital ratio is measured as the ratio of shareholders' equity to risk-weighted assets and is between 15% and 19% for all institutions, except credit companies, which have the highest value of 27% due to their riskier nature. Banks have the highest portfolio concentration, measured by the sum of their squared portfolio share by province, following the definition of a Herfindahl-Hirschman Index (HHI). Mortgage loans as a percentage of total assets are also highest for banks, as they are the main providers of mortgages in Peru. Return on equity (ROE), calculated as net income over average total equity, is also highest for banks, as they are the most profitable. However, the delinquency ratio, which measures non-performing loans as a percentage of total loans, and the operating expense ratio, which measures operating expenses as a percentage of total assets, have the lowest values among banks, representing safety and efficiency.

Table 3: Financial Indicators by Type of Financial Institution

Variable	**Private Banks**	**Financial Companies**	**CMAC**	**CRAC**	**Credit Companies**
N	(13)	(12)	(13)	(12)	(11)
Capital Ratio (%)					
Mean (Std. Dev.)	16.55 (9.36)	18.94 (9.94)	15.32 (2.05)	16.28 (10.57)	27.61 (21.79)
Range	[10.72, 102.99]	[9.82, 126.74]	[10.02, 22.06]	[9.58, 159.16]	[10.72, 138.27]
Observations	1,299	1,133	1,323	868	884
Portfolio Concentration (HHI)					
Mean (Std. Dev.)	7,433.19 (2,448.35)	3,422.51 (3,045.50)	1,899.31 (1,633.76)	4,149.48 (3,255.86)	4,735.55 (4,092.71)
Range	[1,298.95, 10,000]	[0, 10,000]	[0, 8,656.42]	[0, 10,000]	[9.95, 10,000]
Observations	1,299	1,133	1,327	870	884
Mortgage Loans (%)					
Mean (Std. Dev.)	9.44 (12.57)	3.26 (13.47)	3.60 (10.28)	1.67 (9.64)	5.54 (22.64)
Range	[0, 84.21]	[0, 97.55]	[0, 97.06]	[0, 93.11]	[0, 100]
Observations	1,294	1,104	1,262	788	840
Range	[0, 84.21]	[0, 97.55]	[0, 97.06]	[0, 93.11]	[0, 100]
Return on Equity (%)					
Mean	14.71	10.02	8.69	-11.39	-1.22
Std. Dev.	9.72	14.04	10.31	28.01	25.95
Observations	1,299	1,133	1,323	868	884
Range	[-27.39, 34.61]	[-47.32, 41.09]	[-38.97, 27.88]	[-134.3, 42.94]	[-142.07, 61.95]
Delinquency Ratio (%)					
Mean	2.47	5.68	8.13	6.98	6.52
Std. Dev.	1.49	2.39	4.38	4.10	6.49
Observations	1,299	1,133	1,323	868	884
Range	[0, 7.26]	[0.75, 16.01]	[2.62, 23.43]	[0, 31.68]	[0, 82.21]
Operating Expenses Ratio (%)					
Mean	2.18	6.82	4.60	6.09	12.85
Std. Dev.	2.26	4.62	2.71	3.79	13.07
Observations	1,299	1,133	1,323	868	884
Range	[0.08, 17.93]	[0.15, 29.00]	[0.42, 14.82]	[0.32, 22.84]	[0.26, 75.01]

Notes: Capital ratio measured as shareholders' equity over risk-weighted assets; portfolio concentration measured by the sum of squared portfolio share by province as a Herfindahl-Hirschman Index; mortgage loans and operating expenses as a percentage of total assets; ROE calculated as net income over average total equity; delinquency ratio as non-performing loans over total loans. Source: Central Reserve Bank of Peru.

3.3 Credit Registry

For the loan-level analysis, we rely on the Peruvian Credit Registry (Registro Crediticio Consolidado - RCC), which is provided by Peru's financial supervisory authority (SBS). The registry contains confidential, mandatory information on outstanding loans submitted monthly by all financial institutions. We focus on loans provided by private financial institutions to non-financial private sector firms during the period between January 2011 and December 2019. We consider the period 2011 onward, as the current system of classifying credit types by firm size was introduced in mid-2010. The pandemic period was excluded due to the distortions caused by the Reactiva Peru programme, which provided businesses with liquidity support through credit guarantees.[3] Due to the large size of the credit registry, with more than 200 million observations, we select a random sample of 10%. The selection is based on the random number of tax IDs of companies that have ever been in the registry between 2011 and 2019, resulting in a representative sample (Figure D.1). We include all loan activities of a chosen firm in our sample.

The credit registry provides loan-level data of firms and households. We focus on large, medium, small, and micro enterprises, excluding corporations due to the limited number of observations with large loans. Different patterns emerge by firm size: large and medium firms tend to borrow from larger financial institutions with more diversified portfolios, including mortgages, while smaller firms tend to borrow from less profitable and less efficient institutions with lower return on equity and higher operating ratios. The underlying data shows that most Peruvian firms have relationships with a single financial institution (Table 4). This trend has increased over time, especially among small and micro firms, 75% of which have a single relationship, compared to large and medium-sized firms, only 40% of which have single relationships (Figure D.2-Figure D.4).

The economic activity of firms covers six main sectors, where classification follows the 4th Revision of International Standard Industrial Classification (ISIC, Rev.4). Primary production is represented by agriculture, including forestry and fishing, mining and electricity, gas and water supply, including mining, quarrying and utilities. The

[3]For further information, see the description by the Ministry of Finance.

secondary sector includes manufacturing and construction. Services are split into two categories: Market services, including wholesale and retail trade, transport, accommodation, information, finance, real estate and professional and administrative activities, and non-market services, including public administration, education, health, arts, household employment and extra-territorial organisations (Figure D.5). RCC further provides information on the risk of the loan as assessed by the financial institution. However, this level of risk varies across financial institutions as each institution ranks loans individually. Therefore, the level of loan risk is not included in our estimation.

The location data for debtors is based on two main sources. The first and preferred source is the 2017 National Census conducted by the Peruvian National Institute of Statistics (INEI), which accounts for 60% of the location data. The census allows locations to be identified through National Identification numbers for Natural Persons (DNI numbers). This is used for matching medium, small and micro enterprises, as these businesses can apply for loans using their DNI numbers.

The second method of identification is through the tax identification number of firms or natural persons with business activity (RUC) from the RUC Register National Superintendence of Customs and Tax Administration. The tax ID numbers are publicly available online. This source provides the remaining 40% of the location data and is used when the census data does not provide a location for a debtor. The location is assigned to the district in which the firm is registered and categorised at a broader provincial level, which includes districts. Throughout the analysis period, about 86% of the identified enterprises have a location at the district level. When both location measures are available (DNI and tax ID), the DNI, i.e. the census location, is preferred. The two sources match in 85% of the cases at the district level where both datasets are available, suggesting consistency between the sources.

When allocating the locations of firms, we assume that firms do not move. This assumption is based on the demographic data from the INEI 2018 census (INEI, 2018), which shows that between 2012 and 2017, 94.1% of the registered population lived in the same department as five years earlier (25.2 million out of 26.9 million people). This stability rate was similar (94.3%) in the 2012 census. Of the 1.4 million people who migrated between departments, Lima had the highest net migration rate (13.9%), followed by Arequipa (2.5%), while Cajamarca had the highest negative migration rate (-3.9%), followed by Loreto (-3%). In addition, 42.3% of the people who changed departments during the five-year period moved to Lima or Callao.

Table 4: Firms Characteristics: By Type of Credit and Sector

Type of Credit	Sector	Bank Relationships (mean)	Credit (mean)	Credit (SD)	Number of Firms
Large	Total	3.60	4,571.07	10,247.85	496
	Agriculture	3.14	9,383.52	15,589.43	25
	Construction	3.02	1,933.05	3,501.12	32
	Manufacturing	3.60	4,272.42	8,002.72	83
	Market Services	3.83	3,901.10	8,690.38	297
	Mines, Electricity, Gas and Water Supply	2.19	8,383.85	22,951.79	27
	Non-Market Services	2.29	10,150.79	18,399.84	32
Medium	Total	2.77	692.87	3,605.44	6,927
	Agriculture	2.35	1,343.89	5,007.77	176
	Construction	2.34	697.44	2,048.82	422
	Manufacturing	2.84	914.67	5,994.47	712
	Market Services	2.84	625.24	2,833.34	4,672
	Mines, Electricity, Gas and Water Supply	2.29	1,990.06	11,464.69	107
	Non-Market Services	2.37	800.35	3,046.80	524
	Not Available	2.83	208.33	270.03	314
Small	Total	2.00	36.32	62.26	126,571
	Agriculture	1.88	37.98	124.98	3,015
	Construction	1.80	47.58	87.67	2,024
	Manufacturing	2.06	43.90	67.45	6,462
	Market Services	2.04	38.73	62.98	67,930
	Mines, Electricity, Gas and Water Supply	1.93	46.42	149.13	688
	Non-Market Services	1.82	30.47	59.62	22,070
	Not Available	2.01	28.14	29.91	24,382
Micro	Total	1.42	4.44	28.17	550,980
	Agriculture	1.35	4.98	12.18	13,666
	Construction	1.32	5.28	26.83	7,661
	Manufacturing	1.49	5.74	61.49	18,178
	Market Services	1.48	5.19	36.68	216,179
	Mines, Electricity, Gas and Water Supply	1.38	7.13	35.74	1,651
	Non-Market Services	1.38	3.75	12.57	132,155
	Not Available	1.38	3.46	6.63	161,490

Notes: Bank relationships refer to the average number of financial institutions per firm. Credit values are in soles (thousands). Source: Peruvian credit registry.

4 Empirical Approach: El Niño Forecast Revisions and Natural Disasters

To understand how banks adjust their lending behaviour in response to climate-related information and events, focusing on the distinction between pre-emptive and reactive adjustments, we isolate the effects of El Niño forecast revisions from the effects of natural disasters. Specifically, we construct the El Niño forecast revision variable to capture the information content of revised climate probability forecasts and estimate the impact of natural disasters in Peru. By contrasting the effects of these news shocks and actual climate events, both during and outside El Niño episodes, we are able to analyse the extent to which banks pre-emptively adjust their portfolios based on climate news versus reacting to realised disaster events.

To distinguish between credit supply and demand effects, we take several steps. First, we examine how the effects of forecast revisions and natural disasters on credit growth depend on bank characteristics such as portfolio share and market share. These variables capture aspects of bank strategy that are unlikely to be directly relevant to firms' decisions and thus indicate supply-side effects. Second, we analyse the responses to external disaster exposure, focusing on disasters in provinces where the bank operates but the particular firm does not. Responses to these external shocks would indicate supply-side bank effects rather than demand-side firm effects. Finally, we examine bank capital responses, which directly reflect banks' risk management decisions rather than firms' demand for credit. For the sake of brevity, we will use the terms financial institutions and banks interchangeably for the rest of the paper.

4.1 El Niño Forecast Revision as a Measure of Climate News Shock

El Niño forecast revisions measure changes in the probability of El Niño episodes over time. These revisions are entirely exogenous, as they are based on meteorological data such as changes in atmospheric pressure and sea surface temperature. By analysing forecast revisions, we can examine how financial institutions incorporate revised probability estimates into their lending decisions without introducing bias. We expect that large forecast revisions should have a greater impact on lending decisions than smaller ones, as they indicate a climate news shock. In this case, we suspect that financial institutions will be more likely to revise their lending decisions to reflect the higher probability of an El Niño event. For firms, however, we expect that they will be less affected by forecast revisions, as their main increase in demand should come from the impact of actual natural disaster events.

We construct the forecast revision by calculating the difference between the current month's El Niño probability forecast and the probability forecast made six months earlier for the same period. Specifically, for each month, we compute

$$\text{Forecast Revision}_t^{t/(t+2)} = \text{Probability}_t^{t/(t+2)} - \text{Probability}_{t-6}^{t/(t+2)} \tag{1}$$

where Forecast Revision$_t^{t/(t+2)}$ depicts the changes in forecasted probabilities for season $t/t+2$, Probability$_t^{t/(t+2)}$ is the probability of experiencing El Niño between seasons t and $t+2$ predicted in period t, and Probability$_{t-6}^{t/(t+2)}$ is the probability for season $t/t+2$ predicted in $t-6$.[4] For example, to calculate the forecast revision for July, Probability$_t^{t/(t+2)}$ would be the probability of El Niño occurring during the July-August season as predicted in July, and Probability$_{t-6}^{t/(t+2)}$ would be the probability for the same July-August season but as predicted in January. We opted for a 6-month lag to reflect the necessary lead time for a period to be classified as El Niño and to capture the impact of medium-term climate information on credit decisions. This approach measures how forecasts change as new information becomes available, capturing the shock component of climate forecasts. We calculate forecast revisions for each month, both during and outside of El Niño episodes. For the sake of brevity, we drop the target period, $t/t+2$, from the notation in the superscript, and show only the time of issued prediction, t, in the subscript.

The interpretation of forecast revisions differs depending on whether we consider El Niño episodes or non-El Niño episodes. During El Niño, only high-probability forecasts correctly anticipate actual conditions. Therefore, positive forecast revisions represent correct upward revisions, while negative values indicate incorrect downward

[4]For more information on El Niño and its probability forecasts, see Section 2.

revisions (Table 5). Conversely, outside El Niño, only low-probability forecasts are correct. Negative values indicate correct downward revisions, while positive values indicate incorrect upward revisions (Table 6). The distinction between El Niño and non-El Niño episodes is important not only for interpretation purposes, but also for representing different risk environments. During El Niño episodes, the market may incorporate the higher probability of natural disasters and adjust accordingly. Although the occurrence of El Niño event can only be confirmed after five months of observing oceanic and atmospheric changes, the market has access to information much sooner than this, sometimes a year or half a year sooner, from scientists and news outlets.[5]

The distribution of forecast revisions differs significantly during and outside El Niño. During El Niño, the average upward revision is 11 percentage points, while outside El Niño the average downward revision is -13 percentage points (Table E.1). Although there is a significant difference between the means of the two groups, their variances are similar, both are normally distributed, and there are some overlapping observations (Fig. 3). Given that the same values of forecast revisions have opposite meanings depending on the El Niño season (Table 5 and Table 6), we consider the forecast revisions by El Niño episodes in our estimation strategy.

4.2 Natural Disasters as a Measure of Climate Events

Natural disasters in Peru are highly seasonal, with the highest number occurring during the Southern Hemisphere's summer and early autumn months from January to March. Due to the rainy summer season, three times the average number of disasters occur during these months compared to the rest of the year. These months also affect the greatest number of people (Figures B.1a and B.1b). Although the wet season is the period when disasters are most likely to occur, the dry season also poses risks, with June-July-August period affecting the second-highest number of people on average.

To account for seasonal patterns, we measure the impact of disasters in a given province as the number of people affected in a given month divided by the monthly average. This ratio, therefore, measures the severity of the disaster relative to the typical impact of disasters in that province at that month. For example, if 11 people

[5] https://edition.cnn.com/2023/07/20/us/2024-hotter-than-2023-el-nino-nasa-climate/index.html

Table 5: Forecast revision (FR) scenarios during El Niño Episodes

Probability forecasts for El Niño	**Low**$_t$	**High**$_t$
Low$_{t-6}$	Small forecast revision $\text{FR}_t = \text{Low}_t - \text{Low}_{t-6} \approx 0$ Incorrect anticipation	Positive forecast revision $\text{FR}_t = \text{High}_t - \text{Low}_{t-6} > 0$ Correct upward revision
High$_{t-6}$	Negative forecast revision $\text{FR}_t = \text{Low}_t - \text{High}_{t-6} < 0$ Incorrect downward revision	Small forecast revision $\text{FR}_t = \text{High}_t - \text{High}_{t-6} \approx 0$ Correct anticipation

Notes: Forecast Revision (FR) is the difference between the current probability of El Niño and the probability predicted 6 months ago. During actual El Niño episodes, only high-probability forecasts are correct. Positive errors indicate correct upward revisions, while negative errors indicate incorrect downward revisions. These forecast revisions are calculated backwards: for each month, we first identify actual El Niño/non-El Niño episodes, then examine the initial and current forecasts to determine the type of error.

were affected in Lima in April 2014, the ratio would be calculated by dividing 11 by the average number of people affected in Lima in April, 7, giving a disaster ratio of 1.5 (INDECI, SINPAD). This approach ensures that any changes in lending detected are not influenced by seasonal patterns in Peru. Indeed, we do not detect seasonality in the resulting monthly disaster ratio (Table E.2).

The monthly averages were calculated using all available data from 2003 to 2019. Although the literature generally recommends excluding data after the start of the sample period, 2011 in this case, this approach would have resulted in an outlier due to the extreme coastal El Niño episode in 2017. Including all available years in the calculations reduced the influence of the 2017 outlier. Although the 2017 spike remains visible in the average disaster ratio across provinces, its size is considerably reduced compared to using only observations from 2003 to 2011 (Figure 4).

Table 6: Forecast Revision (FR) Scenarios Outside El Niño Episodes

Probability forecasts for El Niño	**Low$_t$**	**High$_t$**
Low$_{t-6}$	Small forecast revision FR_t = Low_t - $Low_{t-6} \approx 0$ Correct anticipation	Positive forecast revision FR_t = $High_t$ - $Low_{t-6} > 0$ Incorrect upward revision
High$_{t-6}$	Negative forecast revision FR_t = Low_t - $High_{t-6} < 0$ Correct downward revision	Small forecast revision FR_t = $High_t$ - $High_{t-6} \approx 0$ Incorrect anticipation

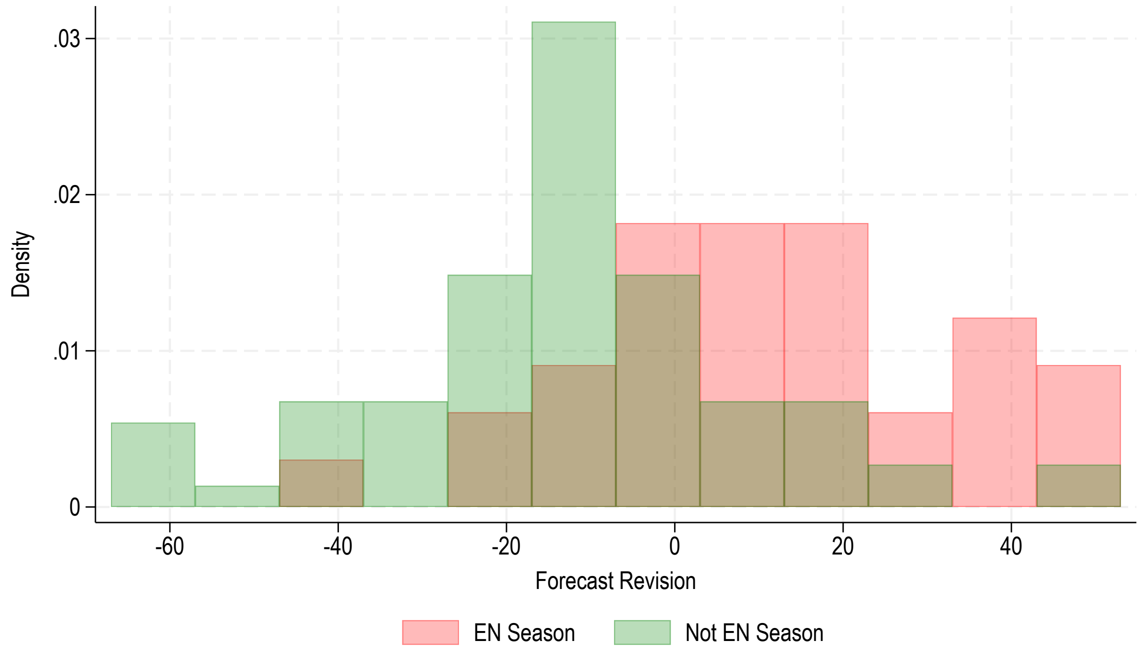
Notes: Forecast Revision (FR) is the difference between the current probability of El Niño and the probability predicted 6 months ago. During non-El Niño episodes, only low-probability forecasts are correct. Negative errors indicate correct downward revisions, while positive errors indicate incorrect upward revisions. These forecast revisions are calculated backwards: for each month, we first identify actual El Niño/non-El Niño episodes, then examine the initial and current forecasts to determine the error type.

4.3 Impact on Credit Growth

To estimate the impact of climate news shocks and actual climate events on firm-level credit growth, we first regress credit growth on forecast revisions and natural disasters, taking into account different bank-level characteristics during and outside El Niño. If the effects of the shocks on credit growth differ according to bank characteristics, this suggests that it is the banks, rather than the firms, that are responding to the shocks. The reason for this is that, unlike banks, firms are less likely to be concerned about the size of a province on a bank's balance sheet.

In the baseline regression (Eq. 2), we estimate the effect of shocks conditional on bank characteristics. As shocks affect credit decisions with lags, we include the first lag of the forecast revision and disaster ratio variables. To account for bank characteristics, we control for market and portfolio share. Market share captures the size and importance of banks in the province calculated by dividing the bank's provincial assets by the total assets of the province. Portfolio share captures the relative importance of

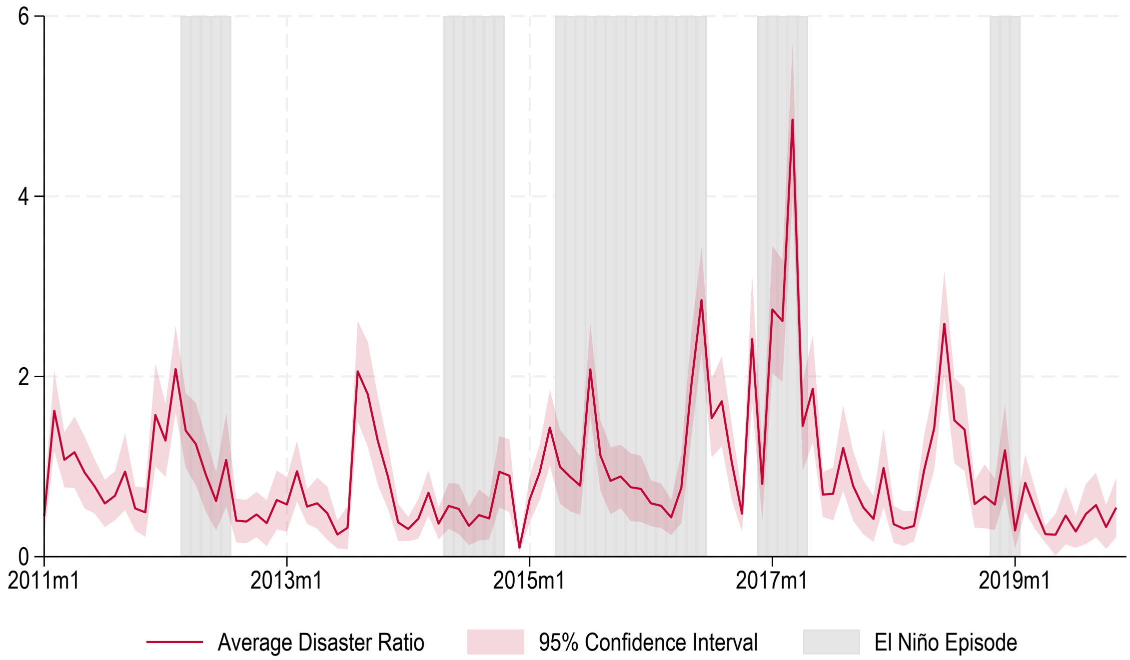
Figure 3: Distribution of Forecast Revisions during El Niño and non-El Niño Episodes



Source: International Research Institute for Climate and Society (IRI), Columbia University. Authors' calculation.

the regional portfolio to the bank, calculated as the ratio of the assets of banks in a given province to the total assets of the bank. We expect higher market and portfolio shares to make banks more responsive to shocks. To avoid endogeneity, we include the second lag of bank characteristics. We also construct portfolio and market share weighted external disaster measures to control for external disaster exposure. If these external disaster exposure measures affect credit growth, it provides further evidence that banks, rather than firms, respond to shocks, as firms would not be expected to respond to a bank's exposure in other provinces. To account for unobserved bank and province characteristics, we use bank-time and province-time fixed effects. Specifically,

Figure 4: Average Disaster Ratio over Time in Peru



Notes: Average Disaster Ratio shows the monthly average of the number of people affected by disasters divided by the seasonal average of a given month. El Niño Episode indicates coastal El Niño. Source: SINPAD, INDECI.

we estimate

$$
\begin{aligned}
\Delta \ln(Credit)_{b,f,p,t} = & \beta_1 \ln MS_{b,p,t-2} + \beta_2 \ln PS_{b,p,t-2} + \\
& + \beta_3 \ln ED\_MS_{b,p,t-1} + \beta_4 \ln ED\_PS_{b,p,t-1} + \\
& + FR_{t-1} \times \big(\beta_5 \ln MS_{b,p,t-2} + \beta_6 \ln PS_{b,p,t-2} + \\
& + \beta_7 \ln ED\_MS_{b,p,t-1} + \beta_8 \ln ED\_PS_{b,p,t-1}\big) + \\
& + ElNino_{t-1} \times FR_{t-1} \times \big(\beta_9 \ln MS_{b,p,t-2} + \beta_{10} \ln PS_{b,p,t-2} + \\
& + \beta_{11} \ln ED\_MS_{b,p,t-1} + \beta_{12} \ln ED\_PS_{b,p,t-1}\big) + \\
& + \ln DR_{p,t-1} \times \big(\beta_{13} \ln MS_{b,p,t-2} + \beta_{14} \ln PS_{b,p,t-2} + \\
& + \beta_{15} \ln ED\_MS_{b,p,t-1} + \beta_{16} \ln ED\_PS_{b,p,t-1}\big) + \\
& + ElNino_{t-1} \times \ln DR_{p,t-1} \times \big(\beta_{17} \ln MS_{b,p,t-2} + \beta_{18} \ln PS_{b,p,t-2} + \\
& + \beta_{19} \ln ED\_MS_{b,p,t-1} + \beta_{20} \ln ED\_PS_{b,p,t-1}\big) + \\
& + \alpha^1_{b,t} + \alpha^2_{p,t} + \epsilon_{b,f,p,t}
\end{aligned} \tag{2}
$$

where $\Delta \ln(\text{Credit})_{b,f,p,t}$ is the first difference of granted firm-level credit from bank b to firm f in province p in time t. The first difference removes any time-invariant firm characteristics from the estimation.

The variable $\ln MS_{b,p,t-2}$ measures the logarithm of the market share of bank b in province p at time $t-2$. It shows the relative importance of a given bank within a province. It is calculated by dividing the bank's provincial assets by the total assets of the province. Provincial assets include all loans and mortgages to individuals and enterprises. A higher market share indicates that the bank is regionally important, as it is responsible for a large share of loans.

The variable $\ln PS_{b,p,t-2}$ depicts the portfolio share. The portfolio share is the ratio of the assets of banks in a given province to the total assets of the bank. Similar to market share, provincial assets include all loans and mortgages to individuals and enterprises. A higher share indicates that the province is important on the bank's balance sheet. Therefore, we expect that higher shares will incentivise banks to react more to the shocks.

The variables $\ln ED\_MS_{b,p,t-1}$ and $\ln ED\_PS_{b,p,t-1}$ show the external disaster exposure to climate disasters occurring in all provinces except the one being analysed, weighted by the bank's market share and portfolio share, respectively. For $\ln ED\_MS_{b,p,t-1}$, external disasters are weighted by market share, which represents a bank's market shares across all provinces excluding province p, weighted by the market share in each of those provinces, and then normalised by the bank's total market share. We calculate this as

$$ED\_MS_{b,p,t} = \frac{\sum_{j \neq p} MS_{b,j,t} \times DR_{j,t}}{\sum_{j \neq p} MS_{b,j,t}} \tag{3}$$

where $MS_{b,j,t}$ is the market share of bank b in province j at time t and $DR_{j,t}$ is the disaster ratio in province j at time t. The summation over $j \neq p$ indicates that we consider all provinces except province p. This normalisation is necessary to make banks of different sizes comparable. Otherwise, larger banks with higher market shares would mechanically have higher values everywhere. A higher external disaster-weighted market share indicates that the bank has a greater presence in other provinces that have experienced relatively severe disasters, suggesting a potentially higher exposure to disaster-related risks outside province p.

The external-disaster weighted portfolio share is calculated similarly. Specifically,

$$ED\_PS_{b,p,t} = \frac{\sum_{j \neq p} PS_{b,j,t} \times DR_{j,t}}{\sum_{j \neq p} PS_{b,j,t}} \tag{4}$$

where the disaster-weighted portfolio share is a weighted average of the disaster ratios across provinces excluding province p, where the weights are the bank's portfolio shares in those provinces. This measure reflects the average disaster exposure in a bank's portfolio outside province p, weighted by the bank's lending to the remaining provinces.

Finally, we measure the effects of climate shocks. $FR_{p,t-1}$ is the forecast revision variable and depicts the climate news shock during and outside El Niño. $\ln DR_{p,t-1}$ represents the Disaster Ratio in logarithmic terms, measuring the actual climate event shock during and outside El Niño.

Bank- and province-time fixed effects, $\alpha^1_{b,t}$ and $\alpha^2_{p,t}$, respectively, are added to control for unobserved characteristics at the bank and province level. Therefore, the direct impacts of $FR_{p,t-1}$ and $\ln DR_{p,t-1}$ are absorbed, meaning that the estimated impacts of β_5 to β_{20} will reflect the effect of various characteristics on the impact of climate shocks, $FR_{p,t-1}$ and $\ln DR_{p,t-1}$. To calculate the individual effects of climate shocks, we will estimate their marginal effects by bank characteristics. The error term is shown by $\epsilon_{b,f,p,t}$ at the firm level.

4.4 Impact on Bank Capitalisation

In this section, we examine how climate news shock and the actual disaster shock affect banks' capital ratios. We compare these climate-related shocks and banks' capital decisions during and outside El Niño episodes, controlling for various bank characteristics. We rely on the previously introduced method of using forecast revision as the main channel for the climate news shock. To estimate banks' exposure to disaster risk, we use the two disaster measures introduced earlier, but now in two separate regressions. First, the market share-weighted disaster measures the size of natural disasters by weighting with the bank's market presence. Second, the portfolio share-weighted disaster measures the bank's balance sheet exposure. In contrast to the previous firm-level regression, we compute these variables for the bank without provincial differentiation in order to estimate bank-level effects. The separate disaster measures allow us to identify potential channels of disaster effects and detect if the market share or portfolio share weighting plays a more important role. We include bank and time fixed effects in both specifications to control for unobserved heterogeneity across institutions and over time.

We expect that if banks rely on the climate news shock in their decisions, the capital ratio will be affected differently during and outside El Niño seasons, depending on bank characteristics. We expect that during El Niño, forecast revisions would increase the level of capital, while outside El Niño, the effect would be insignificant.

Specifically, we estimate

$$
\begin{aligned}
Capital\ Ratio_{b,t} =& \beta_1 DisasterExposure_{b,t-1} + \beta_2 HHI_{b,t-1} + \beta_3 Mortgage_{b,t-1} \\
& \quad + \beta_4 ROE_{b,t-1} + \beta_5 Delinquency_{b,t-1} + \beta_6 OperativeRatio_{b,t-1} \\
& + DisasterExposure_{b,t-1} \times (\beta_7 HHI_{b,t-1} + \beta_8 Mortgage_{b,t-1} \\
& \quad + \beta_9 ROE_{b,t-1} + \beta_{10} Delinquency_{b,t-1} + \beta_{11} OperativeRatio_{b,t-1}) \\
& + ElNino_{t-1} \times DisasterExposure_{b,t-1} \times (\beta_{12} HHI_{b,t-1} + \beta_{13} Mortgage_{b,t-1} \\
& \quad + \beta_{14} ROE_{b,t-1} + \beta_{15} Delinquency_{b,t-1} + \beta_{16} OperativeRatio_{b,t-1}) \\
& + FR_{t-1} \times (\beta_{17} HHI_{b,t-1} + \beta_{18} Mortgage_{b,t-1} \\
& \quad + \beta_{19} ROE_{b,t-1} + \beta_{20} Delinquency_{b,t-1} + \beta_{21} OperativeRatio_{b,t-1}) \\
& + ElNino_{t-1} \times FR_{t-1} \times (\beta_{22} HHI_{b,t-1} + \beta_{23} Mortgage_{b,t-1} \\
& \quad + \beta_{24} ROE_{b,t-1} + \beta_{25} Delinquency_{b,t-1} + \beta_{26} OperativeRatio_{b,t-1}) \\
& + \alpha_b + \gamma_t + \epsilon_{b,t}
\end{aligned} \tag{5}
$$

This regression model examines the determinants of the capital ratio, a measure of bank risk that indicates the amount of capital the bank holds in reserve to finance its activities. It is denoted as $Capital\ Ratio_{b,t}$ for bank b at time t. Our main explanatory variables include two climate-related shock measures: $DisasterExposure_{b,t-1}$ (disaster exposure representing actual natural disasters) and FR_{t-1} (forecast revision, representing climate news). To account for the different importance of disasters for financial institutions, we compute $DisasterExposure_{b,t-1}$ as in Equation 3 and 4 with an important change. Previously, when calculating external disasters for a specific province, that province was excluded from the calculation. Now, we calculate disaster exposure at bank level rather than at provincial level, since all disasters need to be included in each bank's exposure measure.

We also contrast how these shocks affect bank capital ratios differently during and outside of coastal El Niño, denoted by $ElNino_{t-1}$. We control for several bank characteristics, such as $HHI_{b,t-1}$, which represents portfolio concentration, $Mortgage_{b,t-1}$, which represents mortgage loan ratio, $ROE_{b,t-1}$, which represents return on equity, $Delinquency_{b,t-1}$, which represents loan delinquency ratio, and $OperatingRatio_{b,t-1}$, which represents operating expense ratio. All variables are in percentages, except $HHI_{b,t-1}$ which is between 0 and 10 000. For more information on the variables, see Section 3.2.

We include interactions between both shock variables and bank characteristics, and triple interactions with the El Niño indicator to capture differential responses to climate shocks during El Niño. The specification also includes bank fixed effects (α_b), time fixed effects (γ_t), and an error term ($\epsilon_{b,t}$). All explanatory variables are lagged by one period to account for possible endogeneity.

5 Results

To understand whether banks react pre-emptively to potential climate news shocks measured by forecast revisions or reactively to natural disasters, we implement a two-pronged empirical strategy. First, we estimate the effect of these shocks on firm-level credit growth to measure changes in lending behaviour. We analyse how responses vary with financial institutions' characteristics and exposure to external shocks to identify supply-side versus demand-side drivers. Second, we examine how the same shocks of forecast revisions and natural disasters affect financial institutions' capital levels. The focus on capital levels allows us to assess financial institutions' risk management responses as a supply-side factor. In both strategies, we estimate the effects of forecast revisions and natural disasters using a triple-difference approach. We then compare their marginal effects during and outside El Niño episodes. Finally, we conduct robustness tests.

5.1 Impact on Credit Growth

To establish the baseline relationship between bank characteristics and credit growth under normal conditions, we first estimate their effects without climate shocks and outside El Niño episodes, based on Equation 2 (Table 7, *Panel A*). We find that if portfolio and market share increase by 1%, credit growth will increase by 0.0021% and 0.0011%, respectively, at the 1% significance level. These numbers may seem small, but we are considering the amount of change in monthly credit growth at the loan level. To illustrate, a 1 percentage point increase in the average portfolio and market share across all banks in the market is associated with an increase in credit growth of between 128 thousands and 207 thousands soles in the market per month. For calculation details, see Appendix F.1.

The measured effect of portfolio share indicates supply-side impacts on credit growth. This interpretation is based on the premise that debtors are less concerned about a province's balance sheet exposure than creditors are. Specifically, for every 1 percentage point increase in banks' portfolio share, available credit in the Peruvian economy increases by 128 thousand soles per month. This reflects the fact that a bank's increased exposure on its balance sheet translates into much greater credit availability. This could potentially reflect economies of scale in lending, greater availability of information for creditors, or relationship lending in concentrated markets (Tomarchio, 2022). Market share effects, which translate into 207 thousand soles economy-wide, are more ambiguous. It shows either easier credit access where a financial institution is stronger, reflecting increased demand, or a willingness to provide credit where it is responsible for more lending, indicating a supply-side factor.

Next, we examine the remaining two effects in *Panel A*, external disasters weighted by portfolio and market share. We find that there is no effect of portfolio- and market-share-weighted external disasters on credit growth. This suggests that financial institutions' greater exposure to natural disasters in regions outside the debtor's province has no impact on credit growth, without changes in forecast revisions and natural disasters within the province, and outside El Niño episodes. Having established these baseline relationships, we now examine how these variables will affect climate shocks, as measured by forecast revisions and natural disasters (Table 7, *Panel B-E*).

5.1.1 Effect of Forecast Revisions

Forecast revisions represent ex-ante information about climate risk before events materialise, allowing us to measure pre-emptive responses by banks. To study whether banks react pre-emptively to climate information, we contrast the effects of forecast revisions with the interaction of bank characteristics during and outside of El Niño episodes (Table 7, *Panel B* and *C*). We find that forecast revisions have a significant effect on credit growth, with different signs depending on El Niño. Specifically, during El Niño episodes, if portfolio share or portfolio-share weighted external disaster exposure increases by 1%, the effect of a 10 percentage points forecast revision will increase by 0.0004% and 0.0017%, respectively (Table 7, *Panel C*). This means that when the portfolio share of a financial institution is higher in a province, a positive forecast revision will further boost credit growth.

Nonetheless, outside of El Niño episodes, we estimate negative interaction terms between both forecast revisions and portfolio share and market share-weighted external disasters (Table 7, *Panel B*). We find that, when portfolio share or market share-weighted external disaster exposure increases by 1%, the effect of a 10 percentage points forecast revision decreases by -0.0002% and -0.0027%, respectively. This suggests that, outside of El Niño episodes, the changes of forecast revisions will have a smaller impact and even decrease credit growth.

To determine whether the effects of forecast revisions vary according to bank characteristics, we estimate their marginal effects (Figure 5). First, we estimate the effect of forecast revisions by local bank characteristics measured by portfolio and market share. Figure 5a shows the effect of the triple difference estimator of the forecast revision depending on the level of portfolio share. We find that during El Niño, a 10 percentage points forecast revision increases credit growth by 0.005%. This corresponds to 8% of the absolute average credit changes. After aggregating the number over all firms, we measure an increase in credit by 54 million soles (For calculation details, see Appendix F.2). This amount equals to 0.06% of the monthly Peruvian GDP (World Bank, 2023). Outside of El Niño, however, the effect is negative, equal to 4% of the absolute average credit changes. These results suggest that climate news shocks about the probability of El Niño, as measured by forecast revisions, have a positive effect on credit growth during El Niño and a negative effect outside El Niño. That is, during El Niño a news shock of increased probability of experiencing El Niño, increases credit growth. Outside El Niño, a negative forecast revision, reflecting a decreased probability of El Niño, increases credit growth.

Second, we estimate the marginal effects of forecast revision at different values of market share. We find that the estimated effects are similar to those for portfolio share. Specifically, we find that the estimated effects are equivalent to 8% of average credit growth during El Niño and 4% outside of El Niño (Figure 5b).

Having examined how forecast revisions interact with a bank's local characteristics measured by portfolio and market share, we now measure how they interact with a bank's external disaster exposure. This external exposure provides a stronger test for supply-side mechanisms, as it reflects each bank's external risk management considerations rather than local market conditions. First, we estimate the effect of forecast revisions and find that it varies significantly with the size of the external disaster exposure weighted by portfolio share. During El Niño, the effect of the forecast revision increases from zero to 0.01%, which equals 17% of average credit growth, as the portfolio share-weighted external disaster exposure increases (Figure 5c). This reflects that banks adjust their balance sheets as external disaster exposure increases. Outside of El Niño, the effect is slightly negative and does not vary with the size of the portfolio share-weighted external disaster exposure.

Second, we estimate how the effect of forecast revisions varies with market share-weighted external disaster exposure, finding a different pattern than with portfolio weighting (Figure 5d). We estimate that a 10 percentage point forecast revision increases credit growth by 0.008%, equivalent to approximately 14% of average credit growth, when the external disaster exposure of a financial institution, weighted by market share, is small. However, when external disaster exposure is large, credit growth is reduced by about the same amount. The pattern is the same outside El Niño, but the estimated effects are not significant at the 5% level. These results suggest that, if forecast revisions increase and the bank has a prominent presence in disaster-hit provinces, it will reduce credit growth in its unaffected provinces. However, this effect is smaller, or may even disappear, if the bank does not have a strong presence in the other disaster-hit provinces. In this case, the bank will increase average credit growth. Overall, these results demonstrate that banks respond pre-emptively to climate forecast information that vary systematically with both their local market presence and external risk exposure. We now examine whether banks also react to actual natural disasters after they occur.

5.1.2 Effect of Natural Disasters

We repeat the same exercise using the second shock in our study, the impact of natural disasters during and outside of El Niño episodes. We find that the impact of natural disasters, as measured by the changes in the affected population relative to the provincial average, has no significant effect at the 5% significance level, either during or outside of El Niño episodes (Table 7, *Panel D* and *E*). This result has two implications. First, the lack of reaction to disasters suggests that debtors do not increase their demand for loans for rebuilding purposes after disasters strike. Therefore, we conclude that demand-side effects do not appear to play an important role in the estimated outcomes. Second, financial institutions do not react to natural disasters ex-post. These results suggest that natural disasters do not have an effect on credit growth.

To see if the effect of natural disasters varies by bank characteristics, we measure their marginal effects by local bank characteristics and external exposure to disasters. We find that natural disasters have no effect on credit growth regardless of bank characteristics, such as portfolio or market share, and external disasters weighted by portfolio and market share (Figure 6). In addition, there is no significant difference between the response during and outside El Niño episodes. These results suggest that, after controlling for the average disaster in a province using province-time fixed effects, the remaining variation in credit growth is not affected by the size of the disaster, whether it occurs during or outside El Niño.

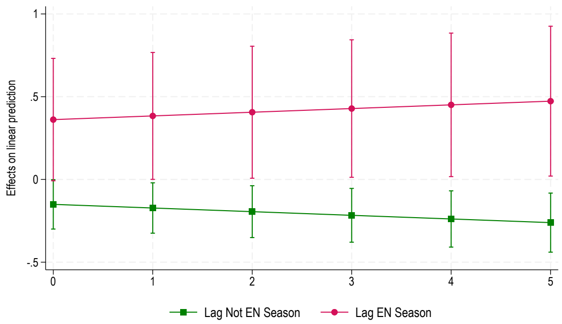
Our findings reveal a clear pattern in how financial institutions respond to climate shocks. We found that they react pre-emptively to revisions in climate forecasts, yet show no significant reaction to actual natural disasters. Alongside the observed patterns in bank-specific characteristics, these results suggest that financial institutions, rather than debtors, drive the estimated effects and engage in pre-emptive portfolio adjustments based on climate forecasts.

Table 7: Effect of climate shocks on log firm credit growth, multiplied by 100

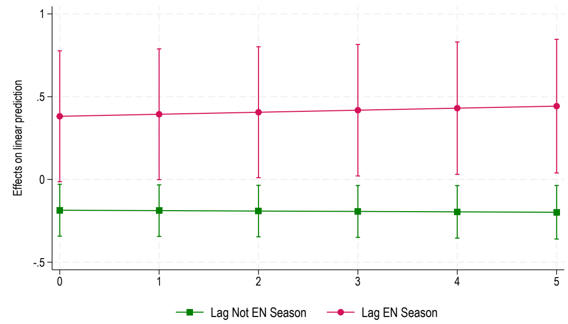
Variable	Coefficient	S.E.
Panel A: Covariates		
Portfolio Share ($\ln PS_{t-2}$)	0.2139***	(0.0535)
Market Share ($\ln MS_{t-2}$)	0.1102***	(0.0303)
External Disaster - Portfolio ($\ln ED\_PS_{t-1}$)	0.2156*	(0.1256)
External Disaster - Market ($\ln ED\_MS_{t-1}$)	-0.3528	(0.2784)
Panel B: Forecast Revision Interactions		
$FR_{t-1} \times \ln PS_{t-2}$	−0.0221***	(0.0083)
$FR_{t-1} \times \ln MS_{t-2}$	-0.0025	(0.0066)
$FR_{t-1} \times \ln ED\_PS_{t-1}$	0.0003	(0.0141)
$FR_{t-1} \times \ln ED\_MS_{t-1}$	−0.2732**	(0.1315)
Panel C: El Niño × Forecast Revision Interactions		
$ElNino_{t-1} \times FR_{t-1} \times \ln PS_{t-2}$	0.0444***	(0.0172)
$ElNino_{t-1} \times FR_{t-1} \times \ln MS_{t-2}$	0.0147	(0.0129)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_PS_{t-1}$	0.1677**	(0.0724)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_MS_{t-1}$	-0.2405	(0.2495)
Panel D: Disaster Ratio Interactions		
$\ln DR_{t-1} \times \ln PS_{t-2}$	0.0759*	(0.0455)
$\ln DR_{t-1} \times \ln MS_{t-2}$	-0.0034	(0.0230)
$\ln DR_{t-1} \times \ln ED\_PS_{t-1}$	0.0151	(0.0418)
$\ln DR_{t-1} \times \ln ED\_MS_{t-1}$	0.0414	(0.0716)
Panel E: El Niño × Disaster Ratio Interactions		
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln PS_{t-2}$	0.0042	(0.0439)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln MS_{t-2}$	0.0033	(0.0341)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_PS_{t-1}$	-0.0580	(0.0545)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_MS_{t-1}$	0.0763	(0.1078)
Observations	22,857,025	
R-squared	0.0028	
Adjusted R-squared	0.0017	
Bank × Time FE	Yes	
Province × Time FE	Yes	

Notes: This table reports the results of regressing the firm-level credit growth (multiplied by 100) on bank exposure measures. $\ln PS$ shows Portfolio Share, $\ln MS$ is Market Share, $\ln ED\_PS$ is External Disaster weighted Portfolio Share, $\ln ED\_MS$ is External Disaster weighted Market Share, FR shows Forecast Revision, with the unit being 10 percentage points, DR depicts Disaster Ratio, $ElNino$ is the El Niño indicator being equal to one during coastal El Niño. Standard errors are clustered at the bank-province level. * p<0.1, ** p<0.05, *** p<0.01.

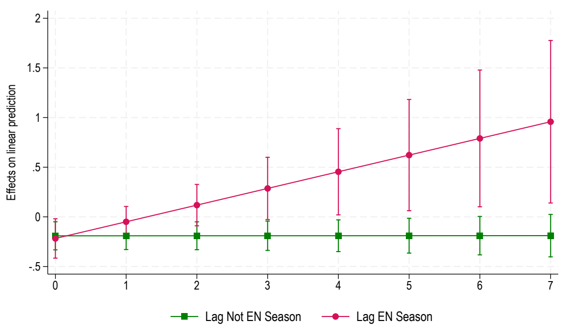
Figure 5: Marginal effects of forecast revision by bank characteristics on firm-level credit growth



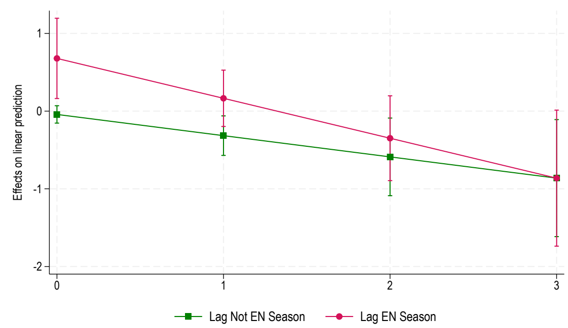
(a) Portfolio Share



(b) Market Share



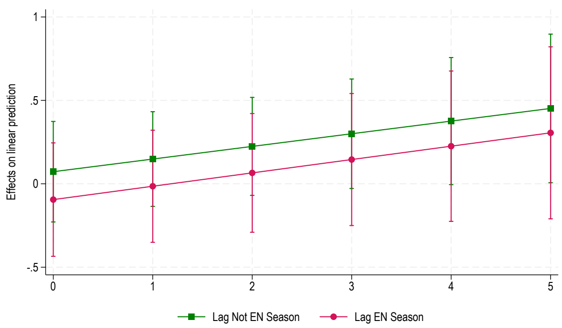
(c) ED PS



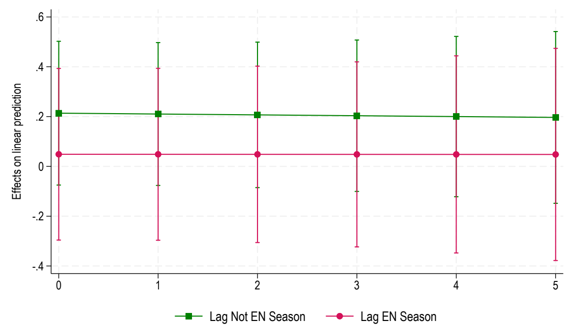
(d) ED MS

Notes: This figure shows the marginal effects of climate forecast revisions on firm-level credit growth conditional on bank characteristics, during El Niño (red circle) and non-El Niño (green square) periods. Each panel represents a different bank characteristic: Portfolio Share (PS) measures the importance of provincial lending on a bank's balance sheet; Market Share (MS) captures a bank's relative importance within a province; ED PS (External Disasters - Portfolio weighted) quantifies a bank's exposure to climate disasters in other provinces weighted by its portfolio allocation; and ED MS (External Disasters - Market weighted) represents a bank's exposure to climate disasters in other provinces weighted by its market presence. The vertical error bars represent the 95% confidence interval. All specifications include bank-time and province-time fixed effects. Standard errors are clustered at the bank-province level.

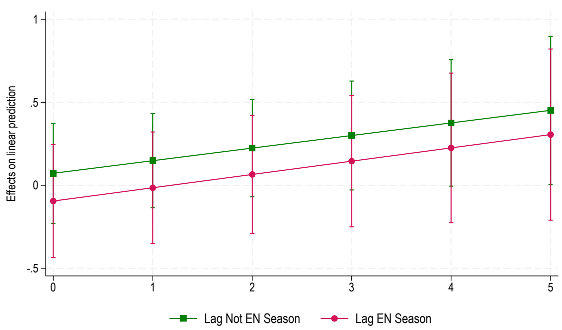
Figure 6: Marginal effects of natural disasters by bank characteristics on firm-level credit growth



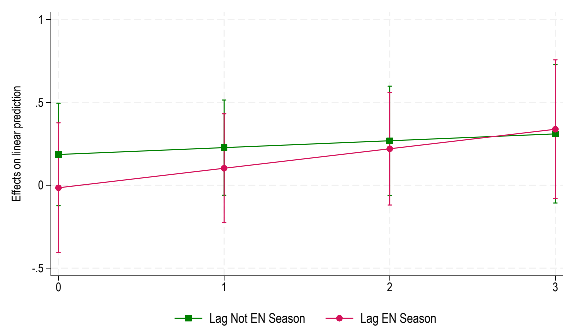
(a) Portfolio Share



(b) Market Share



(c) ED PS



(d) ED MS

Notes: This figure shows the marginal effects of natural disasters on firm-level credit growth conditional on bank characteristics, during El Niño (red) and non-El Niño (green) periods. Each panel represents a different bank characteristic: Portfolio Share (PS) measures the importance of provincial lending on a bank's balance sheet; Market Share (MS) captures a bank's relative importance within a province; ED PS (External Disasters - Portfolio weighted) quantifies a bank's exposure to climate disasters in other provinces weighted by its portfolio allocation; and ED MS (External Disasters - Market weighted) represents a bank's exposure to climate disasters in other provinces weighted by its market presence. The vertical error bars represent the 95% confidence interval. All specifications include bank-time and province-time fixed effects. Standard errors are clustered at the bank-province level.

5.2 Impact on Bank Capitalisation

To understand how banks incorporate perceived risk into their operations, we examine how banks' capital ratios, a measure of bank risk that indicates the amount of capital the bank holds in reserve to finance its activities, respond to the forecast revision and the actual disaster shock, shown in Equation 5. We follow the same empirical approach as in the firm-level estimation, with two modifications in the disaster exposure variable. First, we calculate the disaster exposure measures at the bank level without distinguishing between external and internal disasters. This change is necessary because we want to measure the impact of shocks at the bank level rather than at the bank-province level. Second, we now consider the two different measures of disaster exposure separately in order to compare their effects. We aim to distinguish between the effects of disasters to see whether portfolio-weighted or market-share-weighted disaster exposure plays a more important role. These two specifications allow us to compare our two weighting techniques and examine whether they have different effects on banks' capital ratios.

Table 8 shows the measured effects of climate shocks, bank characteristics and their interactions with the two different weighting techniques used to calculate disaster severity. We start by interpreting the results without changes in forecast revisions and natural disasters, outside of El Niño episodes (Table 8, *Panel A*). We find that the HHI Portfolio, which shows the portfolio concentration of a given bank, has a significant positive effect on the bank's capital ratio. The capital ratio increases by 3 percentage points when the HHI increases by 1000 points, which is significant at the 1% level in both specifications. This means that if a bank is more exposed to a province, it will have higher capital ratios. Other bank characteristics, such as mortgage loan ratio, ROE, delinquency ratio and operating ratio, do not show statistically significant effects in either specification. These results suggest that the interaction terms, bank fixed effects and time fixed effects account for most of the variation, and after controlling for the average of bank characteristics by bank and time, only the HHI remains significant.

5.2.1 Effect of Forecast Revisions

To understand whether forecast revisions affect the capital ratio differently during and outside El Niño, we measure their interactions with bank characteristics (Table 8, *Panel*

B, C). In particular, we find that outside El Niño, they do not affect the capital ratio differently in either specification as depicted by the insignificant coefficients of the forecast revision interactions (Table 8, *Panel B*). During El Niño, however, we measure several significant positive interactions (Table 8, *Panel C*). In particular, the forecast revision has a positive coefficient between 0.11-0.12 percentage point with ROE, significant at the 5% and 1% levels, depending on whether portfolio or market share-weighted disaster exposure was used in the estimation. This implies that if ROE increases by 1 percentage point, the effect of forecast revision will increase by 0.11-0.12 percentage point. For the delinquency rate, we estimate a coefficient between 0.71 and 0.74 percentage point, significant at the 5% and 1% levels. These results suggest that forecast revisions affect banks' capital ratios differently during El Niño and outside El Niño episodes. We see that banks will adjust their capital ratios more after a shock in forecast revision if they have larger ROE or higher delinquency ratios. Specifically, this increase corresponds to 1.2 and 7.5 times the average change in a bank's capital ratio over time, for ROE and delinquency ratio, respectively.

To estimate the impact of forecast revisions alone, we calculate their total marginal effects during and outside El Niño. We find that during El Niño, the effect of the forecast revision is 1.1 and significantly different from zero at 1% level. This means that if the forecast revision increases by 10 percentage points, the capital ratio increases by 1.1 percentage points. This value is 6% of the average capital ratio, equal to 18.5%. Outside of El Niño, however, the effect is not significantly different from zero.

To see if the estimated effect differs according to different values of bank characteristics, we calculate the marginal effects by bank variable (Figure 7). We find that the pattern of forecast revisions does not change. The effects outside the El Niño period remain insignificant and are positively significant during the El Niño period. However, we find that forecast revisions increase more for banks with specific characteristics. First, we find that the effect of forecast revisions during El Niño is between 1 and 2 percentage points of capital ratio for banks with different HHI and mortgage loan values (Figure 7a and 7b).

For other bank-level variables, the effect differs much more. For ROE, the effect of forecast revision increases up to 2 percentage points, equivalent to 11% of the average capital ratio, conditional on the largest value of ROE (Figure 7c). This means that banks will increase their capital ratios more in response to a 10 percentage points forecast revision during El Niño if they have a higher ROE. This result may seem counterintuitive at first, as a higher capital ratio conventionally reduces ROE. However, in this case, we see that the effect of the forecast revision is larger for a bank with a higher ROE, i.e., a more profitable bank. More profitable banks may have more financial flexibility to increase capital during expected climate shocks while still maintaining acceptable returns to shareholders, or they may be more proactive in building capital buffers when climate risks are forecasted.

Second, the effect of forecast revisions increases up to 10 percentage points, equivalent to 54% of the average capital ratio, for large delinquency ratios (Figure 7d). This means that as banks accumulate larger amounts of non-performing loans, they will react more strongly to forecast revisions, especially during a period of known climate risk. This result is more intuitive, showing that more exposed banks will react more strongly to risks.

Third, the relationship with the operating ratio is similar to that with the ROE and the delinquency ratio. Specifically, banks with higher operating ratios will increase their capital by up to 4 percentage points, equivalent to 22% of the average capital ratio, when the forecast revision increases by 10 percentage points (Figure 7e). This implies that less efficient banks will increase their adjustment during an El Niño period.

These positive and significant interactions suggest that during El Niño episodes, banks respond to forecast revisions by increasing their capital positions, especially banks with higher ROEs, higher delinquency rates and higher operating ratios. This indicates that during periods with a high probability of climate shocks, such as El Niño, banks consider forecasted climate risks more and adjust their behaviour pre-emptively via their capital ratios.

5.2.2 Effect of Natural Disasters

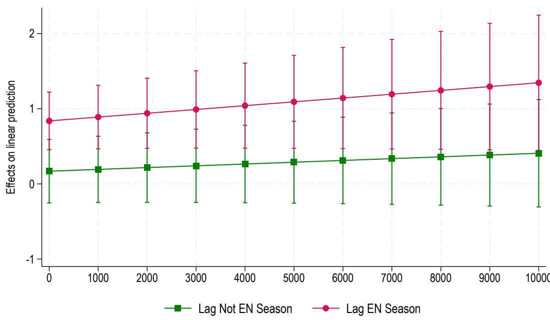
To contrast the effect of climate shocks, we estimate the effect of disaster exposure weighted by the bank's portfolio share. We find that disaster exposure has no significant effect on the capital ratio during or outside of El Niño episodes (Table 8, *Panel D, E*). We also examine the marginal effects by bank characteristics. We find no significant effect by HHI, mortgage loans, ROE, delinquency ratio, and operating ratio (Figure 8a-8e). Effects are also not significant for the average financial institution. Similar results from estimation based on banks' market share are in Appendix F in Figure F.1 and F.2.

Table 8: Effect of Climate Shocks on Bank Capital Ratio

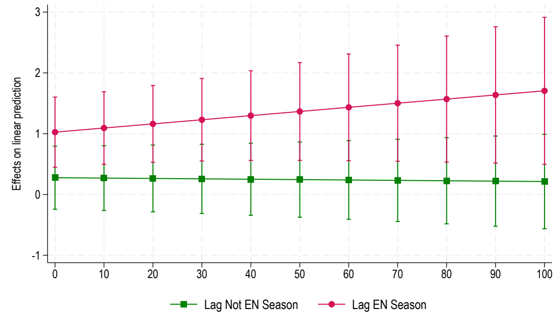
	Portfolio Share		Market Share	
Variable	Coef.	S.E.	Coef.	S.E.
Panel A: Covariates				
$Disaster\ Exposure_{t-1}$	0.0004	(0.0018)	0.116	(0.186)
$HHI\ Portfolio_{t-1}$	3.001***	(0.0114)	2.994***	(0.0011)
$MortgageLoan_{t-1}$	0.0990	(0.0983)	0.1032	(0.0944)
ROE_{t-1}	0.3702	(0.5081)	0.3890	(0.5320)
$Delinquency\ Rate_{t-1}$	2.9177	(2.4919)	3.0147	(2.4581)
$Operating\ Ratio_{t-1}$	-0.3598	(1.0627)	-0.2418	(1.0331)
Panel B: Forecast Revision Interactions				
$FR_{t-1} \times HHIPortfolio_{t-1}$	0.0000	(0.0000)	0.0000	(0.0000)
$FR_{t-1} \times MortgageLoan_{t-1}$	-0.0063	(0.0235)	-0.0055	(0.0241)
$FR_{t-1} \times ROE_{t-1}$	0.0112	(0.0334)	0.0194	(0.0346)
$FR_{t-1} \times Delinquency_{t-1}$	0.1317	(0.3238)	0.1444	(0.3222)
$FR_{t-1} \times OperatingRatio_{t-1}$	0.1500*	(0.0817)	0.1725**	(0.0773)
Panel C: El Niño × Forecast Revision Interactions				
$ElNino_{t-1} \times FR_{t-1} \times HHIPortfolio_{t-1}$	0.0000	(0.0000)	0.0000	(0.0000)
$ElNino_{t-1} \times FR_{t-1} \times MortgageLoan_{t-1}$	0.0743	(0.0640)	0.0682	(0.0657)
$ElNino_{t-1} \times FR_{t-1} \times ROE_{t-1}$	0.1190***	(0.0440)	0.1113**	(0.0493)
$ElNino_{t-1} \times FR_{t-1} \times Delinquency_{t-1}$	0.7387***	(0.2901)	0.7068**	(0.2826)
$ElNino_{t-1} \times FR_{t-1} \times OperatingRatio_{t-1}$	0.2222*	(0.1221)	0.2227*	(0.1269)
Panel D: Disaster Exposure Interactions				
$Disaster_{t-1} \times HHI\ Portfolio_{t-1}$	0.0000	(0.0000)	-0.0000	(0.0000)
$Disaster_{t-1} \times Mortgage\ Loan_{t-1}$	-0.0004	(0.0003)	-0.0481	(0.0376)
$Disaster_{t-1} \times ROE$	-0.0002	(0.0005)	-0.0135	(0.0290)
$Disaster_{t-1} \times Delinquency_{t-1}$	0.0015	(0.0023)	0.0685	(0.2404)
$Disaster_{t-1} \times OperatingRatio_{t-1}$	-0.0026***	(0.0009)	-0.1810***	(0.0432)
Panel E: El Niño × Disaster Exposure Interactions				
$ElNino_{t-1} \times Disaster_{t-1} \times HHIPortfolio_{t-1}$	-0.0000	(0.0000)	-0.0000	(0.0000)
$ElNino_{t-1} \times Disaster_{t-1} \times MortgageLoan_{t-1}$	0.0010*	(0.0005)	0.1174**	(0.0534)
$ElNino_{t-1} \times Disaster_{t-1} \times ROE_{t-1}$	0.0003	(0.0003)	-0.0102	(0.0393)
$ElNino_{t-1} \times Disaster_{t-1} \times Delinquency_{t-1}$	-0.0022	(0.0019)	-0.2310	(0.1493)
$ElNino_{t-1} \times Disaster_{t-1} \times OperatingRatio_{t-1}$	0.0042	(0.0055)	0.1186	(0.0857)
Observations	5,223		5,223	
Adjusted R-squared	0.7363		0.7365	
Bank FE, Time FE	Yes		Yes	

Notes: This table reports the results of regressing bank capital ratio on climate shocks and bank characteristics. The first two columns use portfolio share-weighted disaster exposure, while the last two columns use market share-weighted disaster exposure. All explanatory variables are lagged by one period. FR is the Forecast Revision. Forecast revisions are in 10 percentage points, HHI's unit is 1000, and the remaining variables are in percentages. Standard errors are clustered at the bank level and shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

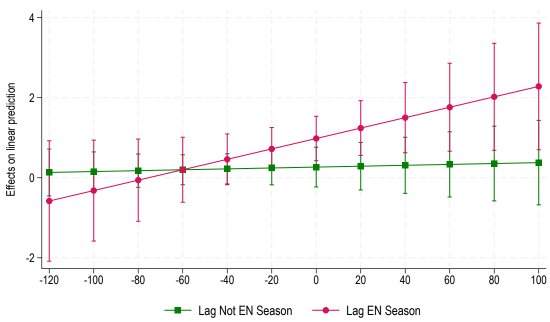
Figure 7: Marginal Effects of Forecast Revision by Bank Characteristics on Capital Ratio



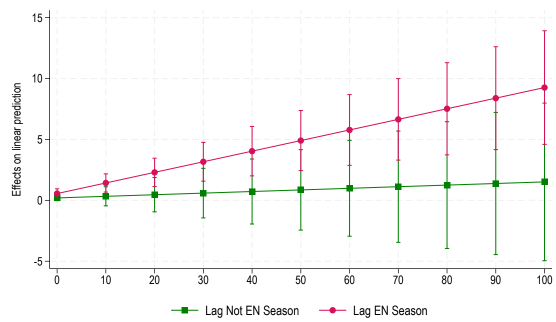
(a) HHI



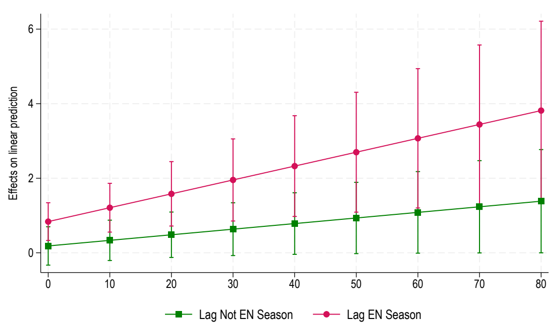
(b) Mortgage Loan



(c) ROE



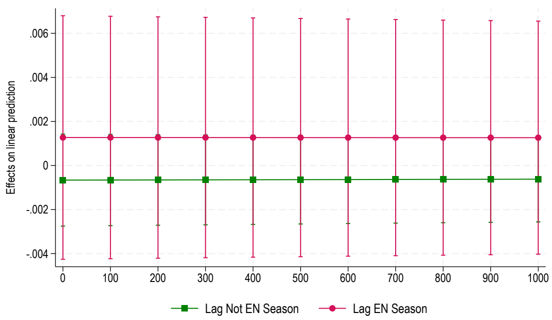
(d) Delinquency Ratio



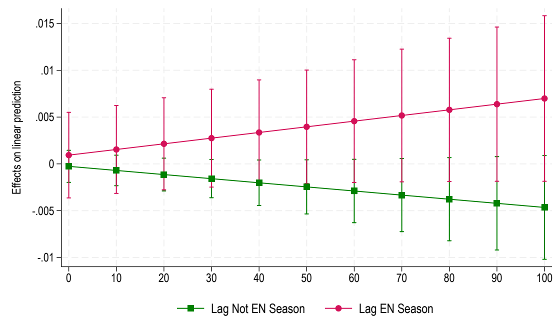
(e) Operating Ratio

Notes: This figure shows the marginal effects of forecast revisions on bank capital ratios during El Niño (red circle) and non-El Niño episodes (green square). The x-axis represents the values of bank characteristics (HHI = portfolio concentration, ROE = return on equity, Operating Ratio = operating expense ratio), while the y-axis shows the percentage change in the capital ratio due to a one percent change in the forecast revision, conditional on bank characteristics, with 95% confidence intervals. The Portfolio Share-Weighted Disaster Exposure is used in the regression.

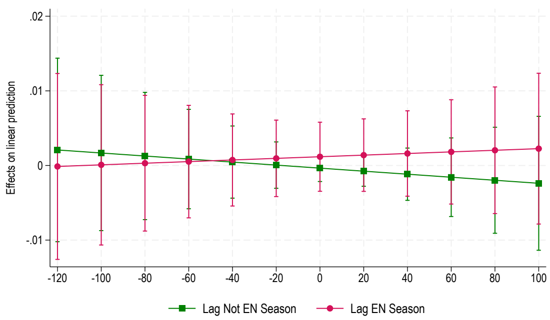
Figure 8: Marginal Effects of Portfolio Share-Weighted Disaster Exposure by Bank Characteristics on Capital Ratio



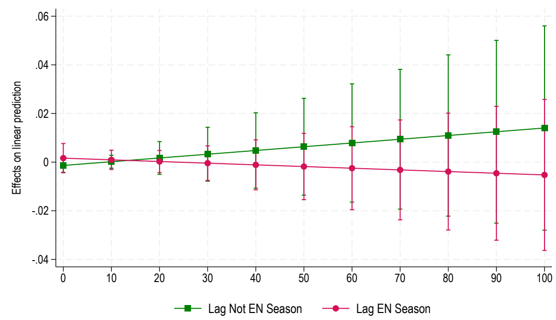
(a) HHI



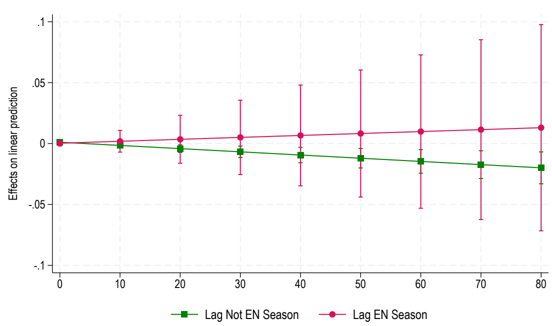
(b) Mortgage Loan



(c) ROE



(d) Delinquency Ratio



(e) Operating Ratio

Notes: This figure shows the marginal effects of portfolio share-weighted disaster exposure on bank capital ratios during El Niño (red circle) and non-El Niño episodes (green square). The x-axis represents the values of bank characteristics (HHI = portfolio concentration, ROE = return on equity, Operating Ratio = operating expense ratio), while the y-axis shows the percentage change in the capital ratio due to a one percent change in disaster exposure, conditional on bank characteristics, with 95% confidence intervals.

5.3 Robustness

We take several further steps to reflect on our results. First, we re-estimate the effects of different financial institutions. We find that the effects primarily come from financial companies. Specifically, Table F.1 shows that the effect of the portfolio share in the baseline estimation, without climate shocks and outside of El Niño, is 0.00646, which is three times the size of the portfolio share in the regression including all financial institutions (*Panel A*). This result indicates that the balance sheet exposure of a financial company in a province will increase credit growth relatively more than other financial institutions, such as banks. However, market share is no longer significant, reflecting that financial companies usually have smaller market shares compared to banks, 4% and 12%, respectively. Focusing on forecast revisions, their effects outside El Niño periods are insignificant (*Panel B*). During El Niño periods, however, the effects of market share and external disaster-weighted portfolio share are significant at the 1% level, reflecting that, as these values increase, the effect of forecast revisions will also increase (*Panel C*). We repeat the calculation for the marginal effects of forecast revisions. Similar patterns emerge, with effects two to four times greater than in the main sample (Figure F.3).

Second, we test if the results remain if we concentrate only on firms with multiple bank relations allowing for demand side control (Khwaja & Mian, 2008). We rerun our firm-level estimations on firms having multiple creditors focusing on financial companies (Table F.2). In this setup, we add firm-level fixed effects to control for any remaining demand effects. The results show that patterns remain the same (Figure F.4)

Third, our focus is on the service sector (Table F.3). Unlike agriculture, the service sector is non-tradable and not directly exposed to the effects of climate disasters. Therefore, if the estimated effects persist, this provides further evidence that they originate from the supply side. We find that forecast revisions are significant and positive during El Niño periods (Table F.3, *Panel C*). The pattern for marginal effects is the same, but the estimated effects are much larger, four times larger than in the whole sample (Figure F.5). We also observe positive, significant effects of market-share-weighted external disasters during El Niño, and negative, significant effects outside El Niño episodes. This suggests that, for a financial company with a large market share, the impact of an internal disaster will be greater during an El Niño episode and smaller outside of such episodes.

Finally, we focus on the firm-bank relations in the service sector with multiple bank relations. Again the effects are similar (Table F.4) with similar patterns (Figure F.6).

6 Conclusion

In this paper, we compared the effects of two types of climate shock: forecast revisions, which represent climate news shocks, and natural disasters, which represent actual climate events. We examined these effects during and outside of El Niño episodes in Peru to determine whether financial institutions react pre-emptively or reactively to climate shocks. Our empirical findings provide strong evidence that financial institutions respond pre-emptively to climate information rather than reactively to climate events. This conclusion is supported by three key results.

To distinguish between supply- and demand-driven changes, we took several steps. First, we measured the effects at the firm level and then at the bank level. At the firm level, we were able to calculate extra-provincial disaster measures to account for out-of-province disasters. This step made it possible for lenders to be primarily affected by external disaster measures rather than debtors, who are exposed to disasters that affect them in their place of activity. Second, at the bank level, we focused on changes in the capital ratio. Finally, we examined the effects of forecast revisions on bank characteristics to measure whether the estimated effects would differ across financial institutions based on their characteristics. The premise is that different bank characteristics, such as operating ratios, should primarily be of interest to lenders, rather than borrowers. Indeed, we find different responses of forecast revisions across bank characteristics.

In terms of credit growth, at the level of bank-firm pairs, we find that the effects of forecast revisions are positive during El Niño. That is, credit growth is higher during El Niño when the climate news shock is larger, as measured by higher forecast revisions. The effects vary with higher market or portfolio share-weighted external disaster exposures. We find that if a financial institution's portfolio or balance sheet is highly exposed, it will increase its portfolio share in the unaffected province to reduce its exposure in the affected province and thus protect its balance sheet. However, if their market share in an affected province is high, they will not increase their lending elsewhere. This can happen because financial institutions cannot change their market relevance quickly, especially if they are mainly active in a few regions where other financial institutions are not present.

In terms of bank capitalisation, similar to the firm level, we find that the effect of forecast revision is positive during El Niño. However, we find large heterogeneity across bank characteristics. Specifically, higher delinquency ratio, operating ratio and ROE increase the capital ratio more in the case of a forecast shock.

At first, the two findings may appear paradoxical, as higher capital ratios typically do not coincide with higher credit growth. However, financial institutions may increase the amount of cash they hold in order to become more liquid and reduce their risk-weighted assets, while providing more loans. In that case, their capital ratio would increase. In addition, the financial companies that govern my results are usually subsidiaries of foreign banks and insurance companies. In these cases, they may request a capital injection from their owners in preparation for El Niño. These two scenarios illustrate possible reasons for my results.

The findings on the impact of climate shocks on lenders' behaviour in Peru provide important lessons on financial sector resilience and adaptation to climate risks. Our analysis reveals three key findings. First, lending responses to disasters are primarily from supply-side factors, with bank characteristics and risk assessment practices playing a more important role than realised natural disasters. Second, there is a marked difference in lending patterns between El Niño and non-El Niño episodes, with banks showing a greater willingness to expand credit during El Niño events, suggesting adaptation to predictable climate risks. Third, the impact of climate news shock varies significantly depending on bank characteristics, especially with regard to return on equity, delinquency ratio, and capital ratio.

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Appendix

A El Niño

Table A.1: Descriptive Statistics of Forecasted Probabilities of El Niño Episodes (2011-2019)

Forecasts	Obs.	Mean (%)	Std. Dev.	Min (%)	Max (%)
Current	108	34.06	37.28	0	100
1-Month Lead	108	36.37	35.55	0	100
2-Month Lead	108	38.28	33.82	0	100
3-Month Lead	108	39.69	31.97	0	100
4-Month Lead	108	40.31	29.90	1	100
5-Month Lead	108	39.85	27.42	3	99
6-Month Lead	108	39.86	25.24	3	98
7-Month Lead	108	38.50	22.67	1	93
8-Month Lead	108	37.04	20.49	1	86
All Combined	972	38.22	29.82	0	100

Notes: The table presents descriptive statistics of probability forecasts of global El Niño episodes between 2011 and 2019. The table shows forecasts with different lead times, from current forecasts to those made 8 months in advance. As the lead time decreases from earlier (8-month) to current forecasts, the mean probability initially increases (peaking at 4-month lead) and then decreases to 34.06% for current forecasts. This difference from the overall average of 38.22% is not statistically significant.

Table A.2: Forecasted Probabilities of El Niño Episodes between 2011 and 2013

El Niño Episodes		**El Niño Probability by Lead Month**									**Forecast**
Coastal	**Global**	t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$	**Revision**
2011m1	2011m1	0	0	1	1	1	3	3	1	3	-3
2011m2	2011m2	0	1	2	2	2	3	4	5	1	-4
2011m3	2011m3	1	3	4	6	6	6	6	6	10	-5
2011m4	2011m4	3	6	9	10	12	13	13	13	13	-10
2011m5	2011m5	13	15	16	16	17	18	20	20	20	-7
2011m6	2011m6	7	21	23	23	24	23	23	24	23	-16
2011m7	2011m7	8	15	23	25	25	24	23	23	25	-15
2011m8	2011m8	1	12	15	23	26	25	24	23	23	-23
2011m9	2011m9	0	2	14	15	23	26	25	24	23	-25
2011m10	2011m10	0	1	2	14	15	23	26	25	24	-26
2011m11	2011m11	0	0	1	2	14	15	23	26	25	-23
2011m12	2011m12	0	1	1	2	2	14	15	23	26	-15
2012m1	2012m1	0	0	3	3	3	3	14	15	23	-14
2012m2	2012m2	0	0	0	5	5	6	7	15	16	-7
2012m3	2012m3	0	0	0	1	12	12	16	17	17	-16
2012m4	2012m4	2	5	5	4	6	22	22	23	24	-20
2012m5	2012m5	13	20	20	20	15	13	25	25	25	-12
2012m6	2012m6	31	37	35	31	27	20	17	25	25	14
2012m7	2012m7	62	48	48	44	35	30	23	24	25	39
2012m8	2012m8	77	71	56	54	46	34	31	24	26	46
2012m9	2012m9	82	78	77	61	55	44	34	30	25	48
2012m10	2012m10	56	83	79	81	64	53	44	37	32	12
2012m11	2012m11	24	56	81	79	78	61	52	41	41	-28
2012m12	2012m12	5	21	48	73	71	69	59	46	39	-54
2013m1	2013m1	0	5	21	40	59	58	58	48	43	-58
2013m2	2013m2	0	1	8	22	33	45	47	44	40	-47
2013m3	2013m3	0	1	4	11	25	30	35	35	35	-35
2013m4	2013m4	1	2	4	10	19	28	29	29	30	-28
2013m5	2013m5	2	7	9	13	19	23	31	27	26	-29
2013m6	2013m6	1	7	12	15	18	19	25	28	24	-24
2013m7	2013m7	1	5	13	16	18	19	19	24	24	-18
2013m8	2013m8	1	4	8	14	17	15	20	19	23	-19
2013m9	2013m9	1	3	5	9	14	16	15	20	17	-14
2013m10	2013m10	0	2	4	6	10	14	16	13	19	-16
2013m11	2013m11	0	1	3	6	9	9	14	16	14	-14
2013m12	2013m12	0	1	2	7	7	10	9	13	16	-9

Notes: Predicted probabilities of global El Niño episodes. The first two columns show the start dates, t, of the 3-month seasons, $t/t+2$. They are shaded when coastal or global El Niño episodes are declared by the Peruvian ENFEN or the US NOAA agencies, respectively. The probability columns show the predicted probabilities of global El Niño episodes starting at time t. They are predicted with a lead time x in month $t-x$. Colours indicate probability ranges: green (0-40%), yellow (41-59%), and red shades (60% and above). The forecast revision, the last column, shows the difference in percentage points between the 1 and the 6-month forecast. Data provided by the International Research Institute for Climate and Society, Columbia University Climate School, Link.

Table A.3: Forecasted Probabilities of El Niño Episodes between 2014 and 2016

El Niño Episodes		**El Niño Probability by Lead Month**									**Forecast**
Coastal	**Global**	t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$	**Revision**
2014m1	2014m1	0	2	4	5	10	10	12	12	14	-12
2014m2	2014m2	0	3	8	11	13	16	17	18	13	-17
2014m3	2014m3	1	5	13	16	21	22	22	23	23	-21
2014m4	2014m4	25	17	21	29	29	34	35	30	32	-10
2014m5	2014m5	50	48	38	37	40	38	42	42	36	8
2014m6	2014m6	61	59	61	50	44	43	43	48	44	18
2014m7	2014m7	51	65	62	68	56	44	45	45	48	6
2014m8	2014m8	42	60	69	67	74	55	46	45	44	-4
2014m9	2014m9	56	56	68	74	69	74	60	45	44	-4
2014m10	2014m10	65	67	64	74	78	70	79	60	45	-14
2014m11	2014m11	75	66	72	70	75	78	72	78	58	3
2014m12	2014m12	83	74	67	72	73	72	74	66	75	9
2015m1	2015m1	64	76	72	67	72	68	64	67	58	0
2015m2	2015m2	47	58	70	68	67	65	62	58	57	-15
2015m3	2015m3	59	47	55	65	66	65	59	55	50	0
2015m4	2015m4	81	69	54	53	61	61	61	53	51	20
2015m5	2015m5	97	80	71	58	52	56	57	55	49	40
2015m6	2015m6	99	93	81	72	61	50	54	53	48	45
2015m7	2015m7	100	97	90	80	70	57	47	51	46	53
2015m8	2015m8	100	99	95	88	80	64	56	46	46	44
2015m9	2015m9	100	100	99	94	87	74	63	53	41	37
2015m10	2015m10	100	100	100	98	92	82	75	59	51	25
2015m11	2015m11	100	100	100	100	97	90	82	73	58	18
2015m12	2015m12	100	100	100	100	99	96	91	79	72	9
2016m1	2016m1	100	100	100	100	100	99	96	88	75	4
2016m2	2016m2	100	100	100	100	100	99	98	93	86	2
2016m3	2016m3	100	99	99	98	98	97	97	91	86	3
2016m4	2016m4	76	80	77	68	71	82	73	78	69	3
2016m5	2016m5	3	19	31	32	28	37	50	36	49	-47
2016m6	2016m6	1	3	8	14	15	14	21	31	21	-20
2016m7	2016m7	1	1	4	6	11	13	9	15	22	-8
2016m8	2016m8	0	3	3	6	8	13	14	10	14	-14
2016m9	2016m9	0	3	5	4	8	10	16	15	10	-16
2016m10	2016m10	0	1	5	6	6	10	10	18	17	-10

Notes: Predicted probabilities of El Niño episodes. The first two columns show the start dates, t, of the 3-month seasons, $t/t+2$. They are shaded when coastal or global El Niño episodes are declared by the Peruvian ENFEN or the US NOAA agencies. The probability columns show the predicted probabilities of El Niño episodes starting at time t. They are predicted with a lead time x in month $t-x$. The forecast revision, the last column, shows the difference in percentage points between the 1 and the 6-month forecast. Data provided by The International Research Institute for Climate and Society, Columbia University Climate School, Link.

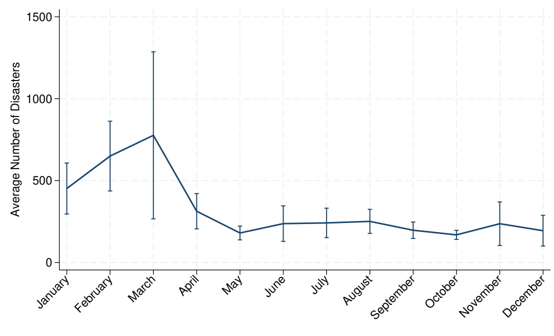
Table A.4: Forecasted Probabilities of El Niño Episodes between 2016 and 2019

El Niño Episods		**El Niño Episode Forecast by Lead Month**									**Forecast**
Coastal	**Global**	t	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$	**Revision**
2016m11	2016m11	0	1	2	5	8	6	9	10	16	-9
2016m12	2016m12	0	0	2	4	5	6	4	7	9	-4
2017m1	2017m1	1	2	1	2	4	4	5	3	6	-4
2017m2	2017m2	4	3	4	2	4	4	3	3	1	1
2017m3	2017m3	23	14	7	8	4	7	4	3	2	19
2017m4	2017m4	38	47	27	15	15	10	16	8	4	22
2017m5	2017m5	50	56	59	41	26	26	24	24	12	26
2017m6	2017m6	32	57	64	66	46	34	33	30	29	-1
2017m7	2017m7	30	35	59	67	68	48	38	33	32	-8
2017m8	2017m8	9	33	39	60	69	67	51	37	35	-42
2017m9	2017m9	1	16	36	41	60	67	66	48	39	-65
2017m10	2017m10	0	2	21	39	43	58	67	62	48	-67
2017m11	2017m11	0	0	3	21	38	42	59	65	60	-59
2017m12	2017m12	0	0	0	3	21	38	42	58	63	-42
2018m1	2018m1	0	0	0	1	4	22	38	40	57	-38
2018m2	2018m2	0	0	0	1	1	5	23	35	35	-23
2018m3	2018m3	0	2	3	0	2	3	7	26	34	-7
2018m4	2018m4	0	0	7	7	4	8	11	16	32	-11
2018m5	2018m5	5	11	9	14	17	16	22	24	29	-17
2018m6	2018m6	28	26	29	24	23	21	28	32	32	0
2018m7	2018m7	45	45	37	40	31	29	25	36	38	20
2018m8	2018m8	51	55	54	45	47	34	33	28	41	18
2018m9	2018m9	55	65	63	60	50	53	40	38	33	15
2018m10	2018m10	86	68	71	68	63	55	57	44	40	29
2018m11	2018m11	95	88	72	74	68	66	58	61	48	37
2018m12	2018m12	96	94	88	72	74	69	71	65	64	25
2019m1	2019m1	87	94	92	88	72	75	71	76	67	16
2019m2	2019m2	74	82	92	89	88	74	78	78	80	-4
2019m3	2019m3	94	76	77	90	85	88	76	78	76	18
2019m4	2019m4	95	90	75	71	85	78	83	71	70	12
2019m5	2019m5	80	83	83	67	65	78	70	73	62	10
2019m6	2019m6	65	66	74	77	61	59	71	66	67	-6
2019m7	2019m7	35	57	60	69	73	55	55	66	61	-20
2019m8	2019m8	25	38	56	57	64	69	51	51	62	-26
2019m9	2019m9	23	33	41	58	56	62	68	48	51	-45
2019m10	2019m10	25	35	39	46	59	55	62	61	48	-37
2019m11	2019m11	46	29	38	41	47	61	56	58	60	-10
2019m12	2019m12	52	40	28	40	41	48	61	56	60	-9

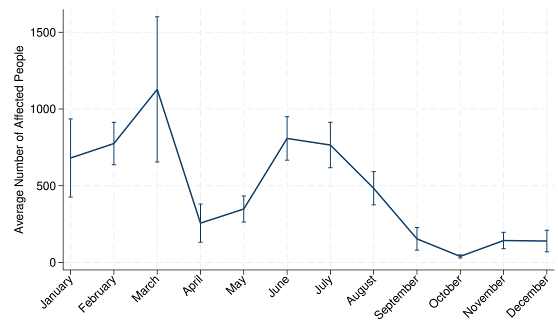
Notes: Predicted probabilities of global El Niño episodes. The first two columns show the start dates, t, of the 3-month seasons, $t/t+2$. They are shaded when coastal or global El Niño episodes are declared by the Peruvian ENFEN or the US NOAA agencies, respectively. The probability columns show the predicted probabilities of global El Niño episodes starting at time t. They are predicted with a lead time x in month $t-x$. Colours indicate probability ranges: green (0-40%), yellow (41-59%), and red shades (60% and above). The forecast revision, the last column, shows the difference in percentage points between the 1 and the 6-month forecast. Data provided by the International Research Institute for Climate and Society, Columbia University Climate School, Link.

B Disasters

Figure B.1: Average Disaster Metrics



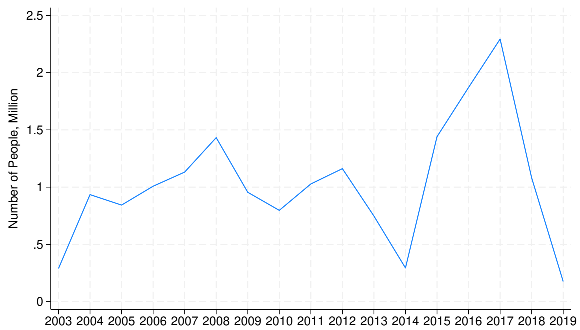
(a) Average number of disasters



(b) Average number of people affected

Notes: The figures illustrate the temporal trends of an average disaster between 2011 and 2019. Figure B.1a shows the yearly average number of disasters by month, showing a seasonal pattern of an increased number of disasters during the southern hemisphere summer. Figure B.1b shows the average number of people affected by month, showing the human impact of these events. Source: INDECI, SINPAD.

Figure B.2: Number of People Affected per Year



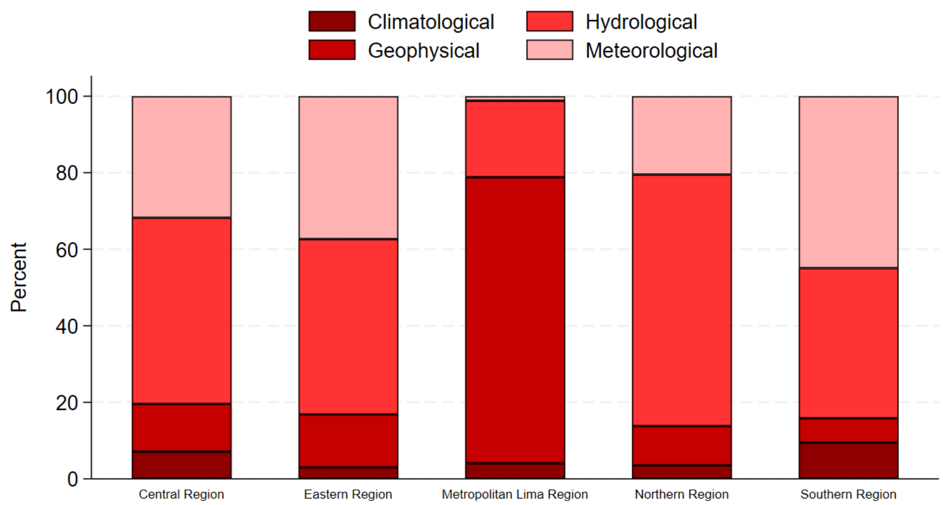
Notes: The figure presents the annual variation in the number of people affected by disasters in Peru. The year-by-year analysis reveals temporal patterns that correlate with coastal El Niño years. Source: INDECI, SINPAD.

Table B.1: Impact of El Niño on Disasters and Affected Population

El Niño	Number of Disasters		People Affected		Observations
	Mean	S.E.	Mean	S.E.	
No	1.52	0.029	370.18	20.66	14,700
Yes	1.95	0.066	719.14	74.28	6,468
Difference	-0.43^{***}		-348.96^{***}		21,168
t-statistic	-6.97		-5.99		

Notes: The table reports results from two-sample t-tests with equal variances. *** indicates statistical significance at the 1% level. During El Niño episodes, disasters are significantly more common and affect more people in Peru. Averages across time and 196 provinces in Peru. Source: SINPAD, INDECI.

Figure B.3: Distribution of N° of disasters by type of disaster across regions



Notes: The graph shows the distribution of disasters by type of disaster over different regions. Climatological emergencies include drought and forest fire. Geophysical emergencies include avalanche, erosion, mudslide, hill collapse and landslide. Meteorological emergencies include low temperature, thunderstorm and strong winds. Hydrological emergencies include flooding, sea storm surge and heavy rain. The Central Region comprises the departments of Ancash, Ayacucho, Huancavelica, Huanuco, Ica, Junín, Lima (excluding the province of Lima) and Pasco. The Eastern Region comprises the departments of Amazaonas, Loreto, San Martín and Ucayali. The Metropolitan Lima Region comprises the province of Lima and Callao. The Northern Region comprises the departments of Cajamarca, La Libertad, Lambayeque, Piura and Tumbes. The Southern Region comprises the departments of Apurimac, Arequipa, Cusco, Madre de Dios, Moquegua, Puno and Tacna. Source: SINPAD, INDECI.

C Financial Institutions

The concentration of Peruvian banks, as measured by the concentration of assets held by the five largest banks, is relatively high (88% of the total commercial banking assets) and stable compared to other Latin American countries, using the Global Financial Development data (code GFDD.OI.06). State-owned banks are not included, as they accounted for only 2% of the total credit stock in December 2019.

The number of banks owning more than 1% of loans decreased in 2015 due to mergers, such as that between Peru's largest bank, Banco de Crédito del Perú (BCP), and MiBanco, a microfinance bank. Multiple mergers occurred between 2015 and 2017, negatively affecting credit growth in districts where the merging companies were present while improving the quality of the credit portfolio and increasing interest rates (Romero, 2023). In addition, some financial institutions closed. For example, the microlender Financiera Edyficar ceased operations, and its branches were renamed MiBanco. Although BCP and MiBanco are both subsidiaries of the Peruvian financial services holding company Credicorp, their loans are listed separately in the credit registry. Following 2015, banks owning more than 1% of total loans emerged, reducing the number of remaining small banks represented by the shaded area (Figure 2).

The same dynamics of the financial system are captured by the evolution in number of branches by financial subsystems in Figure D.11. The number of banks, financieras, and CMAC grew, CRAC and credit companies stagnated. The big jump in the number of bank branches and the fall in the number of branches of Financieras is related to the aforementioned acquisition of the Mibanco bank by Financiera Edyficar.

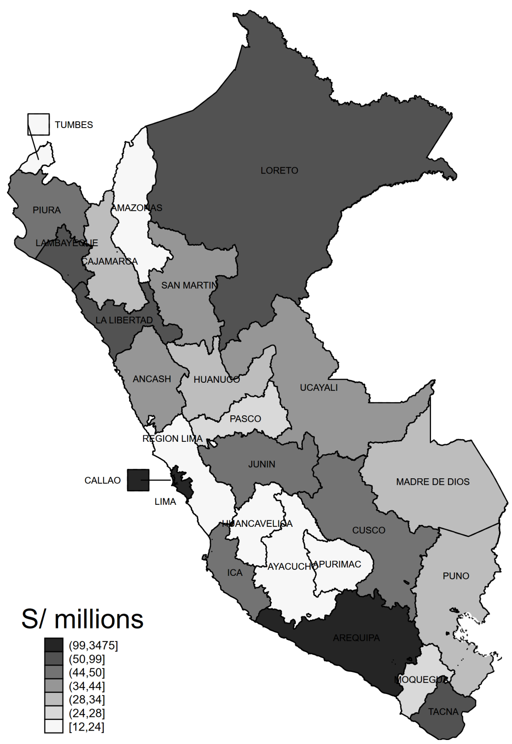
The Peruvian financial system exhibits a high degree of geographical concentration. Figure C.1 shows that the city of Lima accounts for 71.3% of total outstanding credit throughout the period 2011-2019.[6] The city of Lima is followed by Arequipa, La Libertad and Piura, which together account for 9.2% of total credit. The concentration of credit in Lima is related to its population and GDP concentration. For example, by 2019, Lima accounted for 32.4% of the Peruvian population and 43.2% of real GDP. As suggested by Céspedes Reynaga (2017), credit concentration in Lima is explained by the

[6] Total outstanding credit refers to credit for firms, households and mortgages.

higher-than-national-average level of education and income level. Moreover, distance to attention points of the financial system is positively related with access to informal credit (Sotomayor et al., 2018).[7]

The financial system is composed of 5 subsystems: banks, financieras, cajas municipales (CMAC), cajas rurales (CRAC), and credit companies. Figure C.2 shows that while banks tend to concentrate their credit portfolio in Lima (78%), other subsystems tend to have a more diversified portfolio share among departments. This is particularly the case of CMAC, for which Arequipa, Cusco and Piura represent 11.7%, 9% and 8% of credits, respectively, while Lima represents only 16.8% of credits.

Figure C.1: Geographical distribution of credit: 2011-2019

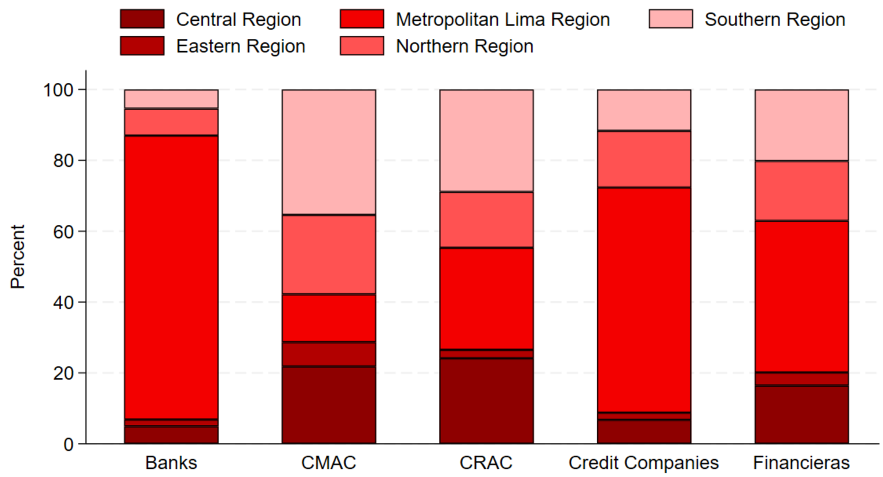


Notes: The graph shows the average outstanding loans in a department during the years 2011-2019. All types of credits refer to credit to firms, credit to households and mortgage credit. Source: Central Reserve Bank of Peru.

Figure C.3 shows that the banking system has remained dominant over time, accounting for over 86.6% of credit. Banks are followed by the CMACs, whose market share rose from 6.8% to 7.1% over 9 years, and Financieras, whose market share declined

[7]Informal credit refers to credit granted outside of the financial system. Informal creditors usually use predatory lending practices.

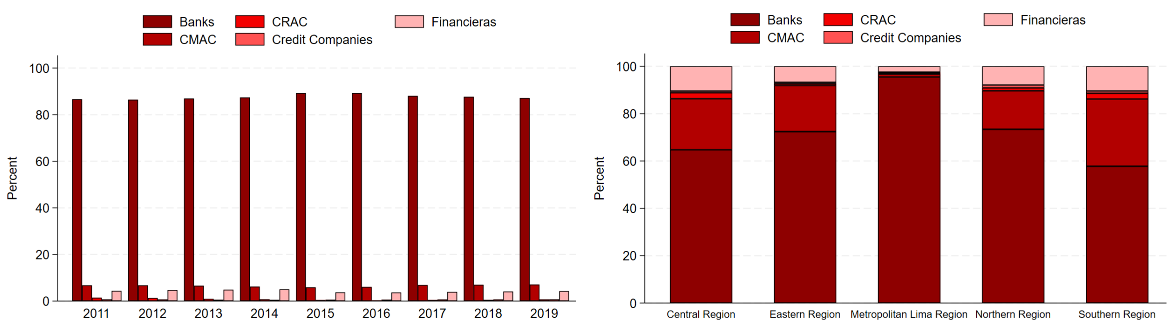
Figure C.2: Portfolio Share by Type of Financial Institution: 2011-2019



Notes: The graph shows the portfolio share of financial institutions in each subsystem. Portfolio share refers to the outstanding loans that a subsystem has in a region as a proportion of the total outstanding loans of that subsystem. The portfolio share is an average across the years 2011-2019. The Central Region comprises the departments of Ancash, Ayacucho, Huancavelica, Huanuco, Ica, Junín, Lima (excluding the province of Lima) and Pasco. The Eastern Region comprises the departments of Amazonas, Loreto, San Martín and Ucayali. The Metropolitan Lima Region comprises the province of Lima and the constitutional province of Callao. The Northern Region comprises the departments of Cajamarca, La Libertad, Lambayeque, Piura and Tumbes. The Southern Region comprises the departments of Apurimac, Arequipa, Cusco, Madre de Dios, Moquegua, Puno and Tacna. Source: Central Reserve Bank of Peru.

slightly during the same period. Shares are different when analysed by department. Banks dominate in Lima and Callao (around 95%), but are less prevalent in regions such as Huancavelica (14.5%) and Apurímac (24.5%). On the other hand, CMACs dominate the credit market in regions such as Apurímac (56.7%), Huancavelica (62.3%) and Madre de Dios (59.1%). Departments outside Lima and Callao generally exhibit a more balanced distribution of financial subsystems than the capital region.

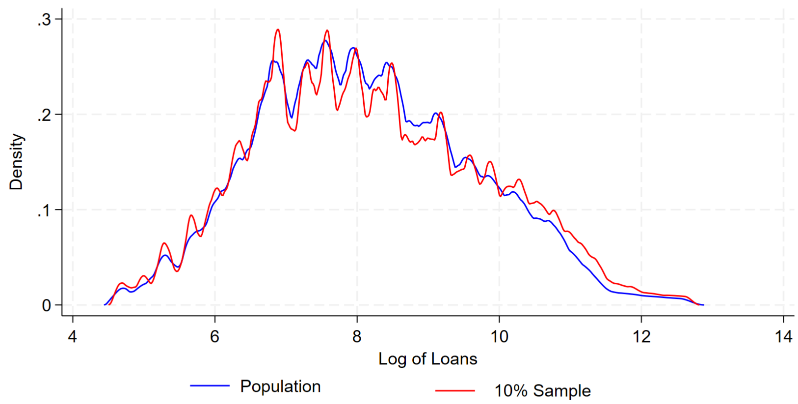
Figure C.3: Market Share of Subsystems: Over time (left) and Region (right)



Notes: The graph at the left shows the evolution of market shares by subsystem over the years 2011-2019 at the national level. The graph at the right shows the market share over the period 2011-2019 of each subsystem across each region. The Central Region comprises the departments of Ancash, Ayacucho, Huancavelica, Huanuco, Ica, Junín, Lima (excluding the province of Lima) and Pasco. The Eastern Region comprises the departments of Amazonas, Loreto, San Martín and Ucayali. The Metropolitan Lima Region comprises the province of Lima and the constitutional province of Callao. The Northern Region comprises the departments of Cajamarca, La Libertad, Lambayeque, Piura and Tumbes. The Southern Region comprises the departments of Apurimac, Arequipa, Cusco, Madre de Dios, Moquegua, Puno and Tacna. Source: Central Reserve Bank of Peru.

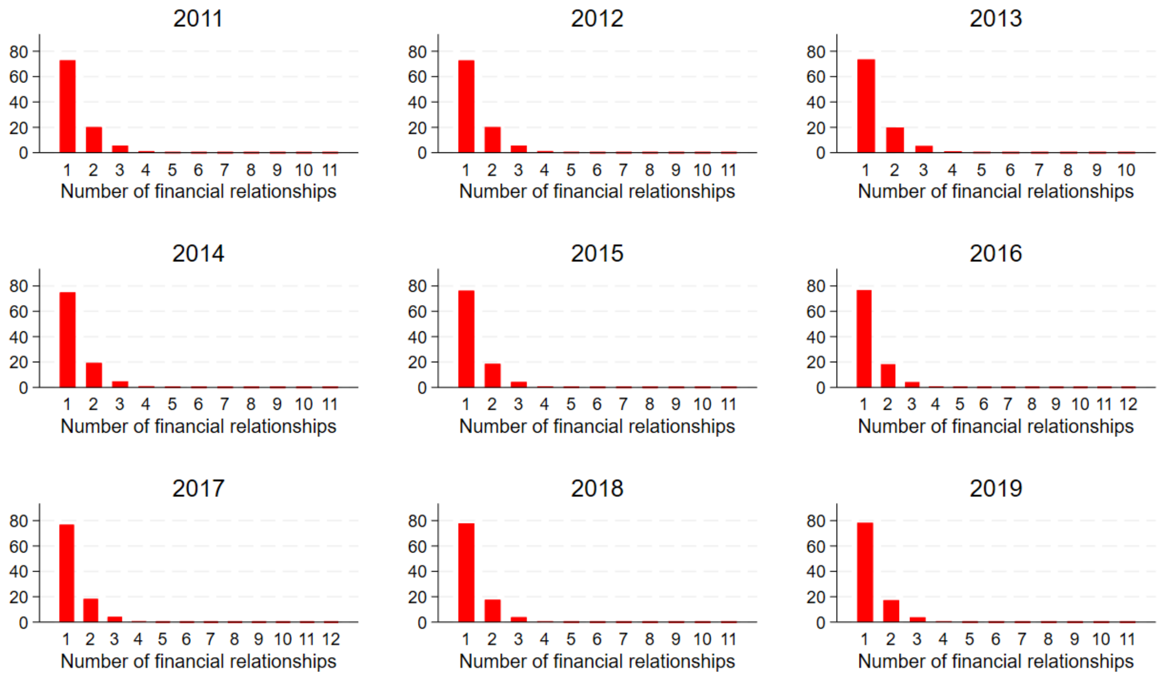
D Credit Registry

Figure D.1: Distribution of Loan Sizes: Population and 10% Sample



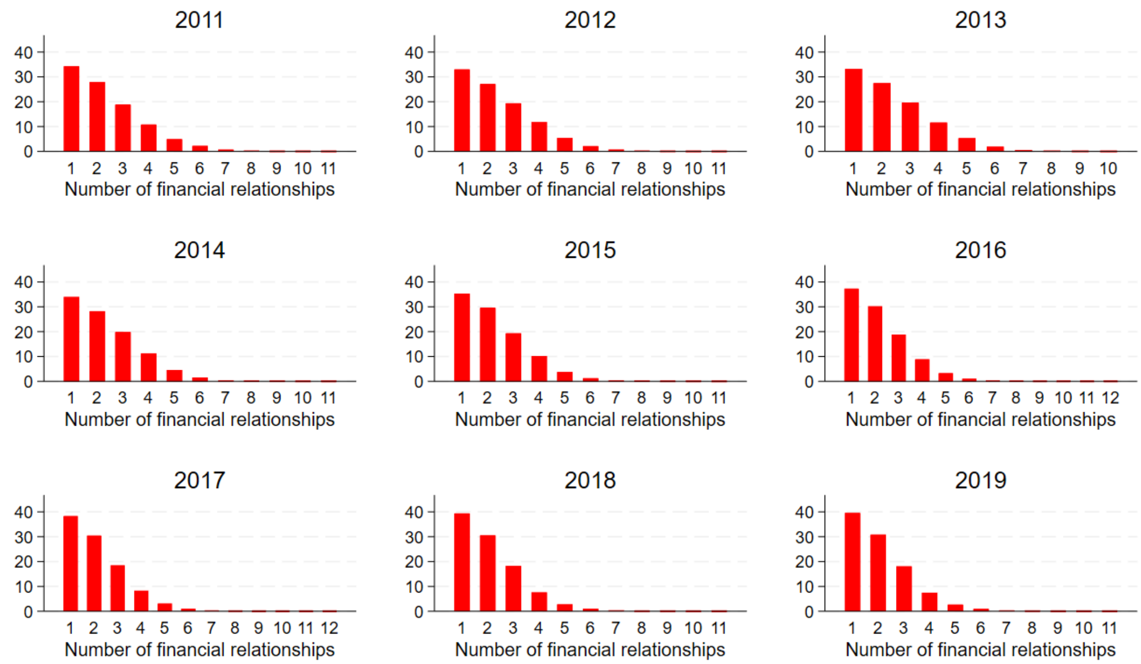
Notes: Kernel density plots of log-transformed loan values. The 10% sample (red line) follows the population distribution (blue line), indicating representativeness of the sample. Source: Peruvian Credit Registry.

Figure D.2: Distribution of Number of Financial Relationships per Firm over Time



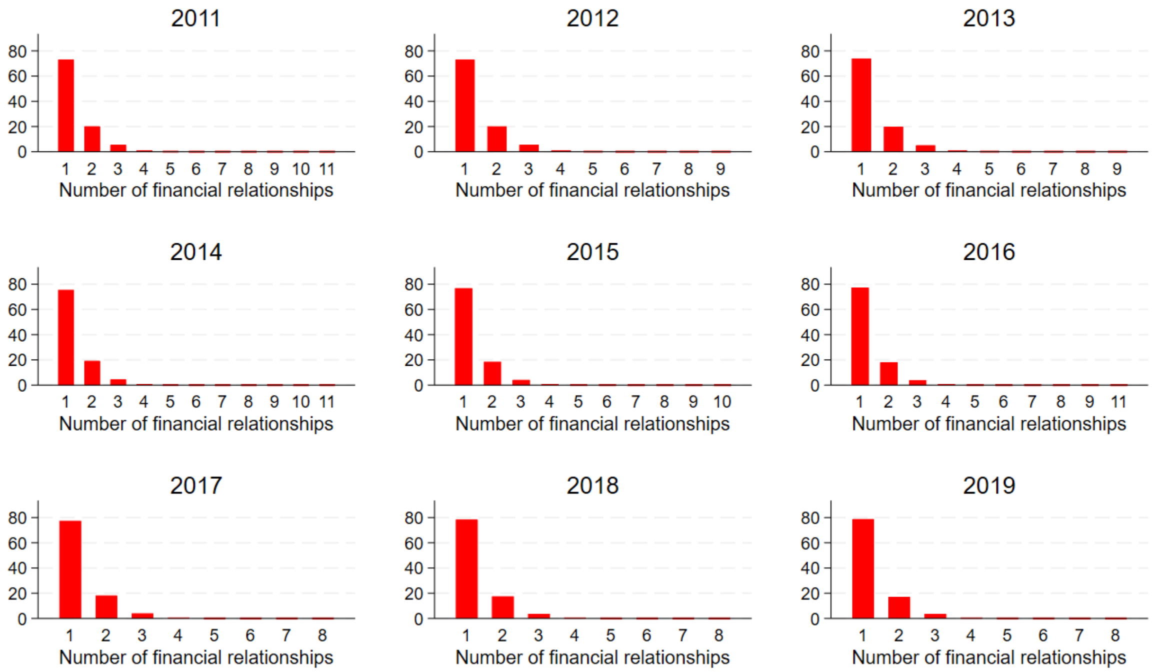
Notes: The graph shows the relative frequency of financial relationships that firms have on average by year. A new financial relationship is defined as a loan from a newly registered financial institution. Source: Peruvian Credit Registry.

Figure D.3: Distribution of the number of loans for large and medium firms over time



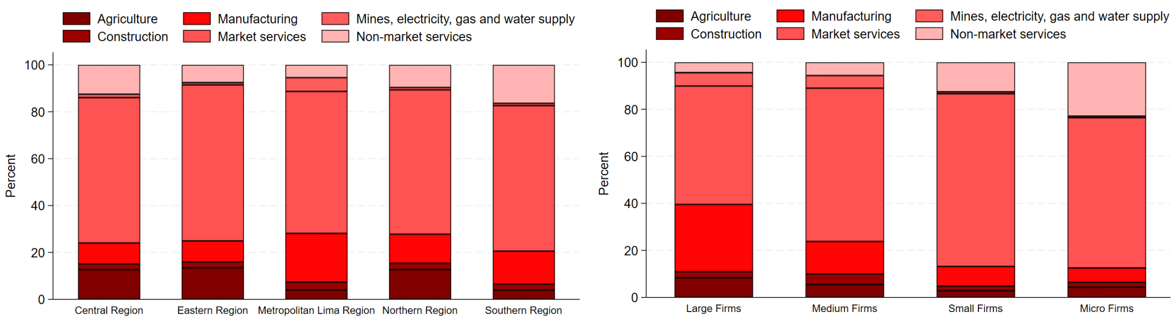
Notes: The graph shows the relative frequency of each number of financial relationships that large and medium firms have over the months in each year in the period 2011-2019. A new financial relationship is registered when a firm gets a loan from a different financial institution. Source: Peruvian Credit Registry.

Figure D.4: Distribution of the number of loans for small and micro firms over time



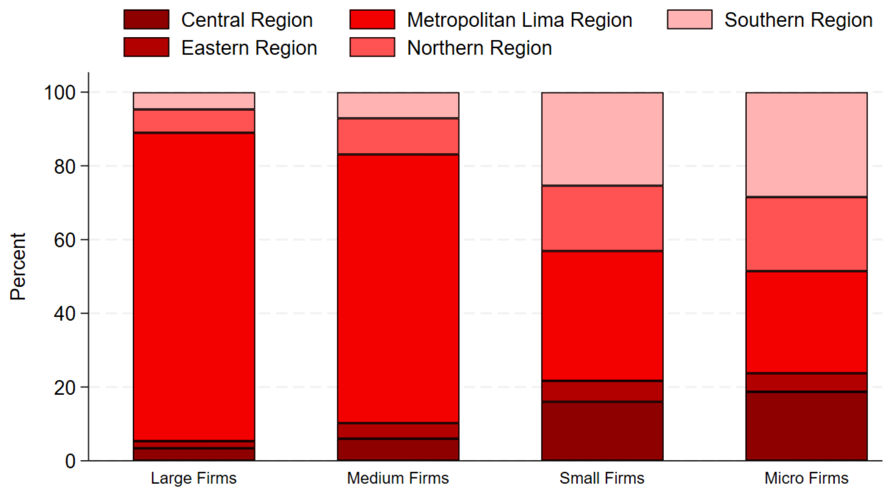
Notes: The graph shows the relative frequency of each number of financial relationships that small and micro firms have over the months in each year in the period 2011-2019. A new financial relationship is registered when a firm gets a loan from a different financial institution. Source: Peruvian Credit Registry.

Figure D.5: Distribution of Credit by Sector over Regions (left) and Types of Credit (right)



Notes: The graphs show the sectoral distribution of outstanding loans over firm size and regions between 2011 and 2019. Sectors are defined by ISIC (Rev4). Source: Peruvian Credit Registry.

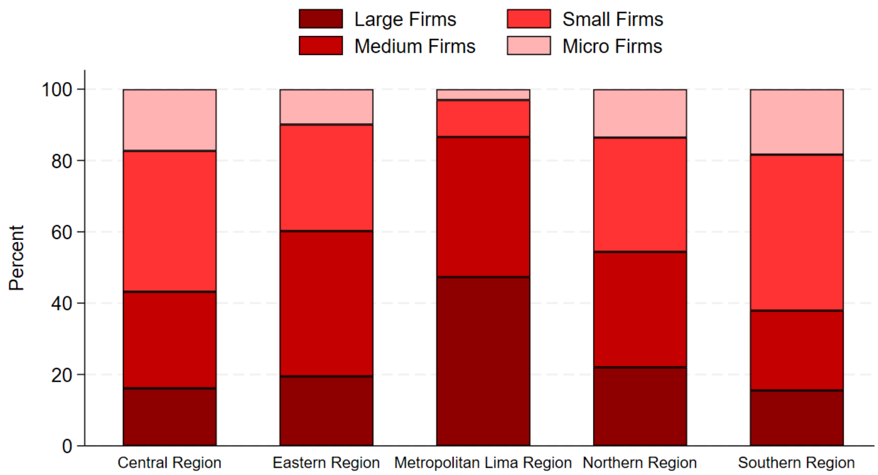
Figure D.6: Distribution of credit by region over types of credit



Authors' calculation.

Notes: The graph shows the distribution of the outstanding loans by region for the different types of credit (firm sizes), over the years 2011-2019. The Central Region comprises the departments of Ancash, Ayacucho, Huancavelica, Huanuco, Ica, Junín, Lima (excluding the province of Lima) and Pasco. The Eastern Region comprises the departments of Amazonas, Loreto, San Martín and Ucayali. The Metropolitan Lima Region comprises the province of Lima and Callao. The Northern Region comprises the departments of Cajamarca, La Libertad, Lambayeque, Piura and Tumbes. The Southern Region comprises the departments of Apurimac, Arequipa, Cusco, Madre de Dios, Moquegua, Puno and Tacna. Source: Peruvian Credit Registry.

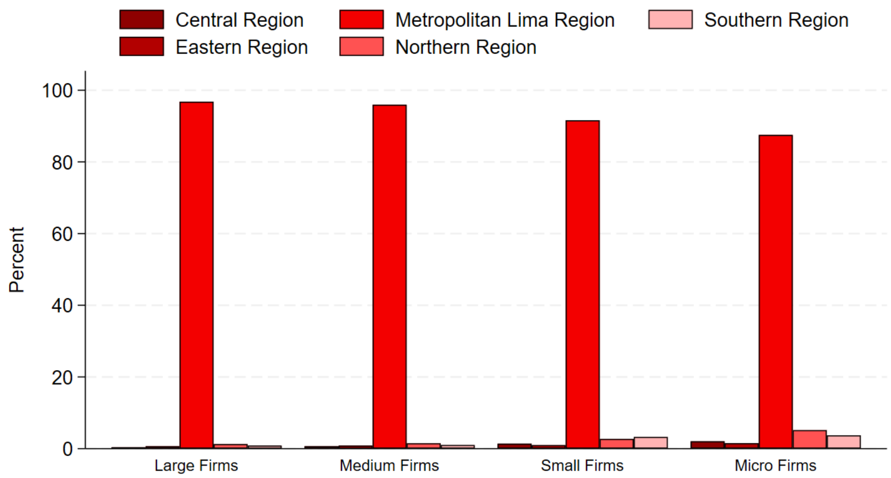
Figure D.7: Distribution of credit by type of credit over region



Authors' calculation.

Notes: The graph shows the distribution of the outstanding loans by type of credit (firm size) over regions, over the years 2011-2019. The Central Region comprises the departments of Ancash, Ayacucho, Huancavelica, Huanuco, Ica, Junín, Lima (excluding the province of Lima) and Pasco. The Eastern Region comprises the departments of Amazonas, Loreto, San Martín and Ucayali. The Metropolitan Lima Region comprises the province of Lima and Callao. The Northern Region comprises the departments of Cajamarca, La Libertad, Lambayeque, Piura and Tumbes. The Southern Region comprises the departments of Apurimac, Arequipa, Cusco, Madre de Dios, Moquegua, Puno and Tacna. Source: Peruvian Credit Registry.

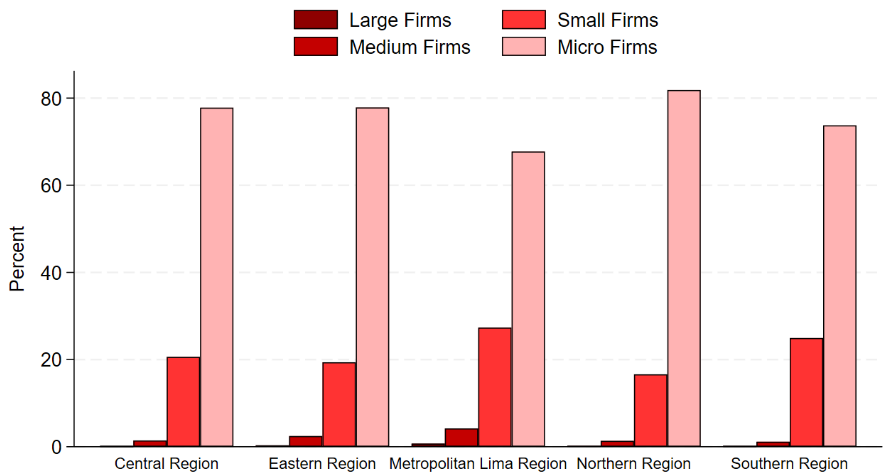
Figure D.8: Distribution of number of loans by region over types of credit



Authors' calculation.

Notes: The graph shows the distribution of the number of loans by region for the different types of credit (firm sizes), over the years 2011-2019. The Central Region comprises the departments of Ancash, Ayacucho, Huancavelica, Huanuco, Ica, Junín, Lima (excluding the province of Lima) and Pasco. The Eastern Region comprises the departments of Amazonas, Loreto, San Martín and Ucayali. The Metropolitan Lima Region comprises the province of Lima and Callao. The Northern Region comprises the departments of Cajamarca, La Libertad, Lambayeque, Piura and Tumbes. The Southern Region comprises the departments of Apurimac, Arequipa, Cusco, Madre de Dios, Moquegua, Puno and Tacna. Source: Peruvian Credit Registry.

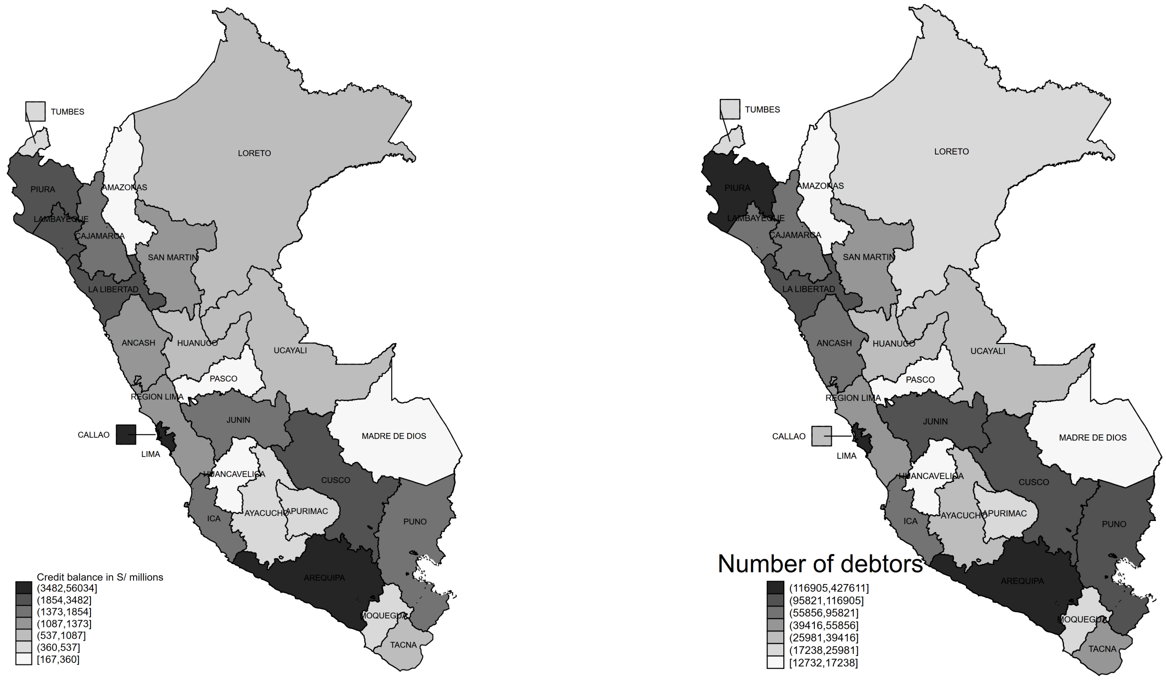
Figure D.9: Distribution of number of loans by type of credit over regions



Authors' calculation.

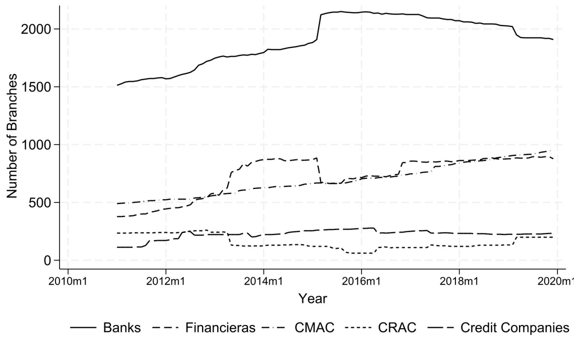
Notes: The graph shows the distribution of the number of loans by type of credit (firm size) over regions, over the years 2011-2019. The Central Region comprises the departments of Ancash, Ayacucho, Huancavelica, Huanuco, Ica, Junín, Lima (excluding the province of Lima) and Pasco. The Eastern Region comprises the departments of Amazonas, Loreto, San Martín and Ucayali. The Metropolitan Lima Region comprises the province of Lima and Callao. The Northern Region comprises the departments of Cajamarca, La Libertad, Lambayeque, Piura and Tumbes. The Southern Region comprises the departments of Apurimac, Arequipa, Cusco, Madre de Dios, Moquegua, Puno and Tacna. Source: Peruvian Credit Registry.

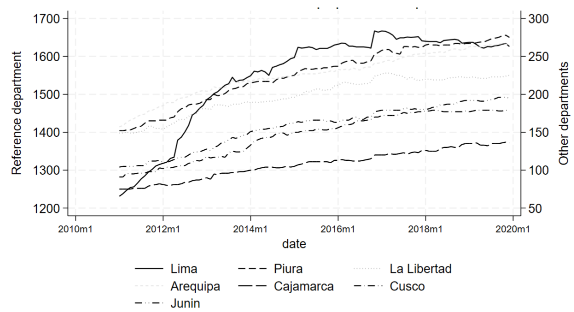
Figure D.10: Credit Balance of Firms (left) and Number of Firm Debtors (right)



Notes: Average outstanding loans and average number of firms by department between 2011 and 2019. Source: Peruvian Credit Registry.

Figure D.11: Number of Branches by Subsystem (left) and in Selected Departments (right)





Notes: These graphs show the number of branches by subsystem and in selected departments. The selected departments were chosen based on their population at year-end 2019. Source: Central Reserve Bank of Peru.

E Methodology

Table E.1: Two-sample t-test comparing Forecast Revision values between El Niño Seasons

El Niño	N	Mean	SE	SD	95% CI
No	74	-13.1	2.6	22.7	[-18.4, -7.9]
Yes	33	10.5	3.9	22.5	[2.5, 18.5]
Difference		-23.6***	4.7		[-33, -14.2]

Notes: $t = -4.98$, $df = 105$, $p < 0.001$. Samples are normally distributed. SE is standard error. SD is standard deviation. CI is confidence interval.

Table E.2: Average disaster ratio time series - No seasonality detected

	Average Disaster Ratio
February	0.342 (0.343)
March	0.453 (0.343)
April	0.0605 (0.343)
May	0.220 (0.343)
June	0.255 (0.343)
July	0.132 (0.343)
August	0.254 (0.343)
September	0.0155 (0.343)
October	-0.122 (0.343)
November	0.0149 (0.343)
December	-0.00363 (0.354)
Constant	0.805^{**} (0.243)
Observations	107

Average disaster ratio time series regression analysis using monthly data between 2011-2019. No statistically significant seasonality detected when using dummy variables for month ($F(11, 95) = 0.5$ with F-test p-value= 0.9). Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

F Results

F.1 Calculation of Economy-wide Effect of Baseline Regression

Starting Model:

$$\ln(Y_{f,t}) - \ln(Y_{f,t-1}) = \beta_1 \ln(x_{1,f,t}) + \beta_2 \ln(x_{2,f,t}) + \beta_3 \ln(x_{3,f,t}) + \beta_4 \ln(x_{4,f,t}) + \varepsilon_t \quad (6)$$

Step 1: Marginal Effect on Growth Rate Taking the partial derivative with respect to $x_{1,f,t}$:

$$\frac{\partial[\ln(Y_{f,t}) - \ln(Y_{f,t-1})]}{\partial x_{1,f,t}} = \beta_1 \frac{\partial \ln(x_{1,f,t})}{\partial x_{1,f,t}} \quad (7)$$

Since $\frac{\partial \ln(x_{1,f,t})}{\partial x_{1,f,t}} = \frac{1}{x_{1,f,t}}$:

$$\frac{\partial[\ln(Y_{f,t}) - \ln(Y_{f,t-1})]}{\partial x_{1,f,t}} = \frac{\beta_1}{x_{1,f,t}} \quad (8)$$

Step 2: Express in Terms of Growth Rate Since $\ln(Y_{f,t}) - \ln(Y_{f,t-1}) \approx \frac{\Delta Y_{f,t}}{Y_{f,t-1}}$ for small changes, where $\Delta Y_{f,t} = Y_{f,t} - Y_{f,t-1}$:

$$\frac{\partial}{\partial x_{1,f,t}} \left[\frac{\Delta Y_{f,t}}{Y_{f,t-1}}\right] = \frac{\beta_1}{x_{1,f,t}} \quad (9)$$

Therefore:

$$\frac{\partial \Delta Y_{f,t}}{\partial x_{1,f,t}} = \frac{\beta_1 Y_{f,t-1}}{x_{1,f,t}} \quad (10)$$

Step 3: Effect on Level of Y Since $Y_{f,t} = Y_{f,t-1} + \Delta Y_{f,t}$:

$$\frac{\partial Y_{f,t}}{\partial x_{1,f,t}} = \frac{\partial Y_{f,t-1}}{\partial x_{1,f,t}} + \frac{\partial \Delta Y_{f,t}}{\partial x_{1,f,t}} \quad (11)$$

Assuming $Y_{f,t-1}$ is predetermined (not affected by current $x_{1,t}$):

$$\frac{\partial Y_{f,t-1}}{\partial x_{1,f,t}} = 0 \quad (12)$$

Therefore:

$$\frac{\partial Y_{f,t}}{\partial x_{1,f,t}} = \frac{\partial \Delta Y_{f,t}}{\partial x_{1,f,t}} = \frac{\beta_1 Y_{f,t-1}}{x_{1,f,t}} \quad (13)$$

Interpretation: A 1 percentage point increase in portfolio share ($x_{1,f,t}$) increases the level of credit ($Y_{f,t}$) by:

$$\Delta Y_{f,t} = \frac{\beta_1 Y_{f,t-1}}{x_{1,f,t}} \text{ Peruvian soles} \quad (14)$$

Economy-wide effect: To have the economy-wide effect, we aggregate the individual firm effects. This gives us the total economy-wide change in credit for a one-unit increase in the average X across all firms and time. As a simplified calculation,

$$\frac{\beta_1 \times \sum_f \bar{Y}_f}{\sum_f \bar{X}_f / N} \tag{15}$$

where $\bar{Y}_f$ is the average credit of firm f, $\bar{X}_f$ is the average portfolio or market share of firm f, and N is the number of firms in our sample.

Interpretation: A percentage point increase in the average X across all firms in the economy is associated with a change of $\frac{\beta_1 \times \sum_f \bar{Y}_f}{\sum_f \bar{X}_f / N}$ units in total economy-wide credit.

Sample Example: We have 8.83 billion soles as total of average firm credit across time, 13.83 as the average portfolio share and 8.52 as the average market share. Therefore, the economy-wide effects are:

$$\frac{\beta_1 \times \sum_f \bar{Y}_f}{\sum_f \bar{X}_f / N} = 0.0002 \times \frac{8.83 \times 10^9}{13.83} \approx 127\,725 \tag{16}$$

and

$$\frac{\beta_1 \times \sum_f \bar{Y}_f}{\sum_f \bar{X}_f / N} = 0.0002 \times \frac{8.83 \times 10^9}{8.52} \approx 207\,189 \tag{17}$$

These calculations are illustrations as they assume that firm-level responses can be summed to get economy-wide effects, which might not be representative in case the marginal effects are not constant across firms.

F.2 Calculation of Economy-wide Effect of Forecast Revisions during El Niño

Starting Model: Based on Equation 2, we want to calculate the aggregated effect of forecast revisions on credit during El Niño periods. To simplify, we concentrate on the equation

$$\ln(Credit_{b,p,f,t}) - \ln(Credit_{b,p,f,t-1}) = A_{b,p,f,t} + FR_{t-1} \times (B_{b,p,f,t}) + ElNino_{t-1} \times FR_{t-1} \times (D_{b,p,f,t}) + \varepsilon_t \tag{18}$$

where A, B, and D reflect the bank characteristic variables presented in Equation 2.

Step 1: Marginal Effect on Growth Rate Taking the partial derivative with respect to FR_{t-1}:

$$\frac{\partial[\ln(Credit_{b,p,f,t}) - \ln(Credit_{b,p,f,t-1})]}{\partial FR_{t-1}} = B_{b,p,f,t} + ElNino_{t-1} \times D_{b,p,f,t} \tag{19}$$

Step2: $Credit_{b,p,f,t-1}$ is not affected by FR_{t-1}.

$$\frac{\partial \ln(Credit_{b,p,f,t})}{\partial FR_{t-1}} = B_{b,p,f,t} + ElNino_{t-1} \times D_{b,p,f,t} \tag{20}$$

then

$$\frac{\partial \ln(Credit_{b,p,f,t})}{\partial FR_{t-1}} = \frac{\partial \ln(Credit_{b,p,f,t})}{\partial C_{b,p,f,t}} \frac{\partial C_{b,p,f,t}}{\partial FR_{t-1}} = \frac{1}{C_{b,p,f,t}} \frac{\partial C_{b,p,f,t}}{\partial FR_{t-1}} \tag{21}$$

which equals:

$$B_{b,p,f,t} + ElNino_{t-1} \times D_{b,p,f,t} = \frac{1}{C_{b,p,f,t}} \frac{\partial C_{b,p,f,t}}{\partial FR_{t-1}} \tag{22}$$

therefore

$$\frac{\partial C_{b,p,f,t}}{\partial FR_{t-1}} = C_{b,p,f,t} \times (B_{b,p,f,t} + ElNino_{t-1} \times D_{b,p,f,t}) \tag{23}$$

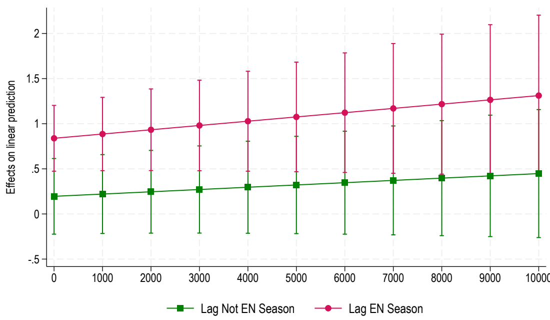
Step 3: Summing over bank and province to get the monthly effect in soles:

$$\sum_{b,p} C_{b,p,f,t} \times (B_{b,p,f,t} + ElNino_{t-1} \times D_{b,p,f,t}) \approx 54 \text{ million soles} \tag{24}$$

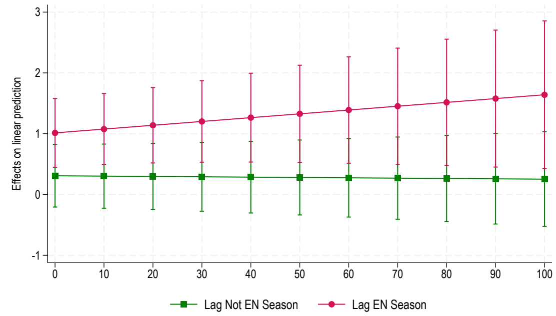
where firms, f are in province p, therefore, they are summed over.

F.3 Marginal Effects

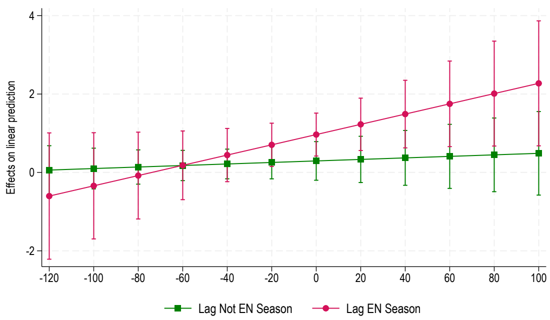
Figure F.1: Marginal Effects of Forecast Revision by Bank Characteristics on Capital Ratio with Market share-weighted Disaster Exposure



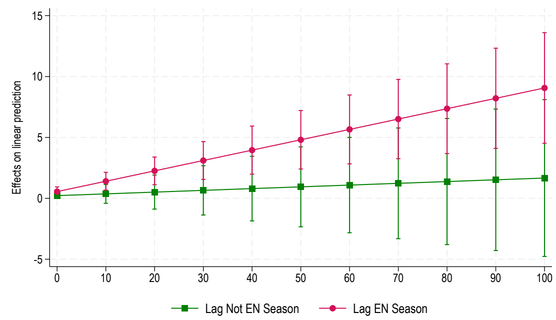
(a) HHI



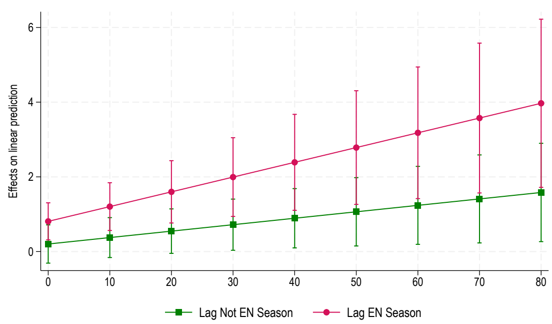
(b) Mortgage Loan



(c) ROE



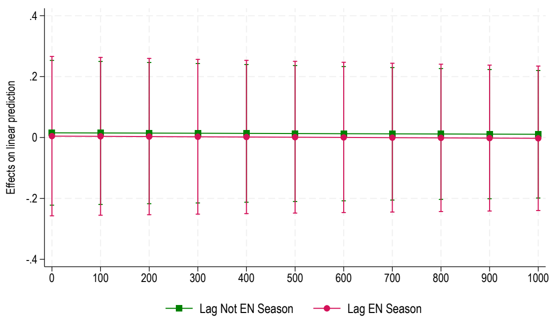
(d) Delinquency Ratio



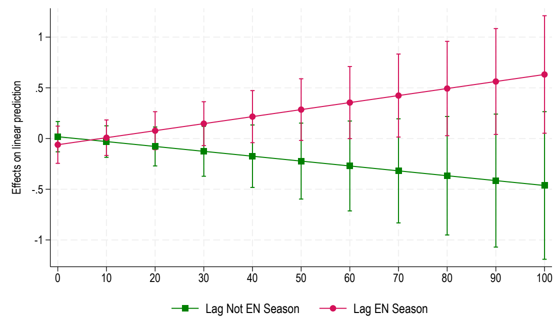
(e) Operating Ratio

Notes: This figure shows the marginal effects of forecast revisions on bank capital ratios during El Niño (red circle) and non-El Niño episodes (green square). The x-axis represents the values of bank characteristics (HHI = portfolio concentration, ROE = return on equity, Operating Ratio = operating expense ratio), while the y-axis shows the percentage change in the capital ratio due to a one percent change in the forecast revision, conditional on bank characteristics, with 95% confidence intervals. The Market Share-Weighted Disaster Exposure is used in the regression.

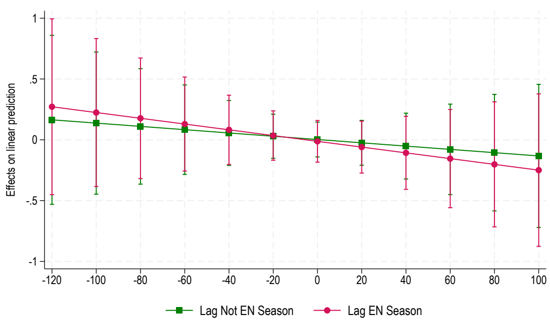
Figure F.2: Marginal effects of market share-weighted disaster exposure by bank characteristics on capital ratio



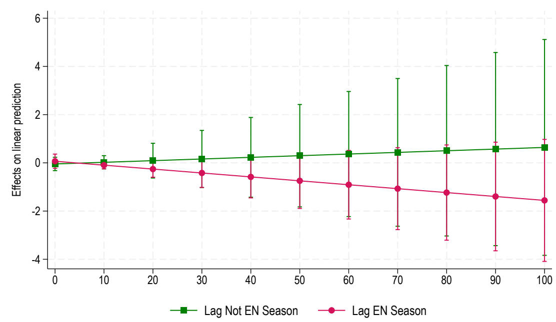
(a) HHI



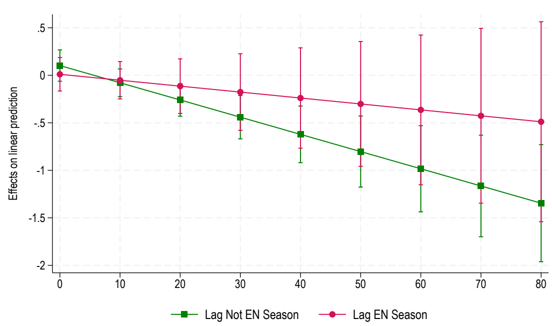
(b) Mortgage Loan



(c) ROE



(d) Delinquency Ratio



(e) Operating Ratio

Notes: This figure shows the marginal effects of market share-weighted disaster exposure on bank capital ratios during El Niño (red circle) and non-El Niño episodes (green square). The x-axis represents the values of bank characteristics (HHI = portfolio concentration, ROE = return on equity, Operating Ratio = operating expense ratio), while the y-axis shows the percentage change in the capital ratio due to a one percent change in disaster exposure, conditional on bank characteristics, with 95% confidence intervals.

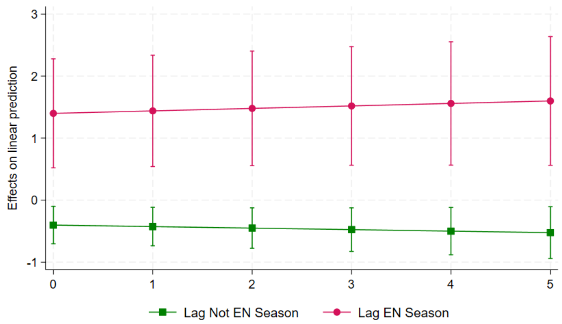
F.4 Robustness

Table F.1: Effect of climate shocks on log firm credit growth, multiplied by 100 - Financial Companies

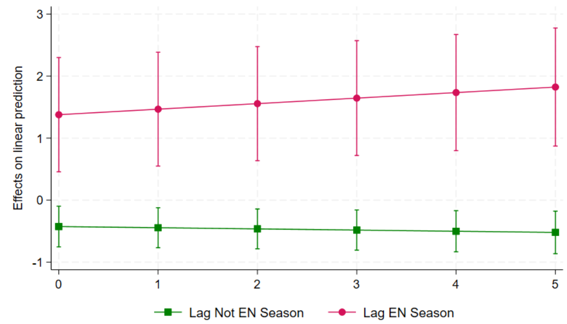
Variable	Coefficient	S.E.
Panel A: Covariates		
Portfolio Share ($\ln PS_{t-2}$)	0.6460***	(0.1438)
Market Share ($\ln MS_{t-2}$)	0.0654	(0.0713)
External Disaster - Portfolio ($\ln ED\_PS_{t-1}$)	-0.5032***	(0.1919)
External Disaster - Market ($\ln ED\_MS_{t-1}$)	-0.0023	(0.8338)
Panel B: Forecast Revision Interactions		
$FR_{t-1} \times \ln PS_{t-2}$	-0.0244	(0.0278)
$FR_{t-1} \times \ln MS_{t-2}$	-0.0190	(0.0192)
$FR_{t-1} \times \ln ED\_PS_{t-1}$	-0.0379	(0.0300)
$FR_{t-1} \times \ln ED\_MS_{t-1}$	-0.4721	(0.3391)
Panel C: El Niño × Forecast Revision Interactions		
$ElNino_{t-1} \times FR_{t-1} \times \ln PS_{t-2}$	0.0643	(0.0463)
$ElNino_{t-1} \times FR_{t-1} \times \ln MS_{t-2}$	0.1081***	(0.0396)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_PS_{t-1}$	0.4722***	(0.1494)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_MS_{t-1}$	-0.0822	(0.5344)
Panel D: Disaster Ratio Interactions		
$\ln DR_{t-1} \times \ln PS_{t-2}$	-0.2083	(0.1281)
$\ln DR_{t-1} \times \ln MS_{t-2}$	0.0597	(0.0723)
$\ln DR_{t-1} \times \ln ED\_PS_{t-1}$	0.2364**	(0.0978)
$\ln DR_{t-1} \times \ln ED\_MS_{t-1}$	-0.1825	(0.1295)
Panel E: El Niño × Disaster Ratio Interactions		
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln PS_{t-2}$	-0.0025	(0.1674)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln MS_{t-2}$	-0.0250	(0.1115)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_PS_{t-1}$	-0.1988	(0.1335)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_MS_{t-1}$	0.2899	(0.2095)
Observations	6,748,583	
R-squared	0.0046	
Adjusted R-squared	0.0015	
Bank × Time FE	Yes	
Province × Time FE	Yes	

Notes: This table reports the results of regressing the firm-level credit growth (multiplied by 100) on bank exposure measures for financial companies. $\ln DR$ shows the Disaster Ratio in logarithmic terms, $\ln PS$ shows Portfolio Share, $\ln MS$ is Market Share, $\ln ED\_PS$ is External Disaster weighted Portfolio Share, $\ln ED\_MS$ is External Disaster weighted Market Share, FR shows Forecast Revision, with the unit being 10 percentage points, DR depicts Disaster Ratio, $ElNino$ is the El Niño indicator being equal to one during coastal El Niño. Standard errors are clustered at the bank-province level. * p<0.1, ** p<0.05, *** p<0.01.

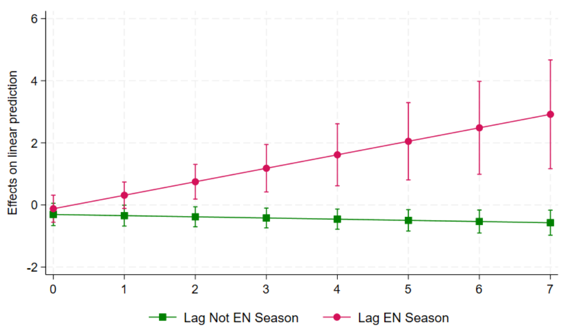
Figure F.3: Marginal effects of Forecast Revision by Bank Characteristics on Firm-level Credit Growth - Financial Companies



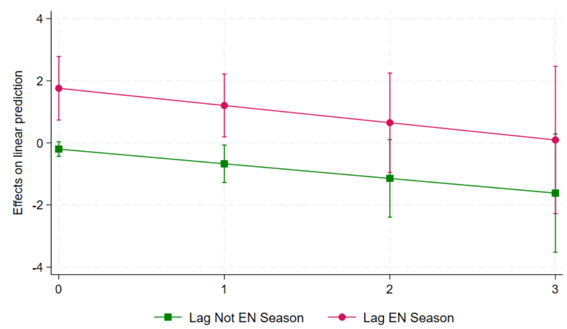
(a) Portfolio Share



(b) Market Share



(c) ED PS



(d) ED MS

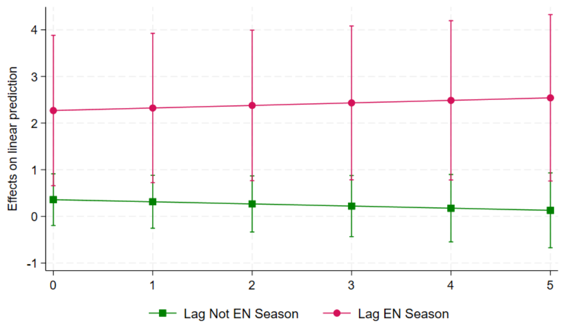
Notes: This figure shows the marginal effects of climate forecast revisions on firm-level credit growth conditional on bank characteristics for financial companies, during El Niño (red circle) and non-El Niño (green square) episodes. Each panel represents a different bank characteristic: Portfolio Share (PS) measures the importance of provincial lending on a bank's balance sheet; Market Share (MS) captures a bank's relative importance within a province; ED PS (External Disasters - Portfolio weighted) quantifies a bank's exposure to climate disasters in other provinces weighted by its portfolio allocation; and ED MS (External Disasters - Market weighted) represents a bank's exposure to climate disasters in other provinces weighted by its market presence. The vertical error bars represent the 95% confidence interval. All specifications include bank-time and province-time fixed effects. Standard errors are clustered at the bank-province level.

Table F.2: Effect of climate shocks on log firm credit growth, multiplied by 100 - Financial Companies with Firms having Multiple Banking Relationships

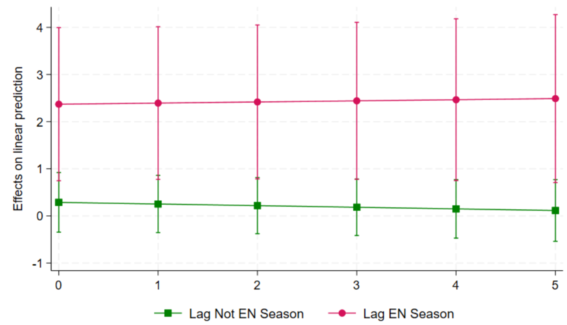
Variable	Coefficient	S.E.
Panel A: Covariates		
Portfolio Share ($\ln PS_{t-2}$)	0.5408**	(0.2297)
Market Share ($\ln MS_{t-2}$)	0.2350*	(0.1347)
External Disaster - Portfolio ($\ln ED\_PS_{t-1}$)	−0.4779*	(0.2480)
External Disaster - Market ($\ln ED\_MS_{t-1}$)	1.3463	(1.9451)
Panel B: Forecast Revision Interactions		
$FR_{t-1} \times \ln PS_{t-2}$	-0.0457	(0.0590)
$FR_{t-1} \times \ln MS_{t-2}$	-0.0345	(0.0498)
$FR_{t-1} \times \ln ED\_PS_{t-1}$	0.0926	(0.0562)
$FR_{t-1} \times \ln ED\_MS_{t-1}$	0.1191	(0.5323)
Panel C: El Niño × Forecast Revision Interactions		
$ElNino_{t-1} \times FR_{t-1} \times \ln PS_{t-2}$	0.1001	(0.1177)
$ElNino_{t-1} \times FR_{t-1} \times \ln MS_{t-2}$	0.0583	(0.1062)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_PS_{t-1}$	0.1946	(0.2026)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_MS_{t-1}$	2.3533	(1.6355)
Panel D: Disaster Ratio Interactions		
$\ln DR_{t-1} \times \ln PS_{t-2}$	-0.2011	(0.2670)
$\ln DR_{t-1} \times \ln MS_{t-2}$	0.0757	(0.1687)
$\ln DR_{t-1} \times \ln ED\_PS_{t-1}$	0.2261	(0.1997)
$\ln DR_{t-1} \times \ln ED\_MS_{t-1}$	-0.4275	(0.3160)
Panel E: El Niño × Disaster Ratio Interactions		
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln PS_{t-2}$	0.6407	(0.3974)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln MS_{t-2}$	-0.2602	(0.2968)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_PS_{t-1}$	-0.2510	(0.2910)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_MS_{t-1}$	1.4223***	(0.5285)
Observations	704,615	
R-squared	0.0580	
Adjusted R-squared	-0.0052	
Bank × Time FE	Yes	
Province × Time FE	Yes	

Notes: This table reports the results of regressing the firm-level credit growth (multiplied by 100) on bank exposure measures for financial companies with debtors having multiple relations. $\ln DR$ shows the Disaster Ratio in logarithmic terms, $\ln PS$ shows Portfolio Share, $\ln MS$ is Market Share, $\ln ED\_PS$ is External Disaster weighted Portfolio Share, $\ln ED\_MS$ is External Disaster weighted Market Share, FR shows Forecast Revision, with the unit being 10 percentage points, DR depicts Disaster Ratio, $ElNino$ is the El Niño indicator being equal to one during coastal El Niño. Standard errors are clustered at the bank-province level. * p<0.1, ** p<0.05, *** p<0.01.

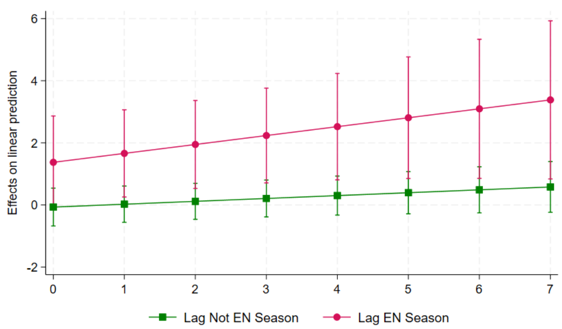
Figure F.4: Marginal effects of Forecast Revision by Bank Characteristics on Firm-level Credit Growth - Financial Companies with Firms having Multiple Banking Relationships



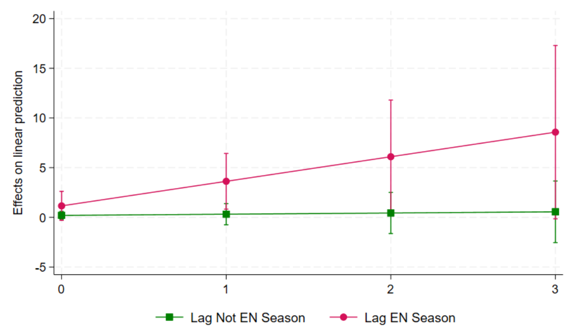
(a) Portfolio Share



(b) Market Share



(c) ED PS



(d) ED MS

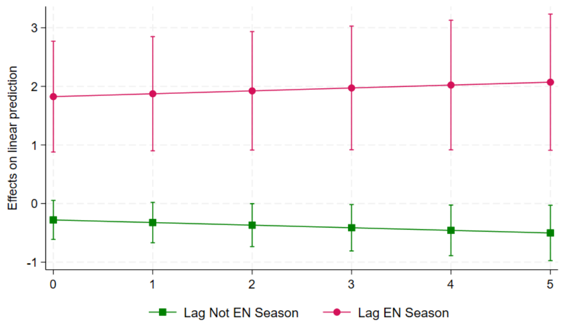
Notes: This figure shows the marginal effects of climate forecast revisions on firm-level credit growth conditional on bank characteristics for financial companies with firms having multiple banking relation, during El Niño (red circle) and non-El Niño (green square) episodes. Each panel represents a different bank characteristic: Portfolio Share (PS) measures the importance of provincial lending on a bank's balance sheet; Market Share (MS) captures a bank's relative importance within a province; ED PS (External Disasters - Portfolio weighted) quantifies a bank's exposure to climate disasters in other provinces weighted by its portfolio allocation; and ED MS (External Disasters - Market weighted) represents a bank's exposure to climate disasters in other provinces weighted by its market presence. The vertical error bars represent the 95% confidence interval. All specifications include bank-time and province-time fixed effects. Standard errors are clustered at the bank-province level.

Table F.3: Effect of climate shocks on log firm credit growth, multiplied by 100 - Service Sector

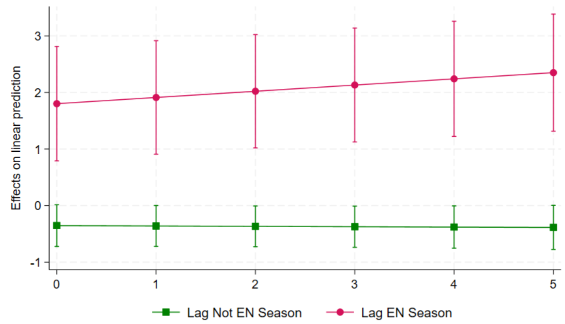
Variable	Coefficient	S.E.
Panel A: Covariates		
Portfolio Share ($\ln PS_{t-2}$)	0.5341***	(0.1340)
Market Share ($\ln MS_{t-2}$)	0.0794	(0.0698)
External Disaster - Portfolio ($\ln ED\_PS_{t-1}$)	-0.4002**	(0.1698)
External Disaster - Market ($\ln ED\_MS_{t-1}$)	0.1346	(1.0205)
Panel B: Forecast Revision Interactions		
$FR_{t-1} \times \ln PS_{t-2}$	-0.0444	(0.0308)
$FR_{t-1} \times \ln MS_{t-2}$	-0.0064	(0.0236)
$FR_{t-1} \times \ln ED\_PS_{t-1}$	-0.0024	(0.0362)
$FR_{t-1} \times \ln ED\_MS_{t-1}$	-0.5176	(0.3775)
Panel C: El Niño × Forecast Revision Interactions		
$ElNino_{t-1} \times FR_{t-1} \times \ln PS_{t-2}$	0.0938*	(0.0538)
$ElNino_{t-1} \times FR_{t-1} \times \ln MS_{t-2}$	0.1161**	(0.0485)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_PS_{t-1}$	0.5076***	(0.1522)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_MS_{t-1}$	0.2679	(0.7129)
Panel D: Disaster Ratio Interactions		
$\ln DR_{t-1} \times \ln PS_{t-2}$	-0.1091	(0.1314)
$\ln DR_{t-1} \times \ln MS_{t-2}$	-0.0079	(0.0897)
$\ln DR_{t-1} \times \ln ED\_PS_{t-1}$	0.2717**	(0.1163)
$\ln DR_{t-1} \times \ln ED\_MS_{t-1}$	-0.4411***	(0.1684)
Panel E: El Niño × Disaster Ratio Interactions		
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln PS_{t-2}$	-0.0808	(0.1663)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln MS_{t-2}$	0.0541	(0.1250)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_PS_{t-1}$	-0.1834	(0.1570)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_MS_{t-1}$	0.5468**	(0.2453)
Observations	4,452,449	
R-squared	0.0059	
Adjusted R-squared	0.0014	
Bank × Time FE	Yes	
Province × Time FE	Yes	

Notes: This table reports the results of regressing the firm-level credit growth (multiplied by 100) on bank exposure measures for the service sector. $\ln DR$ shows the Disaster Ratio in logarithmic terms, $\ln PS$ shows Portfolio Share, $\ln MS$ is Market Share, $\ln ED\_PS$ is External Disaster weighted Portfolio Share, $\ln ED\_MS$ is External Disaster weighted Market Share, FR shows Forecast Revision, with the unit being 10 percentage points, DR depicts Disaster Ratio, $ElNino$ is the El Niño indicator being equal to one during coastal El Niño. Standard errors are clustered at the bank-province level. * p<0.1, ** p<0.05, *** p<0.01.

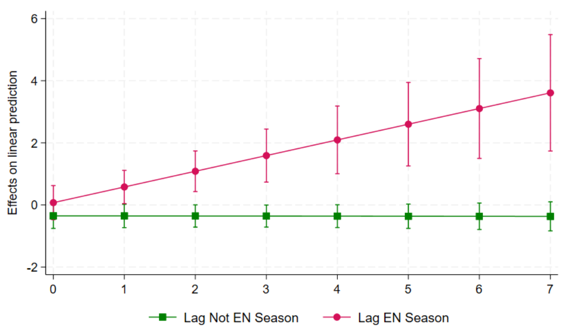
Figure F.5: Marginal effects of forecast revision by bank characteristics on firm-level credit growth - Service Sector



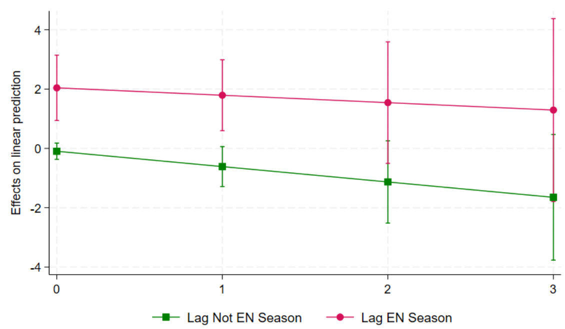
(a) Portfolio Share



(b) Market Share



(c) ED PS



(d) ED MS

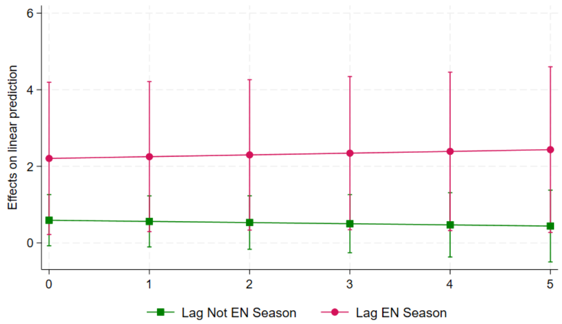
Notes: This figure shows the marginal effects of climate forecast revisions on firm-level credit growth conditional on bank characteristics in the service sector, during El Niño (red circle) and non-El Niño (green square) periods. Each panel represents a different bank characteristic: Portfolio Share (PS) measures the importance of provincial lending on a bank's balance sheet; Market Share (MS) captures a bank's relative importance within a province; ED PS (External Disasters - Portfolio weighted) quantifies a bank's exposure to climate disasters in other provinces weighted by its portfolio allocation; and ED MS (External Disasters - Market weighted) represents a bank's exposure to climate disasters in other provinces weighted by its market presence. The vertical error bars represent the 95% confidence interval. All specifications include bank-time and province-time fixed effects. Standard errors are clustered at the bank-province level.

Table F.4: Effect of climate shocks on log firm credit growth, multiplied by 100 - Service Sector with Firms having Multiple Banking Relationships

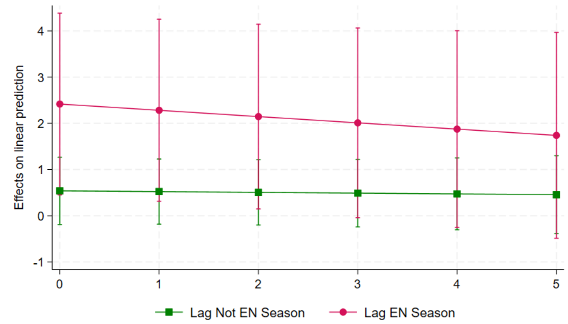
Variable	Coefficient	S.E.
Panel A: Covariates		
Portfolio Share ($\ln PS_{t-2}$)	0.5206**	(0.2647)
Market Share ($\ln MS_{t-2}$)	0.2087	(0.1644)
External Disaster - Portfolio ($\ln ED\_PS_{t-1}$)	−0.5344**	(0.2679)
External Disaster - Market ($\ln ED\_MS_{t-1}$)	0.6012	(1.9679)
Panel B: Forecast Revision Interactions		
$FR_{t-1} \times \ln PS_{t-2}$	-0.0303	(0.0757)
$FR_{t-1} \times \ln MS_{t-2}$	-0.0166	(0.0668)
$FR_{t-1} \times \ln ED\_PS_{t-1}$	0.1716**	(0.0779)
$FR_{t-1} \times \ln ED\_MS_{t-1}$	-0.0027	(0.5685)
Panel C: El Niño × Forecast Revision Interactions		
$ElNino_{t-1} \times FR_{t-1} \times \ln PS_{t-2}$	0.0762	(0.1560)
$ElNino_{t-1} \times FR_{t-1} \times \ln MS_{t-2}$	-0.1192	(0.1340)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_PS_{t-1}$	-0.0361	(0.2448)
$ElNino_{t-1} \times FR_{t-1} \times \ln ED\_MS_{t-1}$	3.6949**	(1.8623)
Panel D: Disaster Ratio Interactions		
$\ln DR_{t-1} \times \ln PS_{t-2}$	-0.2263	(0.2764)
$\ln DR_{t-1} \times \ln MS_{t-2}$	0.2852	(0.2158)
$\ln DR_{t-1} \times \ln ED\_PS_{t-1}$	0.6150**	(0.2459)
$\ln DR_{t-1} \times \ln ED\_MS_{t-1}$	-0.4829	(0.4396)
Panel E: El Niño × Disaster Ratio Interactions		
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln PS_{t-2}$	0.8742*	(0.4822)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln MS_{t-2}$	-0.5351	(0.3628)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_PS_{t-1}$	-0.5914	(0.3607)
$ElNino_{t-1} \times \ln DR_{t-1} \times \ln ED\_MS_{t-1}$	1.3535**	(0.6443)
Observations	471,351	
R-squared	0.0619	
Adjusted R-squared	-0.0075	
Bank × Time FE	Yes	
Province × Time FE	Yes	

Notes: This table reports the results of regressing the firm-level credit growth (multiplied by 100) on bank exposure measures for the service sector. $\ln PS$ shows Portfolio Share, $\ln MS$ is Market Share, $\ln ED\_PS$ is External Disaster weighted Portfolio Share, $\ln ED\_MS$ is External Disaster weighted Market Share, FR shows Forecast Revision, with the unit being 10 percentage points, DR depicts Disaster Ratio, $ElNino$ is the El Niño indicator being equal to one during coastal El Niño. Standard errors are clustered at the bank-province level. * p<0.1, ** p<0.05, *** p<0.01.

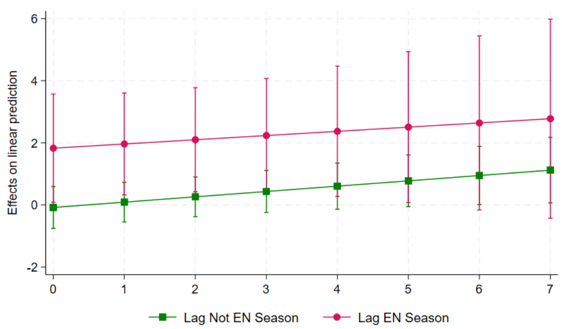
Figure F.6: Marginal effects of forecast revision by bank characteristics on firm-level credit growth - Service Sector with Firms having Multiple Banking Relationships



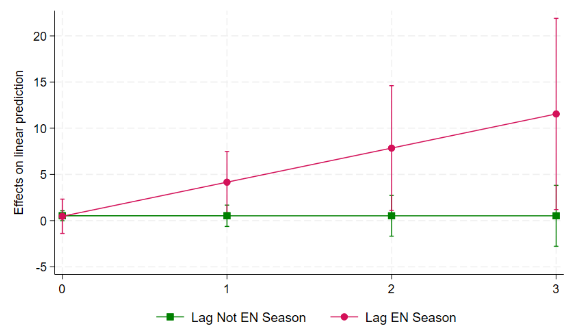
(a) Portfolio Share



(b) Market Share



(c) ED PS



(d) ED MS

Notes: This figure shows the marginal effects of climate forecast revisions on firm-level credit growth conditional on bank characteristics in the service sector with firms having multiple banking relations, during El Niño (red circle) and non-El Niño (green square) periods. Each panel represents a different bank characteristic: Portfolio Share (PS) measures the importance of provincial lending on a bank's balance sheet; Market Share (MS) captatures a bank's relative importance within a province; ED PS (External Disasters - Portfolio weighted) quantifies a bank's exposure to climate disasters in other provinces weighted by its portfolio allocation; and ED MS (External Disasters - Market weighted) represents a bank's exposure to climate disasters in other provinces weighted by its market presence. The vertical error bars represent the 95% confidence interval. All specifications include bank-time and province-time fixed effects. Standard errors are clustered at the bank-province level.