The Financial Transmission of a Climate Shock: El Niño and US Banks*

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December 21, 2023

Abstract

This paper investigates how a climate shock affects the banking system. We leverage El Niño, a recurring natural phenomenon inducing quasi-random variation in temperatures across the US. El Niño leads to lower house prices and mortgage lending in counties experiencing temperature increases. Higher temperatures increase water and soil salinity, which negatively affects both crop yields and local natural amenities. Banks exposed to El Niño reduce their mortgage lending even in counties unaffected by temperature increases. Using a LASSO analysis we find that banks with lower operating leverage (i.e., lower expenses on physical premises) are more climate-resilient.

JEL: G21, Q54, G28 **Keywords**: Banking, Climate, Financial Stability

*We would like to express our gratitude for their useful suggestions to Giorgia Barboni, Elena Carletti, Jean-Edouard Colliard, Ralph De Haas, Klaus Desmet, Sebastian Doerr, Nicola Gennaioli, Mariassunta Giannetti, Nandini Gupta, Ivan Ivanov, Marcin Kacperczyk, Thomas Krause, Asaf Manela, Adair Morse, Martin Oehmke, Daniel Paravisini, Alexander Popov, Simon Rother, Kelly Shue, Jason Sturgess, Stephen Szaura, Nancy Wallace and seminar participants at BI Oslo, Bocconi University, ECB Banking Supervision Conference, Danmarks Nationalbank, ESSFM (Gerzensee), FINPRO-Bank of Italy Conference, Harnessing Finance for Climate, HEC Paris "Banking in the Age of Challenges", Luiss University, MoFir workshop, PSDRN Virtual Seminar, Queen Mary University and Reichman University. Camilla Cherubini, Ilaria Dal Barco, Riccardo Di Cato and Daniel Goffi provided excellent research assistance. This paper previously circulated as "Climate, Amenities and Banking: El Niño in the US". We are grateful for the financial support of the Junior Researcher Grant at Bocconi University. We are responsible for all errors.

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1 Introduction

Global temperatures are increasing: July 2023 marked the hottest month on record in modern history (Copernicus Climate Change, 2023). Rising temperatures and weather-related events are already impacting the economy, thereby affecting financial institutions through their exposures to households and firms. As a result, policymakers and regulators are increasingly evaluating banks' preparedness to effectively managing climate risk, for example through climate stress testing (ECB, 2022; Jung et al., 2021; Acharya et al., 2023).

The existing literature studying the impact of climate shocks on credit markets has mostly focused on extreme weather events (Brown et al., 2021; Ouazad and Kahn, 2022; Nguyen et al., 2022), but has overlooked the role of non-destructive temperature shocks.[1] While studying the impact of extreme weather events is useful, it is also empirically challenging. When natural disasters strike and bring destructive effects on households and firms, there are significant government interventions and insurance payouts (Sastry, 2022; Oh et al., 2023), which affect lending outcomes through their impact on credit demand (Cortés and Strahan, 2017; Ivanov et al., 2022). Given the importance of understanding the total impact of climate change on the financial sector, in this paper we study a climate shock that does not produce destructive effects, but still affects firms, the real economy and financial institutions.

We leverage a setting with a shock to temperatures where the geography is known, but the precise timing is not. This shock can be thought of as a stochastic Poisson process: agents know it is coming sooner or later, but cannot predict either when it will occur nor its intensity. This allows us to isolate the unexpected component of climate and circumvent the usual criticism of measures related to the slow-moving nature of temperatures. This shock is a recurring climate phenomenon affecting local climate across the United States: the El Niño-Southern Oscillation (ENSO) or El Niño. To investigate the impact of El Niño on US climate and banks, we assemble a county-level panel with information on temperatures and other climate events for over 3,000 US counties from the 1980s together with local mortgage lending by more than 6,000 banks. To further understand the bank-level determinants that allow banks to hedge this climate shock, we construct a bank-level measure of exposure to El Niño-induced temperature shocks and

[1] Several papers have instead focused on how the transition to a low-carbon economy and environmental disclosure policies affect banks and credit markets (Accetturo et al., 2022; Kacperczyk and Peydró, 2022; Ivanov et al., 2023; Degryse et al., 2023b; Giannetti et al., 2023).

use a novel tool from the machine learning literature (Belloni et al., 2014; Chernozhukov et al., 2018), implementing a post-LASSO analysis to recover the characteristics of banks that present a high climate resilience.

Our identification strategy combines two key sources of variation created by El Niño. First, in the time series, El Niño is an unpredictable climate phenomenon that occurs if both warm waters of the southern Pacific Ocean spill into other parts of the ocean and exceptional atmospheric conditions arise.[2] El Niño events occur irregularly every two to seven years and cannot be predicted well in advance.[3] Since there is a continuum of potential "positive" El Niño years, we focus our attention on the 5 strongest events between 1980 and 2018, i.e. those years with the largest increase in average oceanic temperatures. Second, in the cross-section, we adopt a map elaborated by climatologists at the National Oceanic and Atmospheric Administration (NOAA), which shows the heterogeneous climate exposure to El Niño across different counties in the US. During El Niño years, the north experiences higher than average temperatures, the south becomes cooler while remaining parts of the country are unaffected.

The first part of our empirical analysis validates the effects of El Niño on local climate and economic outcomes across US counties. First, we confirm that counties with a positive (negative) exposure to El Niño have a higher-than-average (lower-than-average) level and volatility of temperatures during a top 5 El Niño. We also show that the probability of natural disasters is affected by El Niño, but it moves in the opposite direction with respect to the temperature shock, as it declines (increases) in counties with a positive (negative) exposure during El Niño years. Second, we explore whether county house prices and mortgage lending change in response to this climate shock.[4] Our analysis shows that mortgage lending and house prices decline significantly, respectively by 11% and 1.3%, in counties with a positive exposure during a top 5 El Niño event. These estimates are consistent with an elasticity of house prices with

[2] El Niño is referred to as a coupled climate phenomenon, requiring changes in both the ocean surface temperature and atmospheric wind circulation. "Random atmospheric disturbances" in the Pacific Ocean may be responsible for turning a neutral El Niño into a positive one with exceptional force (Fedorov et al., 2003; Rojas et al., 2014). For example, there are instances when the surface temperature of the Pacific Ocean looks like in an ENSO state, but the atmosphere is not (or vice versa).

[3] For example, in June 2023 the National Oceanic and Atmospheric Administration, NOOA, declared 2023 to be an El Niño year. This cannot be considered an early forecast, since it comes in the middle of the year, when El Niño conditions have already developed. Moreover, as of June there is still significant uncertainty whether it will be a strong event at its peak (56% chance). Having a strong El Niño is crucial to see effects in the US, as we show in this paper.

[4] Even if temporary, short-term fluctuations in weather can affect real estate prices, much like the predictable occurrence of hot and cold seasons do within the year (Ngai and Tenreyro, 2014).

respect to credit of about 0.12, in line with Favara and Imbs (2015). At the same time, we cannot reject a null hypothesis of no change in lending and house prices in counties with a negative exposure.

After documenting the county-level effects of El Niño, we study whether and how this shock aggregates at the bank level. To achieve this, we create a measure of bank exposure to the shock by combining information on the share of mortgage lending in a given county by a bank with the county exposure to El Niño. Our findings indicate that in the presence of a top 5 El Niño event, banks with one standard deviation higher exposure experience a decline in lending, as well as total assets, of 1.7% and 0.8% respectively. We also observe that real estate and commercial and industrial loans are the most affected among lending activities, exhibiting a decline of 1.5% and 2.7%, while consumer lending is unaffected.

We then investigate whether the changes in mortgage lending are due to county-level factors, which may be considered close attributes of local credit demand, or bank-level factors, which may be associated with the supply of credit. When we include county-year fixed-effects, which absorb unobserved county-level heterogeneity (i.e. comparing mortgage lending in the same county and year by different banks), we find that banks that are exposed to the (positive) temperature shock reduce lending. However, when we control for unobserved bank-level heterogeneity using bank-year fixed-effects (i.e. comparing lending by the same bank and year to different counties), we do not find that county exposure to El Niño matters anymore. More directly, we find that exposed banks reduce mortgage lending even in areas unaffected by El Niño (i.e., the control group of counties), effectively transmitting the shock from the positively exposed areas in other parts of the country. These results are consistent with the hypothesis that climate shocks impact the supply of credit.

Furthermore, to understand why county house prices and mortgage lending negatively react to the increase in temperatures, we investigate two potential channels: agricultural crop yields and natural amenities. El Niño has the potential to negatively affect both by increasing salinity, which lowers micro-nutrients crucial for the development of vegetation and wildlife (Artiola et al., 2019). We document that water and soil salinity increase during El Niño years by 8% and 21.5% in positively exposed counties and the increase in salinity negatively impacts both crop yields and natural amenities. First, we find that crop yields of both corn and wheat decline in the positively exposed counties, where the increase in salinity happens. Since the positively exposed counties in the north of the US are large producers of corn and other agricultural produce, this means that El Niño represents a significant negative economic shock. Second, we observe that El Niño deteriorates the value of natural amenities, which are defined as the natural characteristics that make a location desirable for people to live in. To test this hypothesis, we employ the cross-sectional "Natural Amenities Scale" for US counties elaborated by the Economic Research Service of the U.S. Department of Agriculture (USDA). We find that the negative effects of higher temperatures on house prices and mortgage lending are increasing in the value of natural amenities.

Finally, to understand the characteristics of banks that make them resilient to this shock, we adopt the post-LASSO estimator, following the work of Belloni et al. (2012, 2014); Chernozhukov et al. (2018). This method allows us to implement a "model selection" through an algorithmic procedure that identifies the variables predicting a successful hedging of this climate shock and, hence, lowering the impact of El Niño on banking. The LASSO analysis highlights that banks with a lower ratio of fixed costs on premises and branches over total assets are less affected by El Niño. This finding suggests that banks with a strong physical presence are more vulnerable and present less flexibility to change their organizational structure to respond to climate shocks. This is in line with literature on the "operating leverage hypothesis" (Lev, 1974; Carlson et al., 2004; Novy-Marx, 2011), where operational costs are as important as other financial characteristics like the capital structure in influencing corporate behaviour. This result offers valuable insights for the theoretical modelling of climate in banking and finance, and to policymakers to understand possible avenues for climate-resilient financial regulation.

Our empirical setting offers a natural "placebo" to test whether our results are driven by the specific north-south geography of the temperature changes induced by El Niño. For this purpose, we study La Niña, which generates a different and opposite cross-sectional heterogeneity in temperatures compared to El Niño, with the north becoming cooler and the south warmer. We replicate the same econometric strategy used for El Niño and we define a dummy for top 5 La Niña years. We digitize the NOAA map of county exposure to La Niña and build a corresponding measure of bank exposure. We further notice that La Niña events are 50% weaker than El Niño in terms of changes in oceanic temperatures, thus providing a "placebo" of weak El Niño years. As a result, we cannot reject the null hypothesis of no effect of a top 5 La Niña event on lending and assets at bank-level. These results are useful to rule out possible alternative stories that the exposure to El Niño picks up geographic time-varying heterogeneity between the North and South of the US rather than the effect of the climate shock.

To address possible confounders, we explore a rich set of alternative specifications. For example, we re-examine our analysis of county-level and bank-level factors using small business lending information from CRA data and find similar results, although not precisely estimated due to the smaller sample. Additional findings show that our key results are robust to: i) using a continuous measure of El Niño instead of top5 dummies; ii) controlling for the bank exposure to precipitations; iii) controlling for the effect of natural disasters; iv) using alternative methods for spatial clustering the standard errors, including wild bootstrap; v) using alternative difference-in-difference estimators Borusyak et al. (2022) and vi) alternative model selection procedures for the LASSO analysis.

The idea that climate may influence economic performance is well established in the existing literature (Dell et al., 2014). Climate volatility affects economic and social outcomes such as productivity, income and growth (Deschênes and Greenstone, 2007; Hsiang, 2010; Dell et al., 2012) or conflict and migration (Hsiang et al., 2013). However, less is known about how climate factors, and climate change in particular, may affect the economy through the financial sector. This project aims to fill this gap by analysing the effects of climate shocks on house prices and local lending, and thus overall bank balance sheets.

The climate finance literature is relatively new and it has mostly focused on whether climate risk is priced in various asset classes, from real estate (Baldauf et al., 2020; Giglio et al., 2021) to fixed income (Painter, 2020; Goldsmith-Pinkham et al., 2021; Acharya et al., 2022) and equity (Engle et al., 2020; Bolton and Kacperczyk, 2021, 2022). A growing number of studies have focused on the impact of physical climate risks on banking and credit markets. Cortés and Strahan (2017), Correa et al. (2020), Brown et al. (2021), Ouazad and Kahn (2022), Nguyen et al. (2022), Blickle et al. (2022) collectively show that weather shocks due to natural disasters and sea level rise affect local credit markets, corporate lines of credit and mortgage rates. Recent work by Sastry (2022) shows that banks distribute the flood risk of residential mortgages with households and the government flood insurer through credit rationing and tightening loan-to-value rations.

Many have also focused on the transition risk to a low-carbon economy (De Haas and Popov, 2022). For example, Oehmke and Opp (2022) show theoretically that imposing higher capital requirements on "brown" firms is not an effective tool to reduce carbon emission. Others have studied how to develop climate stress testing (Jung et al., 2021; Acharya et al., 2023).[5] Using syndicated loans, Degryse et al. (2023a) and Kacperczyk and Peydró (2022) investigate whether climate agreements and de-carbonization efforts affect loan rates and credit allocation, depending on the environmental consciousness of banks and firms. Accetturo et al. (2022) offer evidence that credit supply affects firms' green investments, while Degryse et al. (2023b) show that banks with large legacy positions are less likely to finance green innovations. Giannetti et al. (2023) document a disconnect between banks' environmental disclosures and credit allocation.

We contribute to the broad climate finance and banking literature by examining bank exposure to a climate shock to temperatures and show which balance sheet characteristics allow banks to hedge this climate shock. These results may be particularly valuable to understand the timing dimension of how climate change may affect the economy.

Finally, a key part of this project is to use El Niño as an instrument for climate events, as it has been done in other contexts. For example, Dingel et al. (2019) study the effects of El Niño on global spatial correlation of crop productivity to explain cross-country welfare dispersion. A number of studies have shown a negative impact of El Niño on agricultural crop yields (Tack and Ubilava, 2013), global economic growth (Generoso et al., 2020; Callahan and Mankin, 2023), in particular in developing countries (Smith and Ubilava, 2017). Moreover, El Niño has been related to civil conflict (Hsiang et al., 2011), commodity prices (Brunner, 2002), and market anomalies (Novy-Marx, 2014). This is the first paper that analyzes how El Niño-induced exogenous changes in weather can influence the economy through its effects on banks.

[5]The evidence on the effectiveness of stress testing in affecting credit supply and reducing emissions is mixed (Fuchs et al., 2023), compared to cap-and-trade policies (Ivanov et al., 2023).

2 El Niño, Identification and Data

This section provides general information about El Niño using NOAA data on the cross-sectional exposure of different counties across the United States and the quasi-random occurrence in the time series. It also describes our identification strategy to study the effects of El Niño on banking and presents the key datasets used in this analysis.

2.1 El Niño and the United States

El Niño-Southern Oscillation (ENSO) or El Niño is a recurring climate variation of the ocean-atmosphere system in the tropical Pacific – the world's largest ocean – which has the potential to affect weather around the globe.[6] El Niño events occur irregularly in intervals of 2-7 years and typically last between 12 and 18 months. Its occurrence is determined by changes in both the ocean surface temperature and wind circulation patterns.

El Niño fluctuates between a neutral and two extreme states, depending on the amount the heat that is released from the ocean into the atmosphere. In El Niño "neutral" years, the surface temperature in the central and eastern tropical Pacific Ocean is around average and the normal westward circulation pattern of low-level surface winds keeps the pool of warm water in the South Pacific. In "positive" El Niño years a warming of the surface temperature in the tropical Pacific together with a weakening or even a reversal of the westward circulation patterns causes warm water to spill eastward so that more heat is released over the Pacific ocean near the Americas. When this happens, climate in different areas of the planet is affected heterogeneously: warmer temperatures arise in the tropics and cooler temperatures at higher latitudes. The opposite occurs during a "negative" El Niño event (the so called La Niña): stronger than normal easterly wind keep even more warm water in the South Pacific, thus reducing heat in other parts of the ocean.

For the United States, the most significant impact of El Niño is due to a shift in the location of the jet stream. The jet stream is a strong, high-level wind that typically separates warm from cool air masses and pushes storms from the Pacific across the US. By affecting the location of the jet stream El Niño therefore alters climate and rainfall patterns across the entire United

[6] The Southern Oscillation (SO) is an inter-annual see-saw in tropical sea level pressure between the eastern and western hemispheres. For more information refer to NOAA, at https://www.pmel.noaa.gov/elnino/faq or What is the El Niño–Southern Oscillation (ENSO) in a nutshell?.

States. The shift in the jet stream also leads to changes in the occurrence of severe weather, and the number of tropical cyclones expected within the tropics in the Atlantic and Pacific oceans. Figure 1 shows the weather patterns induced by El Niño and its geographic effects on the US, according to NOAA: during El Niño, the Pacific jet stream flows straight in the southern tier of US states, causing an abnormal cooling in the south and warming up of areas north of the 48^{th} parallel. At the same time, the Midwest (Ohio and Upper Mississippi River Valleys) become unusually dry while the south – from California to the Carolinas – experience more precipitations. During La Niña, these deviations from the average are approximately, but not exactly, reversed (Figure A3 in the Online Appendix).

2.2 Measurement of El Niño

A variety of indices are used to characterize El Niño because it effects so many elements of the atmosphere-ocean climate system. Four widely used indices are:

1. The Southern Oscillation Index (SOI), which is given by the difference in sea-level pressure between Tahiti and Darwin, Australia. The SOI, defined as the normalized difference in surface pressure between Tahiti, French Polynesia and Darwin, Australia is a measure of the strength of the trade winds, which have a component of flow from regions of high to low pressure. High SOI (large pressure difference) is associated with stronger than normal trade winds and La Niña conditions, and low SOI (smaller pressure difference) is associated with weaker than normal trade winds and El Niño conditions.

2. The Niño 3 index, which referes to the anomalous SST within the region bounded by 5N-5S and 150W-90W. The SST indices are measures based the average sea-surface temperature over a fixed area in the tropical Pacific. The SST indices are: Niño 1+2 (0-10South)(90West-80West) Niño 3 (5North-5South)(150West-90West) Niño 4 (5North-5South) (160East-150West) Niño 3.4 (5North-5South)(170-120West). The only difference among them is the area of the Pacific used to measure the sea surface temperature.

3. The anomalous 850 mb zonal winds show how the low-level atmospheric flow is responding to low-level pressure anomalies associated with El Niño and other mechanisms. Often the 850 mb flow (about 1.5 km above sea level) exhibits a "cleaner" signal than the winds

at the surface, which are subject to local effects such as terrain. An index involving the 200 mb zonal flow is used to describe the upper tropospheric winds, whose anomalies tend to be opposite to those at 850 mb and below. The 200 mb flow is particularly important because it is changes at around this level in the tropics that tend to have the biggest consequences for the atmospheric circulation outside of the tropics. The 500 mb temperature represents a proxy for the anomalous heat content of the tropical troposphere. In an overall sense, there is greater heating of the troposphere, and more deep cumulus convection, than normal during warm El Niño events.

4. The outgoing longwave radiation (OLR), the deeper the cumulus convection, the colder the cloud tops, which means the thermal or infrared radiation to space is reduced. It is straightforward to monitor OLR via satellite; its value in the tropical Pacific near the dateline is an effective way to gauge the frequency and magnitude of the thunderstorm activity that changes with El Niño.[7]

We take advantage of a composite index combining all different El Niño measures: the Multivariate El Niño index, version 2 (MEI.v2). This bi-monthly index is calculated for 12 overlapping bi-monthly "seasons" (Dec-Jan, Jan-Feb, Feb-Mar,..., Nov-Dec) in order to take into account El Niño's seasonality, and reduce effects of higher frequency intra-seasonal variability. In particular, the MEI.v2 gives real-time indications of El Niño intensity, it is available from 1979 and it is widely used in the literature.[8]

2.3 Identification

In this section, we provide more details on how we identify shocks to climate risk. In particular, we present the time-series variation in the occurrence of El Niño. We also describe the cross-sectional variation in county exposure to El Niño, which will be used to measure the counties in which this event takes place and aggregated at bank-level to study its financial implications.

[7]More information on all these indices is available at https://www.cpc.ncep.noaa.gov/data/indices/

[8]Refer to this link available by NOAA, https://psl.noaa.gov/enso/mei/.

2.3.1 Time-series variation - the quasi-random nature of El Niño

El Niño generally begins during April-May of a given year and lasts until the following April-May, an interval known as the "tropical year" (Dingel et al., 2019). Because the El Niño index typically peaks in winter, we decided to take the average of the MEI.V2 index from January to May and define a El Niño year if this average is above a threshold of +1 degree Celsius. Figure 2 shows the MEI.V2 average value for the 9 strongest El Niño events during our sample period. By taking the 1-degree cut, we select the top 5 events with the largest positive deviations in the MEI.V2 index. In so doing, we end up with a sample of the 5 major El Niño years: 1983, 1987, 1992, 1998, 2016. Focusing on these 5 events provides us with an opportunity to identify the years in which El Niño took place and with exceptional strength.

Furthermore, there is broad scientific consensus that this time-series variation is quasi-random, as the factors that transform a neutral El Niño event into a forceful one are due to "random atmospheric disturbances". For example Fedorov et al. (2003) state: "*Nobody anticipated that El Niño would be weak and prolonged in 1992, but brief and intense in 1997/98. Why are various El Niño episodes so different, and so difficult to predict? The answer involves the important role played by random atmospheric disturbances (such as westerly wind bursts) in sustaining the weakly damped Southern Oscillation*". In the same spirit, Rojas et al. (2014) discuss the role of unpredictable atmospheric disturbances in creating stronger El Niño events: "*However, while the accuracy of these models in predicting the onset of an El Niño episode is fairly high, the intensity is much more difficult to predict due to random atmospheric disturbances that may dampen or amplify the intensity of an El Niño occurrence and thus its impact on weather patterns*".

As a result, we define the occurrence of this event as "quasi-random" throughout this paper, as this is both unpredictable and orthogonal to economic and financial conditions.

2.3.2 Cross-sectional variation

A large body of scientific evidence allows to measure the heterogeneous effects of El Niño on weather patterns in different areas of the globe. It is also possible to know in advance which parts of the US counties will experience cooler-than-average or warmer-than-average temperatures, as shown in Figure 1. Using QGIS software, we overlay this figure with the

US counties shapefile and we generate Figure 3, a map showing the heterogeneous geographic effects of El Niño on temperatures across the US. The northern tier of the lower 48^{th} parallel in the United States and southern Alaska exhibit above normal temperatures, while areas around the Gulf and other inner parts of the south US experience below normal temperatures.

We use this map to build a variable which measures the exposure of a county to a "positive climate shock" if it is hit by warmer-than-average temperatures, a "negative climate shock" if it is hit by cooler-than-average temperatures, or if it is unaffected. All of our empirical analysis investigating county-level variables (temperatures, lending) adopt these indicators and study their effects. In addition to this, we aggregate these indicators at the bank level and create a measure of bank exposure to El Niño.

2.4 Data

Our empirical analysis relies on a number of different data sources from various US agencies. The main databases we used are the following.

The U.S. Historical Climatology Network (U.S. HCN) from NOAA publishes precipitations, temperature and other climate data from 1,219 weather stations across the United States. This dataset is available at the station-day level and covers a large part of the United States: these stations are selected according to their spatial coverage, record length, data completeness, and historical stability. We collapse this dataset at the county-year level and this includes 3,108 counties from 1979 to 2019.

We take advantage of the FEMA Disaster Declarations Summary to obtain a list of natural disasters in the US from 1980. This dataset features three types of disaster declaration: major disaster, emergency, and fire management assistance. The dataset includes declared recovery programs and geographic areas. We aggregate this data at the county-year level introducing a dummy that takes unit value if a county in a year has experienced a natural disaster. In a robustness check, we also use the Emergency Events Database (EM-DAT).

We use the Home Mortgage Disclosure Act (HMDA), focusing on conventional, originated loans for the purchase of single (one to four) family homes, and collapse this dataset at the bank-county-year level, with bank indicating bank holding company (BHC), and this dataset includes 6,567 bank holding companies, operating in 3,108 counties from 1981 to 2016. We also merge the respondent bank ID in HMDA with bank balance sheet information from the Call Reports using the Avery file from 1993.

We obtain county-level house price index (HPI) from 1975 until 2019 from the Federal Housing Finance Agency (FHFA) as described in Bogin et al. (2019). These indexes are calculated using appraisal values and sales prices for mortgages bought or guaranteed by Fannie Mae and Freddie Mac. Because in some cases sample sizes are too small for the county area, the HPI is not always reported for each county and year. To maximize coverage and because the HPI values reflect cumulative appreciation overtime, we use the index value with a base equal to 1 in 2000, i.e. the change in the HPI reflects an annual percentage change from 2000.

We measure salinity using two different data sources: one on water salinity and another on soil salinity. On water salinity, we use a global, harmonized database provided by Thorslund and van Vliet (2020). The dataset comes from the combination of observational data collected from various sources at the station level, which we process and collapse at the county level. This dataset covers 3144 counties over the period between 1980 and 2019 on surface water, divided into rivers, lakes/reservoirs and groundwater locations. On soil salinity, we adopt the "Global Soil Salinity Map" by Ivushkin et al. (2019). This database contains maps on soil salinity covering 3223 counties for a selected number of years (1986, 1992, 2000, 2002, 2005, 2009 and 2016). In terms of definition of the salinity variables, both are measured through electrical conductivity.[9]

To collect information on the agricultural sector, we rely on the U.S. Department of Agriculture (USDA). Under the National Agriculture Statistics Service, the USDA conducts direct surveys with farmers and ranchers to acquire the most accurate possible estimates of agricultural production in the country. Crop yields are defined as the gross or total amount of a crop produced by plants expressed as a rate per geographic unit; in our context, the unit of measure is bushels per harvested acre. In our analysis, we include the yields of two primary crops: corn and wheat.

Finally, we measure natural amenities exploiting the "Natural Amenities Scale" elaborated by the Economic Research Service of the USDA. This scale is a measure of the natural and physical characteristics of a county that make it as a desirable location for people to live in.

[9]Water salinity is measured in microSiemens per centimetre $\frac{\mu S}{cm}$: an electrical conductivity of 1563 $\frac{\mu S}{cm}$ corresponds to 1,000 parts per million, which equals 1 gram of salt. Soil salinity is measured in deciSiemens per metre $\frac{dS}{M}$: 1 deciSiemens per metre corresponds to 640 parts per million, equalling 0.64 grams of salt per liter.

It combines six variables of climate, topography, and water area, reporting the natural and environmental qualities preferred by people. This is a county-specific time-invariant scale and its map is reported in Figure 4.

3 Empirical Model and Results

This section investigates how El Niño affects banking at the local level and for the bank as a whole. First, we study how El Niño affects county-level climate variables. Second, we investigate how loans and house prices at the county level respond to the variation in climate induced by El Niño depending on the value of natural amenities. The third subsection aggregates the climate exposure at the bank level and studies how banks are affected by El Niño, while the fourth focuses on dissecting the demand and supply factors of this climate shock.

3.1 Climate and Natural Disasters

Our first empirical test validates the effect of El Niño on local climate and natural disasters. We estimate the following equation:

$$Y_{ct} = \sum_{j=P,N} \beta_j Exposure_{jc} \times ElNiño_t + \alpha_c + \gamma_t + \varepsilon_{ct} \tag{1}$$

We focus on three key dependent variables (Y_{ct}) for county c in year t: average temperatures, their volatility (i.e., standard deviation of daily temperatures within a year) and the probability of a natural disaster. We regress these on the interaction between the cross-sectional exposure to El Niño, $Exposure_{jc}$, which can be positive ($j = P$) and negative ($j = N$), and the occurrence of a top 5 El Niño event, which we denote $El\,Niño_t$. $Positive\,Exposure_c$ is a dummy equal to 1 if a county is exposed to an increase in temperatures relative to its average and zero otherwise; $Negative\,Exposure_c$ is a dummy equal to 1 if a county is exposed to a decrease in temperatures relative to its average and zero otherwise (as in Figure 3). The variable $El\ Niño_t$ is a dummy equal to 1 for the years classified as top 5 El Niño events (1983, 1987, 1992, 1998, 2016) and zero for other cases. α_c and γ_t are county and year fixed effects, respectively. Standard errors are clustered at the county level.

The first six columns of Table 2 validate the evidence from NOAA on the impact of El Niño on temperatures across the US. The first and third columns regress the average and volatility of temperatures on the interaction between the positive exposure variable and the dummy for top 5 El Niño events, keeping in the control group both counties with no exposure and those with a negative exposure. Both estimated coefficients are positive, statistically different from zero at the 1% threshold. The second and fourth columns study exclusively the difference between counties with a negative climate exposure and all others are in the control group. In this case, both coefficients are negative, significantly different from zero below the 1% threshold and high in magnitudes. Finally, the third and sixth columns present regressions with both the positive and negative exposures, keeping in the control group only counties that are unaffected by El Niño.

All in all, in the presence of a top 5 El Niño event, counties with a positive climate exposure exhibit yearly average temperatures that are between 0.5 and 0.6 degrees higher and an increase in the standard deviation by 0.2 (i.e., 10% higher than the baseline temperature volatility). At the same time, counties with a negative climate exposure experience temperature averages that are between 0.3 and 0.5 degrees lower and a volatility of temperatures between 0.05 and 0.1 lower (i.e., 2.5% and 5% lower compared to baseline volatility). When both positive and negative exposure are considered together, only the counties with a positive exposure experience higher volatility than the control group, whereas those with negative exposure are not statistically different.

Our next test analyzes the role of natural disasters and their relationship with El Niño. To do so, we regresses a dummy for a FEMA-declared natural disaster on the interaction between the county exposure to El Niño and the occurrence of a top 5 El Niño event. We find that El Niño generates effects on disasters which are opposite with respect to those on temperatures. Counties that experience higher temperatures during a top 5 El Niño event have a lower probability in the occurrence of natural disasters, while counties with a negative exposure have a higher probability of disasters, which is in line with the occurrence of wildfires in the Southern part of the US during El Niño years (Swetnam and Betancourt, 1990; Brenner, 1991). In terms of magnitudes, column (9) of Table 2 shows that the probability of a natural disaster declines by 1.8% in counties with a positive exposure and increases by 13% in counties with a negative exposure during a top 5 El Niño event.

3.2 County Mortgage Lending and House Prices

After validating the climate shock induced by El Niño in our data, we turn to study its effects on local economic and financial outcomes. In particular, we focus on mortgage lending from HMDA and house price indexes (HPI) from the FHFA.

We follow the regression specification in equation (1) and regress the natural logarithm of county mortgage lending from HMDA or the House Price Index (HPI) from FHFA with base year 2000 on county-level climate exposure to a top 5 El Niño event. Table 3 reports the results of this analysis, showing first the effects of positive and negative temperature exposures separately in columns (1)-(2) and (4)-(5) and then combining the two in columns (3) and (6). During a top 5 El Niño event, counties with positive temperature exposures experience a decline in mortgage lending of 11% and a contemporaneous decline in house prices of 1.3% with respect to the 2000 base year, with both coefficients being statistically different from zero below the 1% threshold. The difference in the response of mortgage lending and house prices may seems large at first, but it is consistent with a pass-through elasticity of house prices with respect to credit of about 0.12, which is in line with other estimates found in the literature (Favara and Imbs, 2015). Counties with negative temperature exposure on the other hand experience an increase in lending and house prices which however is small and not statistically significant when we include both exposures. The increase in mortgage lending in the negatively exposed areas is consistent with previous findings in the literature which show that both mortgage (Cortés and Strahan, 2017) and corporate lending (Ivanov et al., 2022) increase in areas hit by natural disasters. When natural disasters strike, there is a significant mobilization of government and insurance resources that are used for reconstruction. Credit demand hence increases and banks accommodate it by drawing liquidity from unaffected areas where they own branches. Negatively exposed areas have a higher likelihood of natural disasters as shown in columns (8)-(9) of Table 2.

All in all, Table 3 shows that during a top 5 El Niño event, both lending and house prices decrease in counties that experience an increase in temperatures. In the following sub-sections we explore a potential channel through which El Niño can have these negative effects on local mortgage lending and house prices through its impact on natural amenities.

3.3 Financial Transmission of El Niño

In this section we explore whether the changes in mortgage lending at the county level documented in the previous section are due to bank-supply side or county-demand side factors . To do so, we expand our dataset to a bank-county-year panel and estimate the following equation:

$$Y_{bct} = \sum_{j=P,N} \sum_{k=b,c} \beta_{jk} Exposure_{jk} \times ElNiño_t + \alpha_{ct} + \gamma_{bt} + \varepsilon_{bct} \quad (2)$$

where the dependent variable (Y_{bct}) is the log of total mortgage origination by bank b in county c in year t. $Exposure_{jk}$ can be positive ($j = P$) and negative ($j = N$) for both banks ($k = b$) and county ($k = c$). The positive and negative county exposures are defined as in equation (1). The positive and negative bank-level exposure to El Niño are defined as the weighted average of the county climate exposure using mortgage lending shares as weights, $\sum_c Exposure_c \times Share_{bc}$, calculated separately for positively exposed and negatively exposed counties. $Share_{bc}$, is the average share of mortgage lending that bank b issues to borrowers in county c relative to the entire stock of mortgages of bank b across all years in the sample. The bank and county exposures are interacted with the occurrence of a top 5 El Niño event, which we denote $El\ Niño_t$. We identify county and bank factors by absorbing county-time (α_{ct}) and bank-time ($\gamma_b t$) fixed-effects, one at a time.

We report the result of this exercise in Table 4. We first regress the natural logarithm of mortgage lending at the bank-county level on both positive and negative bank exposure together with county exposures interacted with the top 5 El Niño year indicator. We only control for bank, county and year fixed-effects in column (1) but not for their double interaction. We find that both positively exposed banks generate a lending reduction of 19.7%, while positively exposed counties induce an increase of 11% respectively. However, this effect could be due to a combination of time-varying demand or supply factors. To absorb unobserved heterogeneity in bank factors, we include bank×year fixed-effects in column (2) we find that county-level exposure to the El Niño shock does not matter anymore: the coefficient declines by a factor of three and is not statistically different from zero. In column (3) instead, we take care of county factors by including county×year fixed-effects, hence absorbing the county-level El Niño shock: we find that banks that are more positively exposed reduce credit by 22% compared to less exposed banks lending to the same county and year.

The last two columns of Table 4 provide additional support to the hypothesis that bank-specific factors rather than county-specific ones are driving the reduction in mortgage lending related to El Niño. These regressions replicate the structure of column (3) but split the sample depending on whether counties were exposed to El Niño or not. We also omit the interaction between negative bank exposure and Niño, since this factor was quantitatively negligible in column (3). These columns show that regardless of whether counties were individually exposed to El Niño, the bank positive exposure to El Niño led to a contraction of credit which is similar in point estimate and we thus conclude that supply-side factors play a larger role in explaining the decline in credit than demand factors.

3.4 Channels: The role of Salinity

Salinity is a key input into natural amenities and agricultural yields: a stable amount of salt in the soil helps vegetation grow and provides micro-nutrients to plants and animals. As described in a FAO (2021) report, saline soils are technically defined as those who contain more soluble than gypsum, a soft sulfate mineral, in a concentration sufficient to negatively affect the ability of plants to take up water and to reduce the availability of micro-nutrients. Many regions of the world present naturally saline soils, hosting a range of valuable ecosystems with the local vegetation adapting to heterogeneous and even extreme conditions.[10]

The salinity of soils can vary over time because of both human activity and environmental conditions. The main reason behind soil salinization due to human activity is the inappropriate management of irrigation, while the common environmental reason behind higher salinity is the saline water intrusion from sea into lakes, rivers and groundwater. Climate change is another important determinant of salinity and over the past decades its effects have been increasing in frequency and size (Vineis et al., 2011). Rising temperatures strengthen water evaporation, which increases the presence of salt in the soil, leading, in the extreme, to aridification. At the

[10] Salinity can be classified in three ways (Bari and Ruprecht, 2003). Primary, or natural, salinity is caused by natural processes such as rainfalls. Small amounts of salt evaporate from ocean water and are carried by rain clouds. Therefore, salt concentration is higher near the coast, and decreases moving inland. Secondary, or dry-land, salinity is the result of the reduction of perennial vegetation in dry areas. When the perennial vegetation is lost, the amount of water lost from the landscape through plants is drastically reduced, and salinity increases. Finally, tertiary salinity is the one caused by irrigation: when water is reapplied to crops over many cycles, each time some of it will evaporate and the salts in the remaining water will become more concentrated.

same time, climate change is also a primary cause of a meaningful rise of sea levels, which has been highlighted as one of the main factors causing saltwater intrusion into groundwater (Xiao et al., 2018).

To quantify the effect of the temperature increase due to El Niño on salinity, we employ a similar specification as in equation (1), but replace the dependent variables to be the average salinity of water in rivers and soils of county c in year t. As discussed in Section 2.4, both of these are measured through electrical conductivity and consist of the concentration of dissolved soluble salts in a sample of water and soil extract respectively..[11] Table 5 presents the results of these regressions. The first three columns display the findings on water salinity, while the last three columns focus on soil salinity.

Columns (1), (2) and (3) indicate the during a top 5 El Niño, counties with a positive exposure experience an increase in water salinity, while counties with a negative exposure see a decline in water salinity. In terms of magnitudes, the results of column (3) show that water salinity increases by 8% relative to the mean during a top 5 El Niño in counties with a positive exposure and decline by 33% relative to the mean in counties with a negative exposure. Columns (4), (5) and (6) show that changes in water salinity transmit to soil salinity. Soil salinity in counties with a positive exposure to El Niño increases by 21.5% relative to the mean during a top 5 El Niño event, while salinity drops by 28.3% relative to the mean during a top 5 El Niño event in counties presenting a negative exposure to El Niño. In the Online Appendix, we extend these results by studying three different types of water salinity, that of rivers, lakes and groundwater. Table A2 shows that in all of these cases during a top 5 El Niño, counties with a positive exposure experience an increase in all types of water salinity and are more likely to present water with levels of salt exceeding 1,000 and 2,000 parts per million.

These findings highlight the detrimental effects of salinity on natural amenities and crop yields: as discussed in section 2.3, an increase in salinity worsens the presence of micro-nutrients in the water and soil, which deteriorates natural amenities like vegetation and animal life. On

[11] According to Mayer et al. (2005), the salinity of status of water is typically characterized with the following scale. Water is considered "Fresh" if salinity defined as the milligrams of salt per litre are lower than 500, which makes it suitable for drinking and all irrigation; "Marginal" water presents salinity between 500 and 1000 and is used for most irrigations, with some adverse effects on ecosystems; "Brackish" water has salinity between 1000 and 2000 and can be used for the irrigation of selected crops only and most livestock; "Saline" water displays a salinity between 2000 and 10,000, cannot be used for irrigation and is used for most livestock; "Highly saline" water contains between 10,000 and 35,000 milligrams of salt per litre and is limited to use of selected livestock; "Brine" water presents a salinity exceeding 35,000 and can be used for mining and some industrial activities.

the contrary, a decline in salinity generally leads to a higher quality of water and potentially a positive, or null, effect on amenities.

3.4.1 Crop Yields

The agricultural economic literature has shown that El Niño negatively affects crop yields in the US (Tack and Ubilava, 2013). This happens because El Niño is correlated with pest damage: increase in insects and germination rates for bacteria and fungi with El Niño (Rosenzweig et al., 2001). Building on the results of the previous section, which show that higher temperatures due to El Niño increase water and soil salinity, we provide a novel channel through which El Niño can affect crop yields: salinity.

Changes in salinity have a direct effect on crop yields. In general, a reduction in salinity may lead some water sources to qualify as fresh water and improve the quality of water, while a substantial increase in the level of salt in the soil and water threatens water quality, especially if used for irrigation. This can be especially detrimental in those habitats where plants are highly sensitive to soil salinity, which can impair the health and development of vegetation. Given the increased in salinity in positively exposed areas during a top 5 El Niño event we documented in Table 5, we expect that the same areas also see a reduction in crop yields.

The US is an important producer of corn (32% of world production) and wheat (6% of world production). Using data from the USDA, we run a specification as in equation (1) and replace the dependent variables to be the average bushels per harvest acre for corn and wheat of county c in year t. We report the results in Table 6. We find that in counties with positive exposure, corn and wheat production decline by 0.9 and 0.8 bushels per harvest acre (0.7% and 1.8% respectively compared to the average) during a top 5 El Niño event. There is no effect on corn production in negatively exposed counties compared to the control group and a positive effect for wheat production. It is important to note that while the "corn belt" (i.e., the area where corn is produced in the US) is almost entirely contained within the positively exposed counties, the "wheat belt" has a significant southward protuberance, hence wheat and corn production are going to be differentially affected by El Niño.

The decline in crop yields is a negative shock for the local economy in some counties. Agriculture, food, and related industries represent about 5.4% of US GDP, with agriculture alone accounting for 1-2% of GDP in the period between 1980 and 2018. However, there is significant cross-state variation and agriculture is a relevant part of the economy in the positively exposed counties. Specifically, agriculture is 4-5% of GDP in the Northern states where corn production is concentrated. Hence El Niño is a significant local economic shock to these areas and has the potential to negatively affect lending and house prices.

3.4.2 Local natural amenities

The results in Table 3 show that El Niño can negatively impact house prices in areas where temperatures increase. However, fluctuations in weather due to El Niño are only temporary deviations from the mean and thus one may wonder how they can have long-run implications for an asset such as real estate. We show that this concern, while valid, does not directly apply in our setting.

First of all, the literature has shown that even temporary shocks can affect house prices: Ngai and Tenreyro (2014) find that house prices in the same location are higher in the hot season compared to the cold season. Thus, a predictable and temporary shock, such as the alternating of the summer and winter seasons, can still induce fluctuations in long-term asset prices. Second, we show that El Niño directly lowers the value of natural amenities, thus affecting the desirability of locations and house prices. To do so, we test whether the negative effects of El Niño on local mortgage lending and house prices are amplified in areas that have a higher value of natural amenities. We use a natural amenities scale from the the USDA, which combines six measures of climate, air, topography, and water surfaces that reflect environmental qualities. Figure 4 shows a map of US counties ranked according to the value of their natural amenities: counties out West, along with Florida and other southern states, tend to have higher values whereas the counties in the Midwest around the Great Lakes have low amenities.

We exploit cross-sectional variation in this map to obtain additional heterogeneity at the county level and show that the negative effects of El Niño are amplified in high amenities areas. We employ a similar specification as in equation (1) but we augment the regression by including an interaction between $Natural\ Amenities_c$, a dummy equal to one if the county has an above the median rank in natural amenities, with the $El\ Nino_t$ top 5 indicator. The additional interaction term $Natural\ Amenities_c \times El\ Nino_t$ either replaces the exposure to positive temperature increases or it is added as an additional control. We show the results in Table 7.

Column (1) and (4) replicate the results in the respective columns of Table 3. Columns (2) and (5) show that, during a top 5 El Niño even, counties with high amenities experience a 1.12% decline in mortgage lending and 3% in house prices (although the effect on lending is not statistically significant), suggesting that these counties suffer more during El Niño events. Finally, columns (3) and (6) explore whether the effects are heterogeneous and the results indicate that during a top5 El Niño year, counties with positive temperature and high amenities lose an additional 6% in mortgage lending and 1.7% in house prices. These interaction effects amplify by about 60-100% the baseline effect of El Niño on lending and house prices in counties with positive temperature exposure. This is a large effect and suggests the presence of a strong channel through which El Niño can influence on real economic or financial outcomes.

3.5 Bank Balance Sheets

The previous results highlight that a top 5 El Niño event induces significant and sizeable effects on county level house prices, mortgages and agricultural outcomes. But is the local impact of El Niño large enough to affect banks and their balance sheets?

In this section we investigate whether banks are hit by this climate shock by building a measure of bank exposure combining the local county exposure to El Niño with bank exposure to the lending in that county. We use the following empirical model:

$$Y_{bt} = \alpha_b + \gamma_t + \sum_{j=P,N} \beta_j Exposure_{jb} \times ElNi\tilde{n}o_t + \varepsilon_{bt} \tag{3}$$

in which we regress key outcomes at the bank level (total assets and lending, including its various subcategories) on bank and year fixed effects, respectively α_b and γ_t, and an interaction between the positive and negative bank exposure to El Niño defined in section 3.3 and the variable measuring whether year t is one of the top 5 El Niño, $El\ Nino_t$. Standard errors are clustered at the bank level.

Table 8 presents the results of the estimation of equation (3). The first column shows that during a top 5 El Niño event, total assets decline by about 0.8% for banks with high exposure to the counties that experience a temperature increase during El Niño. We do not find that bank exposure to counties that experience a temperature decrease compared to the control group predicts a change in total assets. We then investigate the effects on loan portfolios, and find in column (2) that a higher positive bank exposure leads to a decline in total bank lending of about 1.6% during El Niño years. The negative effect on lending is in line with the findings on mortgage lending of Tables 3 and 4, but smaller in magnitude (1.3% vs 10-20%). The difference is given by the fact that equation (3) is estimated on the outstanding stock of loans from balance sheet data, rather than the flow of new loan origination from HMDA as equation (1). We then exploit the granularity of balance sheet data in the last three columns of Table 8 and test which types of loans are particularly responsive to El Niño. We find that both real estate and commercial and industrial loans are negatively affected by El Niño: banks with a one standard deviation higher exposure show a 1.5% decline in real estate lending and 2.7% decline in commercial and industrial loans. At the same time, consumer loans do not respond to El Niño.

3.6 Banking: a LASSO analysis

In this section we want to investigate whether there are specific bank characteristics that make them more resilient to climate shocks. Given the large amount of potential variables at the bank level available in the Call Reports, we decided to exploit a machine learning tool for model selection not to incur the risk of over-fitting. In the last decades, many penalization methods have been proposed to perform model selection. One of the most popular is the LASSO (Least Absolute Shrinkage and Selection Operator), proposed by Tibshirani (1996). The optimization takes place through the solution of the following constrained problem:

$$\hat{\beta} = \underset{\beta}{argmin} \sum_{i=1}^{n} (y - X\beta)^2 \quad s.t. \quad \sum_{j=1}^{p} |\beta_j| < s$$

where p is the number of variables among which the selection should be done and s is a parameter that defines the strength of the penalty. The smaller s, the stronger the penalty.

This corresponds to minimizing the following function:

$$\hat{\beta} = \underset{\beta}{argmin} ||y - X\beta||_2^2 + \lambda||\beta||_1$$

where λ is the parameter that controls the strength of the penalty, often called the tuning parameter. The idea is that since there is a cost to including a large number of regressors, the purpose of the LASSO procedure is to exclude the ones that contribute little to the fit by setting them to 0. The bigger λ the more variables will be excluded. Together with model selection the LASSO procedure also performs regularization. This means that the value of the parameter β estimated, when not 0, is kept small. This is useful when there is a need for shrinking the variance of the estimators. The rationale behind this exercise is to minimize the Mean Squared Error (MSE), as there is a profitable trade-off between unbiasedness and efficiency.

In our specific setting, the LASSO estimation is aimed at model selection rather than regularization. For this reason, we implement the Post-LASSO estimation, which consists in a 2-step procedure. In the first step, the LASSO algorithm is applied to the full set of available regressors, leading to estimates $\tilde{\beta}$; in the second step, an OLS regression is performed including only the regressors for which $\tilde{\beta} \neq 0$. In this way, the regressors included are data-driven and the problem simplifies to:

$$\hat{\beta} = argmin \sum_{i=1}^{n} (y_i - \mathbf{x}_i^{'}\beta)^2 \quad s.t. \quad \hat{\beta}_j = 0 \quad if \quad \tilde{\beta}_j = 0.$$

At the same time, we also want to keep the bank exposure variable among the regressors and this can be done through the method proposed by Belloni et al. (2014). It consists in running the LASSO estimation on to 2 different equations:

$$y_{bt} = \mathbf{x}_b^{'} \times El\ Niño_t \beta + \varepsilon_{bt}$$

$$Exposure_b \times El\ Niño_t = \mathbf{x}_b^{'} \times El\ Niño_t \beta + \kappa_{bt}$$

The first equation regresses the dependent variable, the logarithm of loans, on the vector of potential controls, $\mathbf{x}_b^{'}$, interacted with the variable capturing the occurrence of a top 5 El Niño event, of $El\ Niño_t$. The second equation regresses exposure that we want to be included in the first equation, hence the interaction between the bank exposure and a top 5 El Niño event, $Exposure_b \times El Niño_t$, on the same set of potential control variables interacted with the dummy for a top 5 El Niño event. $Exposure_b$, is defined as a weighted average of the county climate exposure using mortgage lending shares as weights, $\sum_c Exposure_c \times Share_{bc}$. In particular, $Exposure_c$ takes value 1 if the county is exposed to a positive temperature shock, takes 0 if the county is unaffected by El Niño and takes the value -1 if the county is affected by a negative temperature shock. The second variable, $Share_{bc}$, is the average share of mortgage lending that bank b issues to borrowers in county c relative to the entire stock of mortgages of bank b across all years in the sample. After this first step, the second step consists in a OLS post-estimation procedure including as regressors the union of the controls selected by the 2 Lasso procedures.

The need for running two separate LASSO regressions comes from the risk of omitted variable bias. If only the first equation were to be estimated, the selected variables would tend to include the ones with large effects on loans and exclude the ones with moderately-sized coefficients. However, if one of the excluded variables had a strong correlation with exposure, the regression in step 2 would result in an omitted variable bias. The effect of such a variable on the outcome would be erroneously attributed to $Exposure_b \times El\ Niño_t$. Similarly, if only the second equation were to be regressed with LASSO, one could exclude some regressors that are highly relevant for loans, but with only a moderate correlation with exposure. Again this could lead to a non-negligible omitted variable bias. Including the variables selected by both equations ensures that any excluded variables are at most mildly associated with the dependent variables and the bank exposure, which greatly limits the scope for omitted-variables bias.

We follow in detail the algorithm implementing the LASSO estimation provided by Belloni et al. (2012). From the call reports, there are 52 variables that could be included in this estimation. Given our interest in understanding their role on the bank reaction to the El Niño, we take the average of all variables across all periods and divide them by the average of total bank assets across all periods. The list of variables is available at the end of this paper.

The variables selected by the algorithm are summarized in panel E of Table 1 and are the following: 1) Operating Leverage - the ratio of the expenses on premises and fixed assets over total assets; 2) Deposits - the ratio between total deposits over assets; 3) Unused Commitments - the share of unused commitments over total assets (i.e. the undrawn portion of credit lines and other loan commitments); 4) Non-interest Expenses - the ratio of non-interest, operating expenses over total assets; 5) Dividends - the share of dividends paid over total assets; 6) ROA - the return on asset, i.e. net income over total assets.

We then present our results of the LASSO analysis in Table 9. This shows that the most prominent variable in explaining the resilience of banks is their reliance on operating leverage, proxied by the expenses on their physical premises over total assets. Banks with one standard deviation lower expenses in physical capital are essentially not affected by El Niño, as the sum of the coefficient on $BankExposure_b \times ElNino_t$ and the one on $OperatingLeverage_b \times ElNino_t$ are close to zero. This coefficient suggests that banks with a stronger exposure to branches and their own physical assets appear to be suffering the most from the realization of adverse climate shocks.

At the same time, many of the remaining variables are close to statistical significance. For instance the interaction between ROA_b and $El\ Nino_t$ is be borderline insignificant around the 10% conventional threshold for loans, while is significantly different from zero below the 5% threshold when regressed on total assets. This implies that during a climate shock, banks with a high profitability perform better than the others and weather adverse climate effects more effectively.

4 Robustness checks

4.1 La Niña

The opposite of a (positive) El Niño state is a (negative) "La Niña". During La Niña years, the surface temperature of the tropical Pacific Ocean are lower than average because stronger westward wind circulation patterns keep the warm water against Asia, thus reducing heat released from the ocean around the Americas. Figure A2 reports a description based on NOAA elaborations.

Crucially for our purposes, La Niña offers an ideal "placebo" with two convenient elements: 1) a different cross-sectional temperature exposure, which is almost opposite compared to El Niño (left hand panel of Figure A3 in the Online Appendix); 2) different years during which a top 5 La Niña event takes place (left hand panel of Figure A3 in the Online Appendix).

It is also important to notice that the top 5 La Niña events are much weaker than the top 5 El Niño, since the absolute change in oceanic temperature peaks during a top 5 La Niña event are half the size of a top 5 El Niño event. Based on this, we expect milder effects on banks during top 5 La Niña years. Moreover, this specification also allows us to verify whether unobservable geographic factors drive the results in the previous sections (i.e. North versus South). We show the result of this robustness test in Table A1 and find that during a top 5 La Niña event banks with a one standard deviation higher exposure to La Niña do not have different loans or total assets than others.

4.2 Event Study Specification

In this section we explore an event study specification of our bank-level analysis presented in section 3.3. In particular, instead of presenting a difference-in-difference equation, we show the results of a standard event study specification:

$$Y_{bt} = \alpha_b + \gamma_t + \sum_{j=-3}^{3} \beta_j \, Exposure_b \times El\ Nino_{jt} + \varepsilon_{bt} \tag{4}$$

in which the key variables in our study (loans, deposits and assets) are regressed on a set of dummies around the top 5 El Niño events ranging from -3 to +3 interacted with the bank exposure variable, $Exposure_b$, and bank and year fixed effects, $\alpha_b + \gamma_t$. Standard errors are clustered at the bank level as in the difference-in-difference setting.

The two panels of Figure A4 present a similar pattern for the evolution of bank variables over time. In particular, we note that before a top 5 El Niño event, banks with a one standard deviation higher exposure to El Niño are not different than other banks and lie on parallel trends. However, during a a top 5 El Niño year and in the following year, banks banks with a one standard deviation higher exposure experience a lower lending from the upper panel, and lower assets in the lower panel. The effects are temporary and lasts only during the years 0 and 1, with the magnitudes reverting back to zero and becoming statistically indistinguishable from zero during years 2 and 3.

4.3 Demand and Supply using CRA Data

Table 4 presents evidence consistent with a supply-side channel, rather than demand, for the effects of El Niño on credit using HMDA data. However, a potential concern is whether these data are actually representative of bank exposure to specific counties given that most mortgages are not retained on bank balance sheets but are later securitized.

To address this concern we re-examine our bank-county-year analysis using data from the Community Reinvestment Act (CRA). These are loans made to small businesses that are harder to securitize and hence are kept on bank balance sheet, in particular we focus on loans made to firms with revenues below $1 million. We show this robustness test in Table A3.

Before comparing the two tables, it is important to note that we are likely to have lower statistical power in this robustness test, since the CRA dataset contains only 25% of the observations available in the HMDA dataset. The reason for the reduced sample size is due to the fact that CRA loans are made to small and opaque firms for which soft information acquisition is crucial, requiring close interactions between banks and borrowers (Petersen and Rajan, 1994; Degryse and Ongena, 2005). This is likely to be reflected in higher standard errors.

Table A3 shows that the coefficient on the interaction between the positive bank exposure and Niño years using CRA data is close to the one estimated on HMDA in point estimate. However, as anticipated, the standard errors are 3-4 times larger than in Table 4, making the coefficients not statistically different from zero. Overall, these findings are aligned with our results on HMDA lending and suggest that a similar, yet milder, effect may be taking place for other types of loans.

4.4 Continuous measures of El Niño

In our baseline results we rely on an indicator equal to one for top 5 El Niño events. However while this definition is descriptively convenient and allows us to identify with certainty exceptional El Niño years, there is in fact a continuum of El Niño conditions corresponding to the amount of heat released into the tropical atmosphere. This continuum of events is measured by the MEI index described in Section 2.2. We thus replace our dummy for a top 5 El Niño event with the continuous MEI index in Table A4.

We find that when the MEI index is higher (i.e. a Niño-year is more likely) bank assets and lending contract, consistent with our baseline findings. The effects are not statistically significant because the MEI index can take both positive and negative values (i.e. a Niña-year is more likely). However, bank exposure to El Niño can be both positive (i.e. an increase in temperature in the north) or negative (i.e. a decrease in temperature in the south). If we restrict our attention to banks with positive exposure, which are the ones for which we find a supply effect in Table 4, we find that in years where the MEI index is higher lending contracts by about 0.6%, which is in line with our baseline finding.

4.5 Precipitations

El Niño does not only affect the level and variability of temperatures but also the pattern of rainfall and dryness across the US. For example, in a strong El Niño year the West (i.e. California) and South (i.e. Texas and Florida) experience more rainfall while the mid-west becomes drier than usual. We are agnostic as to whether precipitation variation can affect bank lending and other financial variables. We can test the effect of bank exposure to precipitation jointly with temperature exposure, since the temperature and precipitation maps overlap to some degree, but not perfectly, as shown in Figure A5.

This map is valuable in building an additional bank-level measure of exposure to El Niño-induced precipitations from our county-level data. As a result, in Table A5 we can augment our specification from Table 8 with a measure of climate exposure to El Niño, as well as a measure of exposure to precipitations. This specification presents findings in line with Table 8 for temperatures and, at the same time, we can reject that exposure to exogenously higher precipitations generate an effect on banking. We conclude that the most salient climate variation from an El Niño event is the variation induced in temperatures rather than that of rainfall.

4.6 Natural disasters

We perform a robustness check on the role of disasters using an alternative dataset: the Emergency Events Database (EM-DAT), made publicly available by the Centre for Research on the Epidemiology of Disasters (CRED) and the Université catholique de Louvain (UCLouvain). It contains information on events classified as disasters, defined as those in which either at least 10 or more people died, or 100 or more people have been affected or injured or are left homeless, or there has been a declaration by the country of a state of emergency or an appeal for international assistance. The disaster classification is based on and adapted from the Peril Classification and hazard Glossary of the Integrated Research on Disaster Risk (IRDR, 2014). For the purpose of our analysis, we included in the final sample only natural disasters. We are also able to measure in this dataset floods as a separate dummy variable. The dataset provides the geocode for the location starting from the year 2000 onwards. For this reason our sample was limited to US disasters between 2000 and 2016.

The first three columns of Table A6 regress the probability of natural disaster on the variables as presented in equation 1, while the last three columns use a dummy describing the probability that a flood takes place in county c in year t. The results of the first three columns are in line with the results of the last three columns of Table 3: counties with a positive exposure experience fewer disasters during a top 5 El Niño event, while counties with a negative exposure either a small positive effect in column (2) or no effect in column (3). The last three columns focus on floods and, in line with the last three columns of Table 3, we observe that most of the effects take place in counties with a negative exposure to El Niño during a top 5 event, which see a large and significant increase in floods (+17%), while counties with a positive exposure at the center of this analysis see either no effect on floods (column (4)) or a small and imprecise effect (column (6)).

4.7 Alternative diff-in-diff estimation

We verify that our main findings in Table 8 are robust to using the latest framework for difference-in-differences designs with staggered treatment adoption and heterogeneous causal effects proposed by Borusyak et al. (2022). We proceed through the following steps.

First, the treatment variable is discretized. We do this by assigning value 1 to those banks whose exposure to the Niño ($Bank\ Exposure_b$), measured as the product between the county level variables of exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data, is above the median value, and 0 otherwise. The treatment variable is obtained as the interaction between this discretized exposure to the Niño and the variable $El\ Nino_t$, measuring whether year t presents a top 5 El Niño event.

We then use the imputation estimator of Borusyak et al. (2022), which generates the effects of a binary treatment with staggered rollout allowing for arbitrary heterogeneity and dynamics of causal effects. The benchmark case of this method considers each unit i getting treated as of period t and remaining treated forever. In this case, however, multiple events per unit can be accounted for. We provide results from a standard two-way fixed effects model using our new binary treatment variable. As it can be seen in Table A7, this ensures that the new specification of the treatment variable does not change the results: coefficients maintain the sign and the significance of those in Table 8. Results obtained from the estimation using Borusyak et al. (2022) are still very close in point estimate, sign and precision.

4.8 Alternative clustering

In this section we explore alternative methods to cluster our standard errors. In particular, we explore three alternative layers of clustering: 1) clustering at the state level the regressions in which we adopt the county clustering, instead of the county level; 2) a spatial clustering approach, which allows for dependence of the error terms across counties within a 200km radius; 3) a wild bootstrap method on our main tables, following Roodman et al. (2019).

Table A8 replicates the findings on temperatures presented in Table 2, while Table A9 those in Table 3 using state level clustering. In both cases, state-level clusteringleads to higher standard errors compared to the baseline, however the significance of the estimates remains below the 5% conventional threshold. Similarly, Table A10 and Table A11 replicate the baseline results using spatial clustering. The confidence intervals are wider, but the estimates are still significant at the 1 or 5% level.

The following three tables (Tables A12, Table A13 and A14) replicate our baseline findings using wild bootstrap standard errors. In all cases, the standard errors tend to be higher, but close in magnitude to the previous clustering at the state or spatial clustering level. The last rows of each of these columns presents also the specific p-values and statistics associated with this method.

4.9 LASSO: alternative model selections

In this section we provide some model selections alternative to LASSO: the stepwise selections. We use two different stepwise selections, the backward and the forward. The backward procedure works as follows: first, it starts with the full model containing all control variables and then eliminates them one by one starting from the one with the highest p-value, until the remaining covariates all have a p-value below 5% . The forward procedure instead starts with a model containing only the constant term and adds one regressor at a time, starting from the one with the lowest p-value and until it reaches the 5% level.

We report the results of the backward and forward selection in Tables A15 and A16. These procedures select a larger number of covariates, all expressed as a fraction of total assets, compared to the baseline LASSO analysis, such as: Net interest margin (NIM); Past due loans (30-89 days) secured by real estate; Past due commercial and industrial loans (30-89 days) secured by real estate; Currency and coin held in domestic offices; Total securities; Amount of loans secured by nonfarm nonresidential properties with original amounts of $100,000 or less; Amount of loans secured by nonfarm nonresidential properties with original amounts less than $1,000,000; Total interest expense ; Total assets past due 30 through 89 days;Interest expense from deposits; Risk-weighted assets. Notably however, operating leverage, a key regressor that was originally selected by LASSO in Table 9 remain in the set of chosen regressors and has the same sign.

5 Concluding Remarks

Climate change poses risks to households and firms, and therefore to the banking sector. Policymakers and regulators have started to assess banks' level of preparedness for properly managing climate risk, for example, through climate risk stress testing (ECB, 2022). However, limited evidence exists on whether and how banks cope with climate shocks, except for the case of natural disasters. In this paper, we study how banks react to, and whether they are resilient against, climate-related risks induced by El Niño.

Our results show that El Niño leads to large, significant and heterogeneous changes in lending because of its effects on bank balance sheets and credit. A machine learning tool allows us to uncover the characteristics of banks that successfully hedge this climate shock. We find that those with lower operating leverage (i.e. lower cost for premises and branches as a share of assets) have lower exposure to physical risk and hence reduce their lending by less than other banks. Our findings thus offer insights into understanding the theoretical modelling of climate change in finance and key policy implications for regulating climate-resilient financial systems.

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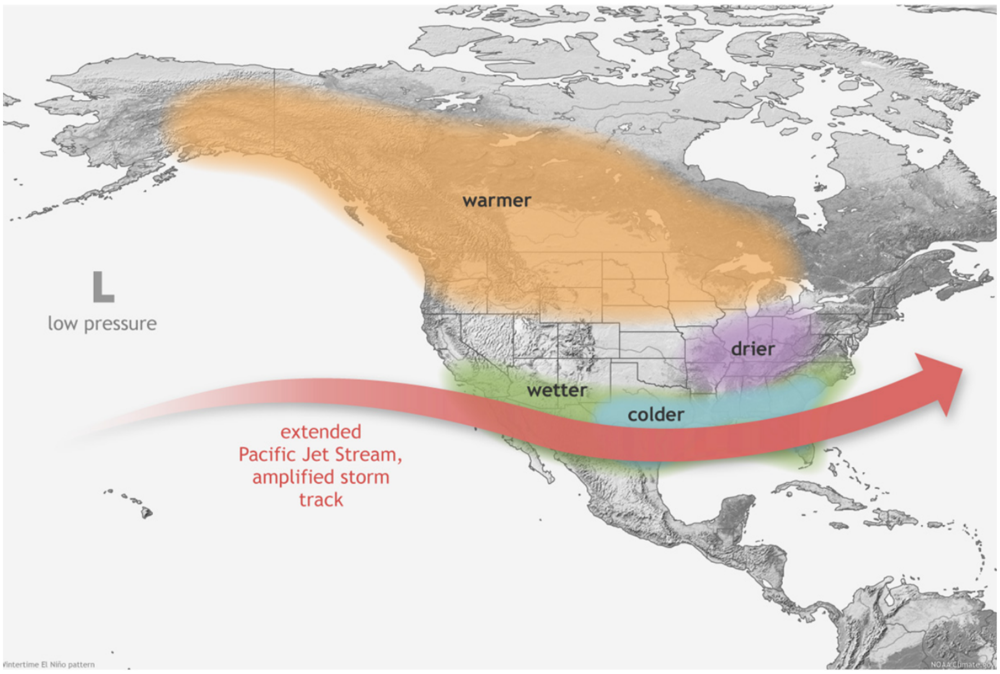
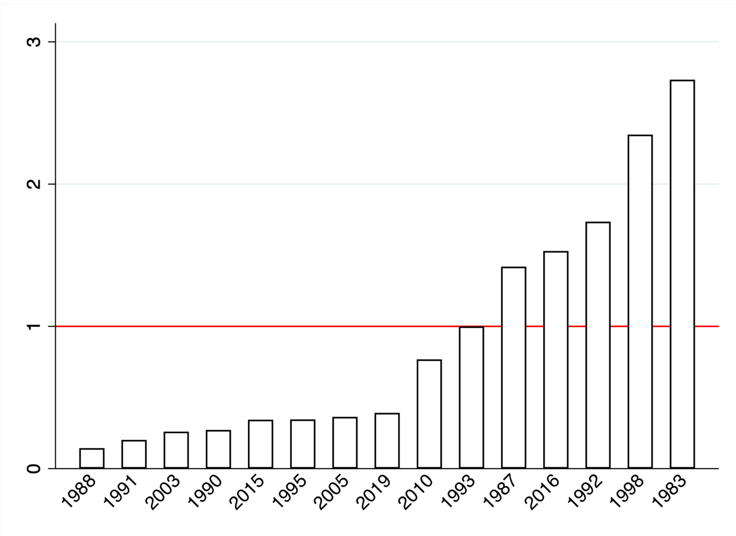
Figures and Tables

Figure 1: El Niño and the Pacific Jet Stream



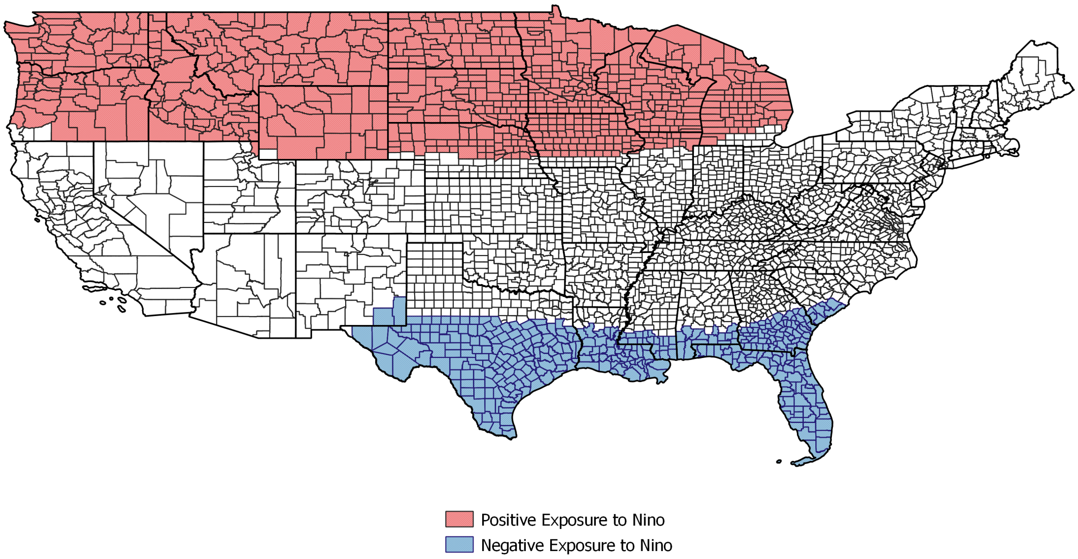
Notes: This figure shows a map elaborated by the National Oceanic and Atmospheric Administration (NOAA) illustrating the effects of El Niño on the Pacific jet stream. More information is provided here.

Figure 2: The 5 strongest El Niño events



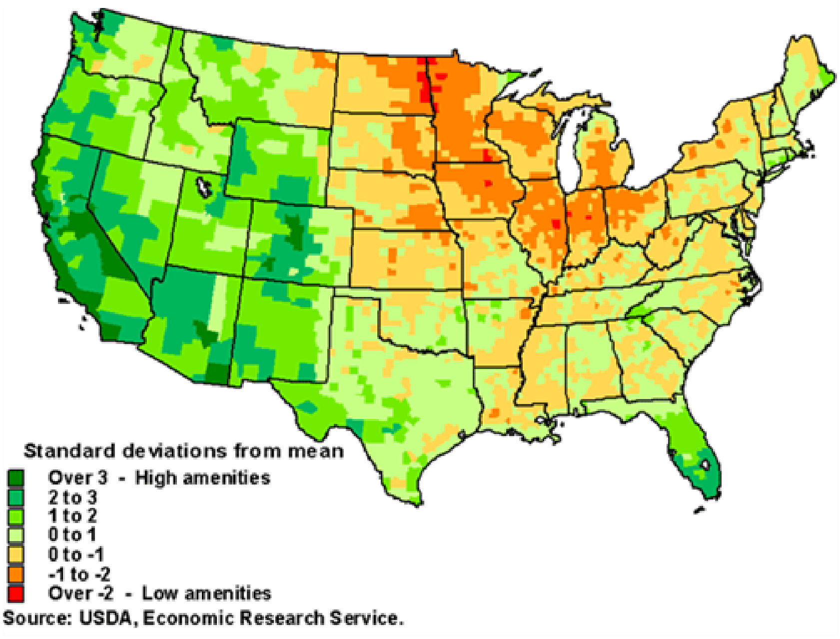
Notes: This figure shows a selected number of years and the corresponding changes in oceanic temperatures determined by their El Niño events. The 5 years with the strongest El Niño events are described by the horizontal line. The x-axis shows the years and y-axis measures the values of the MEI.V2 index, as an average between January and May.

Figure 3: Heterogeneous county exposure to El Niño



Notes: This figure digitizes the map in Figure 1 based on the elaboration of the NOAA for the heterogeneous geographic impact of El Niño on US weather.

Figure 4: Natural Amenities Scale in the US



Notes: This figure shows a map of the natural amenities scale in the United States, as elaborated by the Economic Research Service of U.S. Department of Agriculture. Colors represent the magnitude of the scale going from green to yellow and red. Counties with a dark green color are charactertized by the highest amenities scale, those in yellow report the average amenities and those in dark red by the lowest amenities scale.

Table 1: Summary Statistics

Variable	(1) Obs.	(2) Mean	(3) S.D.	(4) Min	(5) Max
Panel A - County-Level Climate and Disasters					
$Average\ Temperatures_{ct}$	108,761	12.85	4.540	-15.86	32.29
$Volatility\ of\ Temperatures_{ct}$	108,752	1.684	0.805	0.0346	17.06
$Probability\ of\ Nat.\ Disaster_{ct}$	111,888	0.304	0.460	0	1
Panel B - Mortgage Lending, House Prices and Amenities					
$Lending_{ct}$	91,592	10.45	2.591	0	19.31
$House\ Price\ Index_{ct}$	77,708	110.2	36.05	26.42	423.4
$Amenities\ Rank_{c}$	3,107	3.492	1.043	1	7
$Water\ Salinity_{ct}$	53,868	1,045	3,476	0.0583	189,911
$Soil\ Salinity_{ct}$	21,756	0.160	0.280	0	3.364
Panel C - Bank-Level Exposure to El Niño					
$BankExposure_{b}$	6,674	0.0541	0.566	-1	1
Panel D - Bank-Level Variables					
$Lending_{bt}$	81,086	11.72	1.522	-4.605	20.49
$Assets_{bt}$	81,086	12.28	1.423	7.947	21.44
$RE\ Lending_{bt}$	81,086	11.34	1.647	-4.605	20.00
$CI\ Lending_{bt}$	81,086	9.698	1.920	-4.605	19.30
$Ind.\ Lending_{bt}$	81,086	8.807	1.880	-4.605	18.99
Panel E - Bank-Level Variables selected by LASSO					
$Operating\ Leverage_{b}$	6,294	0.00234	0.00108	5.66e-06	0.0298
$Deposits_{b}$	6,294	0.840	0.0669	0.0932	0.986
$Unused\ Commitments_{b}$	6,293	0.0154	0.0192	0	0.239
$NonInterest\ Expenses_{b}$	6,294	0.00582	0.00548	0.000717	0.347
$Dividends_{b}$	6,294	0.00213	0.00245	0	0.0595
ROA_{b}	6,294	0.0127	0.0285	-0.163	0.773

Notes: This table presents summary statistics for the databases presented in section 2.4. Panel A summarises the climate and disaster variables in county c in year t: i) the average temperature in a county; ii) its standard deviation, used as a measure of volatility and iii) the probability of a natural disaster in a county as measured by the FEMA Disaster Declarations Summary. Panel B presents summary statistics for the county c level amount of lending in year t, measured through the aggregation at county level of the Home Mortgage Disclosure Act (HMDA) data; the house price index elaborated by the Federal Housing Finance Agency; the Amenities rank as elaborated by the Natural Amenities Scale; Water and Soil salinity as presented in section 2.5. Panel C reports the measure of bank exposure created combining the local county exposure to El Niño with the bank share of lending in that county (see section 2.4.2 for more details on the definition of bank exposure). Panel D summarises key financial variables for bank b in year t used to investigate the effects of bank exposure on banks and their balance sheets, these are the natural logarithm of loans and assets, and the types of lending (RE standing for Real Estate lending, CI for Commercial and Industrial lending and Ind. for Individual lending). Panel E displays the descriptives for the bank variables selected through the Lasso estimation as controls (see section 3.6 for more). Column (1) reports the number of observations, columns (2) and (3) report the variable's mean and standard deviation, while columns (4) and (5) indicate their corresponding minimum and maximum values.

Table 2: Climate, Disasters and El Niño

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Average Temperatures			Volatility of Temperatures			Probability of Disaster		
$Positive\ Exposure_c \times$	0.518***		0.462***	0.0724***		0.0675***	-0.0270***		-0.00537
$El\ Nino_t$	(0.0190)		(0.0195)	(0.00985)		(0.0101)	(0.00926)		(0.00931)
$Negative\ Exposure_c \times$		-0.479***	-0.362***		-0.0482***	-0.0311***		0.142***	0.141***
$El\ Nino_t$		(0.0181)	(0.0186)		(0.00820)	(0.00853)		(0.00936)	(0.00942)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	108,761	108,761	108,761	108,752	108,752	108,752	111,888	111,888	111,888
Adj. R sq.	0.949	0.949	0.949	0.597	0.597	0.597	0.202	0.204	0.204
Mean Dep. Var.	12.86	12.86	12.86	1.674	1.674	1.674	0.304	0.304	0.304

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the county level. The dependent variable in the first three columns is the average yearly temperature of a county and is defined as the yearly average of monthly averages in Celsius degrees. The dependent variable in the next set of three columns is the yearly standard deviation of the growth rate of daily temperatures. The dependent variable in the last three set of columns is the probability of a natural disaster in a county, which is a dummy that takes value 1 if there have been one or more natural disasters in county c in year t as recorded by the FEMA Disaster Declarations database, and 0 otherwise. $Positive\ Exposure_c$ takes unit value if a county presents a positive climate exposure to El Niño; $Negative\ Exposure_c$ takes unit value if a county presents a negative climate exposure to El Niño and $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 3: Mortgage Lending, House Prices and El Niño

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		Mortgage Lending			House Prices	
$Positive\ Exposure_c \times$	-0.116***		-0.112***	-0.0133***		-0.0130***
$El\ Nino_t$	(0.0170)		(0.0174)	(0.00267)		(0.00275)
$Negative\ Exposure_c \times$		0.0507***	0.0241		0.00531	0.00219
$El\ Nino_t$		(0.0183)	(0.0187)		(0.00374)	(0.00384)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	91,591	91,591	91,591	77,708	77,708	77,708
Adj. R sq.	0.916	0.916	0.916	0.852	0.852	0.852
Mean Dep. Var.	10.46	10.46	10.46	1.102	1.102	1.102

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the county level. The dependent variable in the first three columns is the natural logarithm of HMDA lending at the county level, the dependent variable in the last three columns is the House Price Index elaborated from the Federal Housing Finance Agency. $Positive\ Exposure_c$ takes unit value if a county presents a positive climate exposure to El Niño; $Negative\ Exposure_c$ takes unit value if a county presents a negative climate exposure to El Niño and $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 4: Financial Transmission of El Niño

Variables	(1)	(2)	(3)	(4)	(5)
			Mortgage Lending		
Positive Bank Exposure$_b$ × *El Nino*$_t$	-0.197***		-0.218***	-0.202*	-0.238**
	(0.0725)		(0.0763)	(0.110)	(0.0945)
Negative Bank Exposure$_b$ × *El Nino*$_t$	-0.00193		0.0117		
	(0.0526)		(0.0529)		
Positive County Exposure$_c$ × *El Nino*$_t$	0.112***	0.0476			
	(0.0392)	(0.0321)			
Negative County Exposure$_c$ × *El Nino*$_t$	-0.000218	0.00413			
	(0.0243)	(0.0241)			
County	All	All	All	Exposed	Non-Exposed
Bank FE	Yes		Yes	Yes	Yes
County FE	Yes	Yes			
Year FE	Yes				
County × Year FE			Yes	Yes	Yes
Bank × Year FE		Yes			
Obs.	2,469,262	2,462,802	2,465,501	767,496	1,697,353
Adj. R sq.	0.362	0.402	0.361	0.387	0.377
Mean Dep. Var.	6.552	6.552	6.552	6.447	6.599

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is lending in county c, by bank b in year t. Fixed effects for bank, county and year are present in column (1), only for county and bank-year in column (2) and only for bank and county-year in the remaining columns, and standard errors are clustered at the county level. This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b in year t. Bank and year fixed effects are present in all columns, and standard errors are clustered at the bank level. The dependent variable is the natural logarithm of the mortgage lending at the county level. *Positive Bank Exposure*$_b$ takes unit value if bank b presents a positive exposure to El Niño, as described in section 2.4.2, *Negative Bank Exposure*$_b$ takes unit value if bank b presents a negative exposure to El Niño. *Positive County Exposure*$_c$ takes unit value if county c presents a positive exposure to El Niño as presented in Figure 3. *Negative County Exposure*$_c$ takes unit value if county c presents a negative exposure to El Niño as presented in Figure 3. *El Nino*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 5: Channels: Salinity and El Niño

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Water Salinity			Soil Salinity		
Positive Exposure$_c$ ×	0.134***		0.0831***	0.0413***		0.0344***
El Nino$_t$	(0.0291)		(0.0265)	(0.00413)		(0.00423)
Negative Exposure$_c$ ×		-0.368***	-0.346***		-0.0538***	-0.0452***
El Nino$_t$		(0.117)	(0.118)		(0.00751)	(0.00767)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	53,838	53,838	53,838	21,756	21,756	21,756
Adj. R sq.	0.724	0.724	0.724	0.740	0.740	0.741
Mean Dep. Var.	1.045	1.045	1.045	0.160	0.160	0.160

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the county level. The dependent variable is water salinity in the first three columns and soil salinity in the second three columns, both at the county level. The definition of these variables is available in section 2.4. *PositiveExposure*$_c$ takes unit value if a county presents a positive climate exposure to El Niño; *Negative Exposure*$_c$ takes unit value if a county presents a negative climate exposure to El Niño and *El Niño*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6: Channels - Crop Yields and El Niño

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Corn - Bushels per harvest acre			Wheat - Bushels per harvest acre		
Positive Exposure$_c$	-0.916**		-0.900**	-0.850**		-0.767**
×*El Nino*$_t$	(0.452)		(0.456)	(0.364)		(0.365)
Negative Exposure$_c$		0.606	0.309		1.412**	1.266**
×*El Nino*$_t$		(1.468)	(1.482)		(0.622)	(0.624)
County FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			
Obs.	35,072	35,072	35,072	33,156	33,156	33,156
Adj. R sq.	0.691	0.691	0.691	0.761	0.761	0.761
Mean Dep. Var.	116.4	116.4	116.4	44.42	44.42	44.42

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the county level. The dependent variable is corn yields in the first three columns and wheat yields in the last three columns, both at the county level. The definition of these variables is available in section 2.4. *Positive Exposure*$_c$ takes unit value if a county presents a positive climate exposure to El Niño; *Negative Exposure*$_c$ takes unit value if a county presents a negative climate exposure to El Niño and *El Niño*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 7: Channels - Natural Amenities and El Niño

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Mortgage Lending			House Prices		
$Positive\ Exposure_c$	-0.116***		-0.101***	-0.0133***		-0.0132***
$\times El\ Nino_t$	(0.0170)		(0.0214)	(0.00267)		(0.00286)
$Natural\ Amenities_c$		-0.0112	-0.0165		-0.0339***	-0.0328***
$\times El\ Nino_t$		(0.0136)	(0.0148)		(0.00244)	(0.00282)
$Positive\ Exposure_c \times$			-0.0629*			-0.0176***
$Natural\ Amenities_c \times$			(0.0346)			(0.00520)
$El\ Nino_t$						
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	91,591	91,591	91,591	77,708	77,708	77,708
Adj. R sq.	0.916	0.916	0.916	0.852	0.853	0.853
Mean Dep. Var.	10.46	10.46	10.46	1.102	1.102	1.102

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the county level. The dependent variable in the first three columns is the natural logarithm of HMDA lending at the county level, the dependent variable in the last three columns is the House Price Index elaborated from the Federal Housing Finance Agency. $Positive\ Exposure_c$ takes unit value if a county presents a positive climate exposure to El Niño; $Negative\ Exposure_c$ takes unit value if a county presents a negative climate exposure to El Niño and $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. $Natural\ Amenities_c$ is a dummy variable taking unit value for counties that present a rank of natural amenities beyond the median. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 8: Banks and El Niño

Variables	(1) Assets	(2) Loans	(3) Real Estate	(4) Commercial and Industrial	(5) Consumer Lending
Positive Bank	-0.00801**	-0.0165***	-0.0145**	-0.0268**	-0.00720
$Exposure_b \times El\ Nino_t$	(0.00375)	(0.00519)	(0.00724)	(0.0105)	(0.0101)
Negative Bank	0.00647	0.00412	0.00602	0.000985	-0.00768
$Exposure_b \times El\ Nino_t$	(0.00414)	(0.00622)	(0.00835)	(0.0109)	(0.00893)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	80,750	80,750	80,750	80,750	80,750
Adj. R sq.	0.947	0.910	0.884	0.809	0.848
Mean Dep. Var.	12.28	11.72	11.34	9.698	8.807

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b in year t. Bank and year fixed effects are present in all columns, and standard errors are clustered at the bank level. The dependent variable in the first column is the natural logarithm of assets, the second columns reports the natural logarithm of total loans, the third column presents the natural logarithm of real estate lending, the fourth column presents lending in commercial and industrial activities and the fifth column the natural logarithm of individual loans. *Positive Bank* $Exposure_b$ measures the exposure of bank b to regions positively affected by El Niño and is calculated as the product between the county level variable of positive exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data. *Negative Bank* $Exposure_b$ measures the exposure of bank b to regions negatively affected by El Niño and is calculated as the product between the county level variable of negative exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data. $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 9: A LASSO analysis of climate resilience

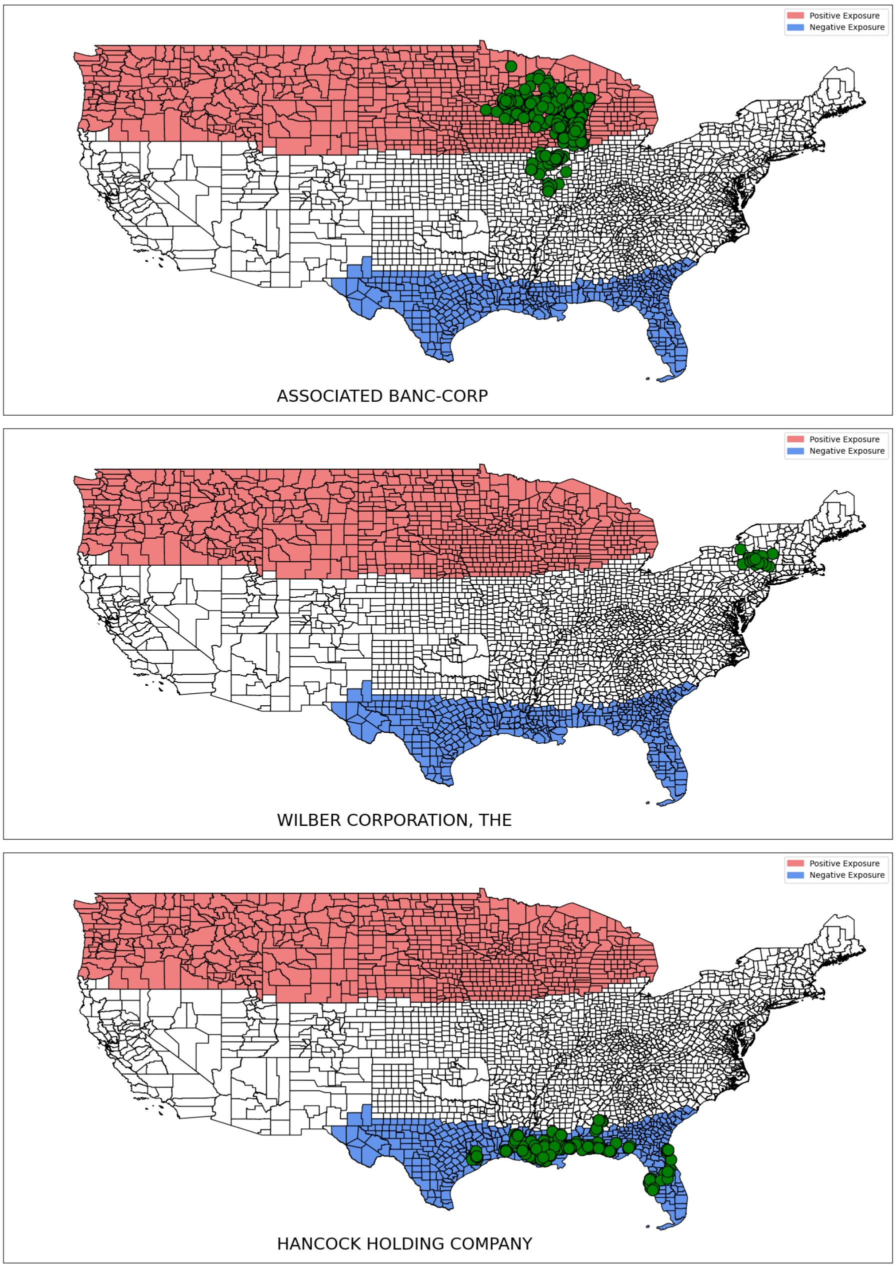
Variables	(1) Loans	(2) Assets
$Bank\ Exposure_b \times$	-0.0207***	-0.0131***
$El\ Nino_t$	(0.00620)	(0.00400)
$Operating\ Leverage_b \times$	-0.0379*	-0.0145**
$El\ Nino_t$	(0.0197)	(0.00630)
$Deposits_b \times$	0.00903	0.00265
$El\ Nino_t$	(0.0263)	(0.00684)
$Unused\ Commitments_b \times$	-0.00576	-0.00131
$El\ Nino_t$	(0.00784)	(0.00435)
$NonInterest\ Expenses_b \times$	0.0231	0.00792*
$El\ Nino_t$	(0.0182)	(0.00411)
$Dividends_b \times$	0.0134	0.00520
$El\ Nino_t$	(0.0181)	(0.00832)
$ROA_b \times$	0.0110	0.0109*
$El\ Nino_t$	(0.0133)	(0.00581)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Obs.	80,748	80,748
Adj. R sq.	0.910	0.947
Mean Dep. Var.	11.72	12.28

Notes: This table presents the second step procedure of the Post-Lasso estimation. It consists on OLS estimates for the model including the controls selected by the Lasso operator. The unit of observation is bank b in year t. The selection is based on 2 equations: 1) a Lasso regression of the logarithm of loans of bank b in year t on a set of controls defined as bank b characteristics averaged over the years and interacted with a dummy that takes unit value if year t exhibits a top 5 El Niño event; and 2) a Lasso regression of the bank b exposure interacted with ta dummy that takes unit value if year t exhibits a top 5 El Niño event on the same set of controls. The union of the two is then included in the OLS regression using as dependent variables the natural logarithm of loans (column 1) and the natural logarithm of assets (column 2). See section 3.6 for the definition of all variables in this table. Bank and year fixed effects are present in both columns, and standard errors are clustered at the bank level. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Online Appendix

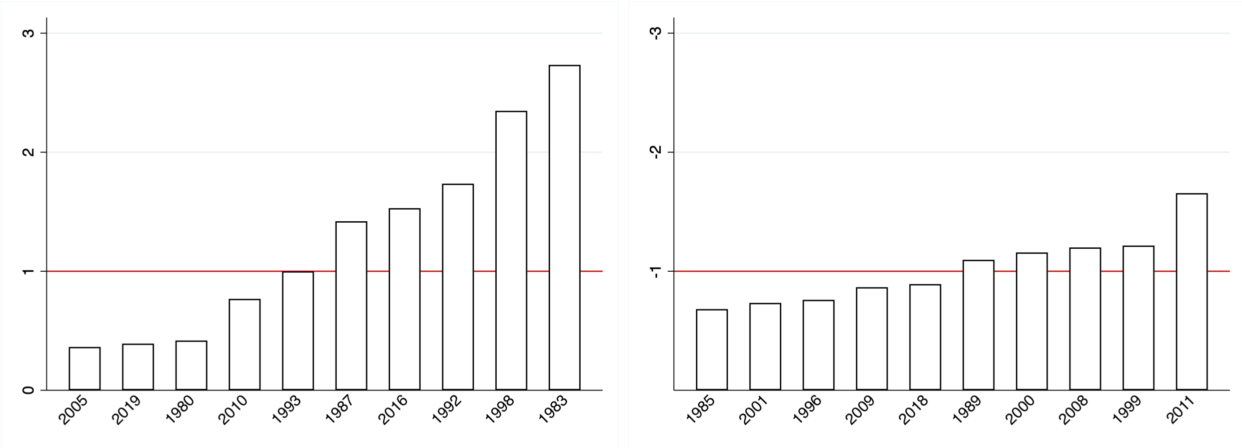
Figures and Tables

Figure A1: Bank exposure to El Niño



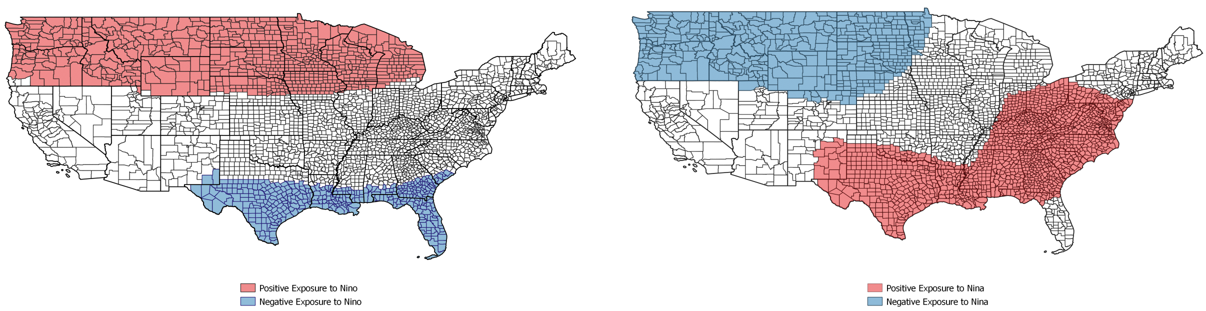
Notes: This figure shows three examples of bank exposure to El Niño. The bank exposure is defined as a weighted sum between the climate exposure of a county in which the bank operates and the share of HMDA lending that the bank conducts in that county as a share of total. The upper panel shows a bank with a highly positive exposure (Associated Bank-Corp), the middle panel shows a bank with a zero exposure (The Wilber Corporation) and the lower panel presents a bank with a highly negative exposure (Hancock Holding Company).

Figure A2: The Top 5 El Niño and La Niña



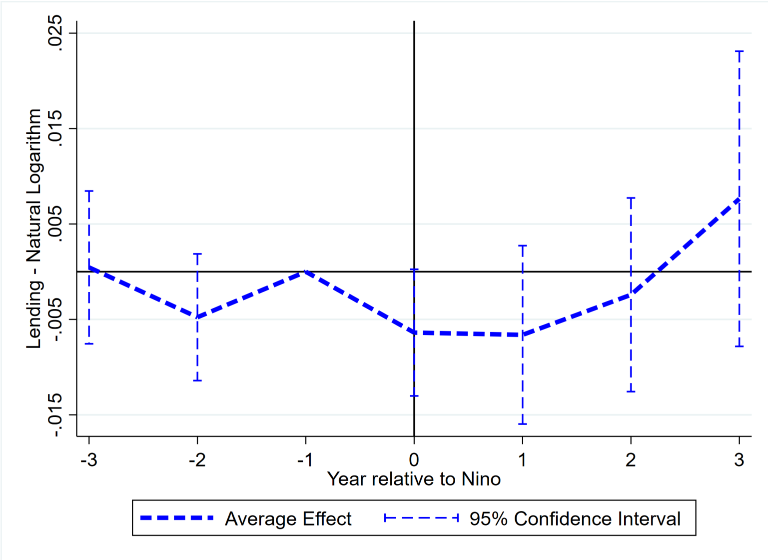
Notes: This figure shows two panels reporting the strongest 10 El Niño and La Niña events, the left picture shows El Niño, while La Niña is reported on the right. The x-axis shows the years and y-axis measures the values of the MEI.V2 index, as an average between January and May.

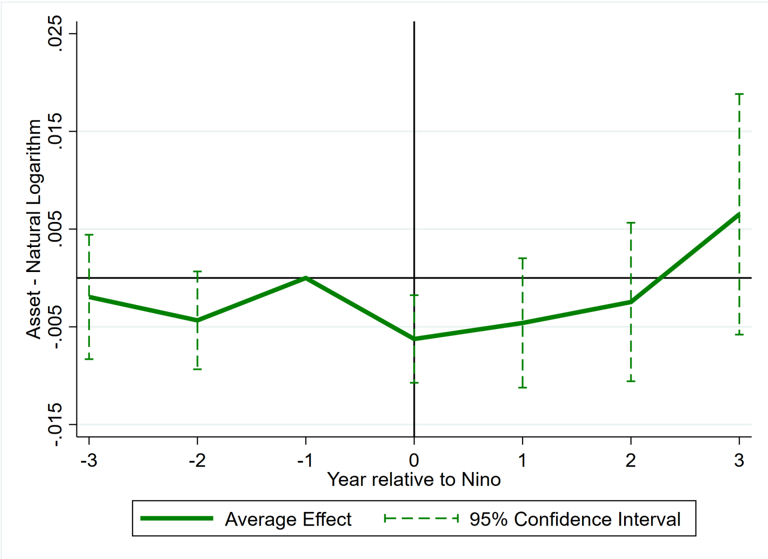
Figure A3: The cross-section of temperatures: El Niño and La Niña



Notes: This figure shows two panels. The left hand panel shows the map of temperature effects due to El Niño, while the right hand panel shows the heterogeneous temperature impact of La Niña. In both cases, counties coloured in light red present a positive exposure (i.e., higher temperatures) and those in blue a negative exposure (i.e., lower temperatures).

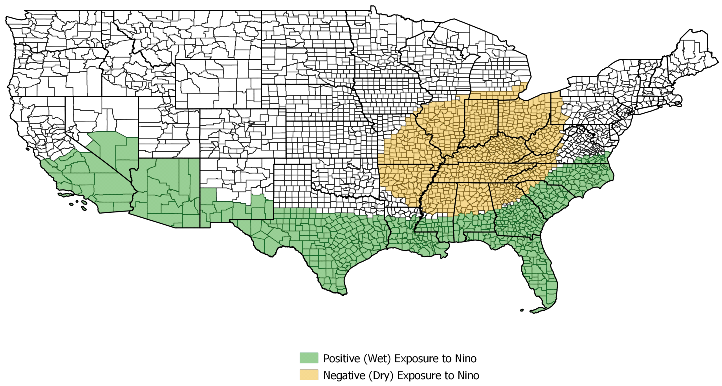
Figure A4: Event Study Specification and El Niño





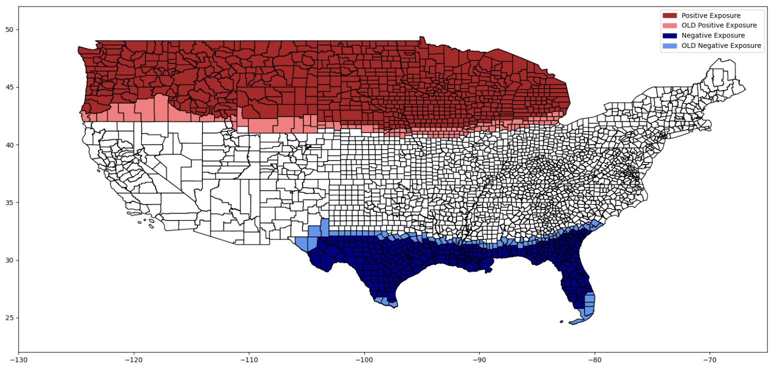
Notes: This figure presents two panels showing the results of the event study specification discussed in section 4.2. The upper panel presents the results for lending and the lower panel for assets. The y-axis reports the magnitudes in points of natural logarithm, the x-axis reports the year relative to El Niño being the zero.

Figure A5: El Niño and Precipitations



Notes: This figure digitizes a map based on the elaboration of the National Oceanic and Atmospheric Administration (NOAA) showing the heterogeneous geographic impact of El Niño on precipitations. The green area presents a positive exposure to precipitations, while the yellow area shows the negative exposure.

Figure A6: Alternative Exposure



Notes: This figure digitizes a map based on the elaboration of the National Oceanic and Atmospheric Administration (NOAA) showing the heterogeneous geographic impact of El Niño on temperatures. The red area presents a positive exposure to precipitations, while the blue area shows the negative exposure.

Table A1: "Placebo": Banks and La Niña

Variables	(1) Loans	(2) Assets
Bank Nina Exposure$_b$ $\times$	0.00138	0.00231
La Nina$_t$	(0.00359)	(0.00251)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Obs.	80,750	80,750
Adj. R sq.	0.910	0.947
Mean Dep. Var.	11.72	12.28

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b in year t. Bank and year fixed effects are present in all columns, and standard errors are clustered at the bank level. The dependent variable in the first column is the natural logarithm of bank loans, while the second columns reports the natural logarithm of total bank assets. *Bank Nina Exposure*$_b$ measures the exposure of bank b to La Niña and is calculated as the product between the county level variables of exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data. *La Niña*$_t$ takes unit value if year t exhibits a top 5 La Niña event. The list of years with top 5 La Niña events can be found in the right panel of Figure A3. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A2: Water Salinity and El Niño

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables		Rivers			Lakes			Groundwater	
Panel A: Probability of Water Salinity > 1000 ppm									
Positive Exposure$_c$ ×	0.0179***		0.0114**	0.0189**		0.0191**	0.0365**		0.0329*
El Nino$_t$	(0.00560)		(0.00552)	(0.00858)		(0.00858)	(0.0162)		(0.0168)
Negative Exposure$_c$ ×		-0.0471***	-0.0441***		-0.00602	0.000847		-0.0229	-0.0129
El Nino$_t$		(0.01000)	(0.0100)		(0.0112)	(0.0112)		(0.0179)	(0.0186)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	53,838	53,838	53,838	16,289	16,289	16,289	17,106	17,106	17,106
Adj. R sq.	0.679	0.679	0.679	0.672	0.672	0.672	0.402	0.402	0.402
Mean Dep. Var.	0.0967	0.0967	0.0967	0.0622	0.0622	0.0622	0.148	0.148	0.148
Panel B: Probability of Water Salinity > 2000 ppm									
Positive Exposure$_c$ ×	0.0128***		0.00840***	0.0164***		0.0149***	0.0194*		0.0110
El Nino$_t$	(0.00302)		(0.00290)	(0.00577)		(0.00558)	(0.0116)		(0.0122)
Negative Exposure$_c$ ×		-0.0324***	-0.0302***		-0.0127	-0.00729		-0.0333***	-0.0299**
El Nino$_t$		(0.00847)	(0.00853)		(0.00981)	(0.00978)		(0.0126)	(0.0132)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	53,838	53,838	53,838	16,289	16,289	16,289	17,106	17,106	17,106
Adj. R sq.	0.703	0.703	0.703	0.653	0.653	0.653	0.198	0.198	0.198
Mean Dep. Var.	0.0466	0.0466	0.0466	0.0239	0.0239	0.0239	0.0474	0.0474	0.0474

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the county level. The dependent variables are two dummy variables that take unit value if water salinity exceeds two thresholds: 1000 parts per million (ppm) in panel A and 2000 ppm in panel B. The first three columns measure water salinity in rivers, the second three columns in lakes and the last three columns in groundwater reserves. *PositiveExposure*$_c$ takes unit value if a county presents a positive climate exposure to El Niño; *NegativeExposure*$_c$ takes unit value if a county presents a negative climate exposure to El Niño and *El Niño*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A3: El Niño, Bank and County Factors - CRA Data

	(1)	(2)	(3)
Variables	CRA Lending		
Positive Bank Exposure$_b$ ×	-0.0690	-0.0417	
El Nino$_t$	(0.130)	(0.137)	
Negative Bank Exposure$_b$ ×	-0.187	-0.182	
El Nino$_t$	(0.126)	(0.148)	
Positive County Exposure$_c$ ×	-0.0260		0.0170
El Nino$_t$	(0.134)		(0.138)
Negative County Exposure$_c$ ×	0.0161		0.00851
El Nino$_t$	(0.0655)		(0.0711)
Bank FE	Yes	Yes	
County FE	Yes		Yes
Year FE	Yes		
County × Year FE		Yes	
Bank × Year FE			Yes
Obs.	817,004	814,772	816,943
Adj. R sq.	0.258	0.234	0.291
Mean Dep. Var.	6.507	6.507	6.507

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is lending in county c, by bank b in year t. Fixed effects for bank, county and year are present in column (1), only for bank and county-year in column (2) and only for county and bank-year in column (3), and standard errors are clustered at the county level. The dependent variable is the natural logarithm of the CRA lending at the county level. *Positive Bank Exposure*$_b$ takes unit value if bank b presents a positive exposure to El Niño, as described in section 2.4.2, *Negative Bank Exposure*$_b$ takes unit value if bank b presents a negative exposure to El Niño. *Positive County Exposure*$_c$ takes unit value if county c presents a positive exposure to El Niño as presented in Figure 3. *Negative County Exposure*$_c$ takes unit value if county c presents a negative exposure to El Niño as presented in Figure 3. *El Nino*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A4: Bank effects, El Niño and the MEI index

Variables	(1) Loans	(2) Assets	(3) Loans	(4) Assets
$Bank\ Exposure_b \times$	-0.00342	-0.00237		
$MEI\ Nino\ Index_t$	(0.00274)	(0.00204)		
$Positive\ Bank\ Exposure_b$			-0.00613*	-0.000869
$\times MEI\ Nino\ Index_t$			(0.00324)	(0.00245)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	80,750	80,750	80,750	80,750
Adj. R sq.	0.910	0.947	0.910	0.947
Mean Dep. Var.	11.72	12.28	11.72	12.28

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b in year t. Bank and year fixed effects are present in all columns, and standard errors are clustered at the bank level. The dependent variable in the first and third columns is the natural logarithm of bank loans, while in the second and fourth columns is the natural logarithm of total bank assets. $Exposure_b$ measures the exposure of bank b to El Niño and is calculated as the product between the county level variables of exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data. $MEI\ Nino\ Index_t$ reports the value of the Pacific Oceanic temperatures for all El Niño events, as described in section 2.2. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A5: Bank effects, El Niño and Precipitations

Variables	(1) Loans	(2) Assets
$Bank\ Exposure_b \times$	-0.0265***	-0.0147**
$El\ Nino_t$	(0.00957)	(0.00689)
$Bank\ Prec.\ Exposure_b \times$	0.00951	0.0145**
$El\ Nino_t$	(0.00815)	(0.00624)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Obs.	80,750	80,750
Adj. R sq.	0.910	0.947
Mean Dep. Var.	11.72	12.28

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b in year t. Bank and year fixed effects are present in all columns, and standard errors are clustered at the bank level. The dependent variable in the first column is the natural logarithm of bank loans while the second columns reports the natural logarithm of total bank assets. $Bank\,Exposure_b$ measures the exposure of bank b to El Niño and is calculated as the product between the county level variables of exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data. $Bank\,Prec.\,Exposure_b$ measures the exposure of bank b to the precipitations induced by El Niño and is calculated as the product between the county level variables of exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data, the map for this exposure is available in Figure A5. $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A6: El Niño and Natural Disasters - Alternative Dataset

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Probability of Natural Disasters			Probability of Flood		
$Positive\ Exposure_c\ \times$	-0.145***		-0.149***	-0.0177		0.00462
$El\ Nino_t$	(0.0165)		(0.0166)	(0.0185)		(0.0189)
$Negative\ Exposure_c\ \times$		0.00817	-0.0292***		0.145***	0.146***
$El\ Nino_t$		(0.00677)	(0.00610)		(0.0239)	(0.0244)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	52,836	52,836	52,836	52,836	52,836	52,836
Adj. R sq.	0.221	0.220	0.221	0.188	0.189	0.189
Mean Dep. Var.	0.851	0.851	0.851	0.266	0.266	0.266

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. It regresses Natural Disasters on the county exposure. to El Niño. County and year fixed effects are present in all columns, and standard errors are clustered at the county level. The dependent variables are $NaturalDisasters_{ct}$ and $Floods_{ct}$, which are two dummy variables that takes value 1 if there have been one or more natural disasters and one or more floods in county c in year t as recorded by EM-DAT database, and 0 otherwise. $Positive\ Exposure_c$ takes unit value if a county presents a positive climate exposure to El Niño; $Negative\ Exposure_c$ takes unit value if a county presents a negative climate exposure to El Niño and $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A7: Banks and El Niño - Alternative Difference-in-Difference Estimation

	(1)	(2)
Variables	Assets	Loans
$Bank\ Exposure_b\ \times$	-0.013	-0.023**
$El\ Nino_t$	(0.008)	(0.011)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Obs.	81,044	81,044
Mean Dep. Var.	12.28	11.72

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b in year t. Bank and year fixed effects are present in all columns, and standard errors are clustered at the bank level. The dependent variable in the first column is the natural logarithm of total assets and in the second column the natural logarithm of total loans. The estimation of the difference-in-difference is described in section 4.7. $Bank\ Exposure_b$ measures the exposure of bank b to El Niño and is calculated as the product between the county level variables of exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data. $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A8: Climate and El Niño - Clustering at the State Level

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Average Temperatures			Volatility of Temperatures		
Positive Exposure$_c$ ×	0.518***		0.462***	0.0724**		0.0675**
El Nino$_t$	(0.0788)		(0.0750)	(0.0318)		(0.0328)
Negative Exposure$_c$ ×		-0.479***	-0.362***		-0.0482*	-0.0311
El Nino$_t$		(0.0648)	(0.0616)		(0.0269)	(0.0276)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	108,761	108,761	108,761	108,752	108,752	108,752
Adj. R sq.	0.949	0.949	0.949	0.597	0.597	0.597
Mean Dep. Var.	12.86	12.86	12.86	1.674	1.674	1.674

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the state level. The dependent variable in the first three columns is the average yearly temperature of a county and is defined as the yearly average of monthly averages in Celsius degrees. The dependent variable in the last three columns is the yearly standard deviation of the growth rate of daily temperatures. *Positive Exposure*$_c$ takes unit value if a county presents a positive climate exposure to El Niño; *Negative Exposure*$_c$ takes unit value if a county presents a negative climate exposure to El Niño and *El Niño*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A9: Mortgage Lending and El Niño - Clustering at the State Level

	(1)	(2)	(3)
Variables	Mortgage Lending		
Positive Exposure$_c$ ×	-0.161***		-0.159***
El Nino$_t$	(0.0342)		(0.0358)
Negative Exposure$_c$		0.0550**	0.0174
×*El Nino*$_t$		(0.0248)	(0.0246)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	91,591	91,591	91,591
Adj. R sq.	0.909	0.909	0.909
Mean Dep. Var.	10.45	10.45	10.45

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, and standard errors are clustered at the state level. The dependent variable is the natural logarithm of HMDA lending at the county level. *PositiveExposure*$_c$ takes unit value if a county presents a positive climate exposure to El Niño; *Negative Exposure*$_c$ takes unit value if a county presents a negative climate exposure to El Niño and *El Niño*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A10: Climate and El Niño - Spatial Clustering

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Average Temperatures			Volatility of Temperatures		
$Positive\ Exposure_c \times$	0.518***		0.462***	0.0724**		0.0675**
$El\ Nino_t$	(0.0684)		(0.0695)	(0.0305)		(0.0313)
$Negative\ Exposure_c$		-0.479***	-0.362***		-0.0482*	-0.0311
$\times El\ Nino_t$		(0.0701)	(0.0696)		(0.0288)	(0.0292)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	108,761	108,761	108,761	108,752	108,752	108,752
R sq.	0.00561	0.00293	0.00722	0.000481	0.000130	0.000533
Mean Dep. Var.	12.86	12.86	12.86	1.674	1.674	1.674

Notes:

Table A11: Mortgage Lending and El Niño - Spatial Clustering

	(1)	(2)	(3)
Variables	Mortgage Lending		
$Positive\ Exposure_c \times$	-0.116***		-0.112**
$El\ Nino_t$	(0.0427)		(0.0439)
$Negative\ Exposure_c$		0.0507	0.0241
$\times El\ Nino_t$		(0.0362)	(0.0371)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	91,592	91,592	91,592
R sq.	0.000526	0.0000641	0.000540
Mean Dep. Var.	10.46	10.46	10.46

Notes:

Table A12: Climate and El Niño - Wild Bootstrap

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Average Temperatures			Volatility of Temperatures		
$Positive\ Exposure_c \times$	0.517***		0.461***	0.0723**		0.0675**
$El\ Nino_t$	(0.0787)		(0.0749)	(0.0318)		(0.0327)
$Negative\ Exposure_c \times$		-0.479***	-0.362***		-0.0481*	-0.0310
$El\ Nino_t$		(0.0647)	(0.0615)		(0.0268)	(0.0276)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	108,761	108,761	108,761	108,752	108,752	108,752
Adj. R sq.	0.222	0.220	0.224	0.0708	0.0704	0.0708
Mean Dep. Var.	12.86	12.86	12.86	1.674	1.674	1.674
Wild Bootstrap p value	0	0.001		0.0601	0.149	
Wild Bootstrap t stat	6.567	-7.401		2.278	-1.791	
Wild Bootstrap p value Pos			0			0.0751
Wild Bootstrap t stat Pos			6.159			2.064
Wild Bootstrap p value Neg			0			0.297
Wild Bootstrap t stat Neg			-5.890			-1.123
Wild Bootstrap p value joint			0			0.103
Wild Bootstrap F stat			70.45			3.763

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, wild bootstrapped standard errors are in parenthesis and their corresponding pvalues and statistics are reported in the last rows. The dependent variable in the first three columns is the average yearly temperature of a county and is defined as the yearly average of monthly averages in Celsius degrees. The dependent variable in the last three columns is the yearly standard deviation of the growth rate of daily temperatures. $Positive\ Exposure_c$ takes unit value if a county presents a positive climate exposure to El Niño; $Negative\ Exposure_c$ takes unit value if a county presents a negative climate exposure to El Niño and $El\ Niño_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A13: Mortgage Lending and El Niño - Wild Bootstrap

Variables	(1)	(2)	(3)
	Mortgage Lending		
Positive Exposure$_c$ ×	-0.145***		-0.141***
El Nino$_t$	(0.0391)		(0.0402)
Negative Exposure$_c$ ×		0.0570**	0.0236
El Nino$_t$		(0.0216)	(0.0209)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	91,592	91,592	91,592
Adj. R sq.	0.755	0.755	0.755
Mean Dep. Var.	10.45	10.45	10.45
Wild Bootstrap p value	0.005	0.0551	
Wild Bootstrap t stat	-3.709	2.640	
Wild Bootstrap p value Pos			0.0110
Wild Bootstrap t stat Pos			-3.518
Wild Bootstrap p value Neg			0.302
Wild Bootstrap t stat Neg			1.129
Wild Bootstrap p value joint			0.004
Wild Bootstrap F stat			11.09

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is county c in year t. County and year fixed effects are present in all columns, wild bootstrapped standard errors are in parenthesis and their corresponding pvalues and statistics are reported in the last rows. The dependent variable is the natural logarithm of HMDA lending at the county level. *Positive Exposure*$_c$ takes unit value if a county presents a positive climate exposure to El Niño; *Negative Exposure*$_c$ takes unit value if a county presents a negative climate exposure to El Niño and *El Niño*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A14: Banking and El Niño - Wild Bootstrap

Variables	(1) Loans	(2) Assets
Bank Exposure$_b$ ×	-0.0300***	-0.0176***
El Nino$_t$	(0.00816)	(0.00679)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Obs.	81,086	81,086
Adj. R sq.	0.400	0.421
Mean Dep. Var.	11.72	12.28
Wild Bootstrap p value	0	0.00500
Wild Bootstrap t stat	-3.673	-2.599

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b in year t. Bank and year fixed effects are present in all columns, wild bootstrapped standard errors are in parenthesis and their corresponding pvalues and statistics are reported in the last rows. The dependent variable in the first column is the natural logarithm of bank loans and in the second column is the natural logarithm of total bank assets. *Exposure*$_b$ measures the exposure of bank b to El Niño and is calculated as the product between the county level variables of exposure and the average share of HMDA lending conducted by bank b in county c across all years available in the data. *El Niño*$_t$ takes unit value if year t exhibits a top 5 El Niño event. Obs. refers to the number of observations, Adj. R sq. refers to the adjusted R^2 and Mean Dep. Var. refers to the mean value of the dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A15: Backward Selection

VARIABLES	(1) Loans	(2) Assets
$Bank\ Exposure_b \times$	-0.0137**	-0.00840*
$El\ Nino_t$	(0.00667)	(0.00437)
$OperatingLeverage_b \times$	-0.0244	-0.0124*
$El\ Nino_t$	(0.0338)	(0.00663)
$NIM_b \times$	-0.0136	-0.00192
$El\ Nino_t$	(0.0104)	(0.00437)
$PastDueRealEstate_b \times$	-0.0669***	-0.0524***
$El\ Nino_t$	(0.0180)	(0.0143)
$PastDueC\&I_b \times$	0.00385	0.00817
$El\ Nino_t$	(0.00980)	(0.00780)
$CashDomestic_b \times$	-0.0266**	-0.0222***
$El\ Nino_t$	(0.0133)	(0.00526)
$Securities_b \times$	2.10e-05	-0.0120**
$El\ Nino_t$	(0.00810)	(0.00540)
$BusinessLoans < \$100K_b \times$	0.0350***	0.0268***
$El\ Nino_t$	(0.00656)	(0.00416)
$IntExpenses_b \times$	-0.0903***	-0.0929***
$El\ Nino_t$	(0.0223)	(0.0150)
$BusinessLoans < \$1mil_b \times$	-0.0373***	-0.0284***
$El\ Nino_t$	(0.0127)	(0.00614)
$PastDueAssets_b \times$	0.0312	0.0265*
$El\ Nino_t$	(0.0197)	(0.0153)
$IntExpensesDeposits_b \times$	-0.00896	-0.000864
$El\ Nino_t$	(0.0251)	(0.0154)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Obs.	69,225	69,225
Adj. R sq.	0.913	0.946
Mean Dep. Var.	11.71	12.28

Notes:

Table A16: Forward selection

VARIABLES	(1) Loans	(2) Assets
$Bank\ Exposure_b \times$	-0.0133*	-0.00909**
$El\ Nino_t$	(0.00689)	(0.00424)
$OperatingLeverage_b \times$	-0.0268	-0.0150**
$El\ Nino_t$	(0.0255)	(0.00648)
$Deposits_b \times$	0.0303	0.0246***
$El\ Nino_t$	(0.0241)	(0.00711)
$Dividends_b \times$	0.0141	0.00313
$El\ Nino_t$	(0.0177)	(0.00788)
$BusinessLoans < \$100K_b \times$	0.0123**	0.0111***
$El\ Nino_t$	(0.00624)	(0.00333)
$BusinessLoans < \$1mil_b \times$	-0.0273***	-0.0201***
$El\ Nino_t$	(0.00786)	(0.00536)
$IntExpensesDeposits_b \times$	-0.0871***	-0.0687***
$El\ Nino_t$	(0.0119)	(0.00607)
$RWA_b \times$	0.00209	0.0125**
$El\ Nino_t$	(0.00890)	(0.00521)
$Intangible_b \times$	-0.00294	0.0257***
$El\ Nino_t$	(0.0399)	(0.00898)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Obs.	77,908	77,908
Adj. R sq.	0.910	0.946
Mean Dep. Var.	11.71	12.28

Notes:

Table A17: Alternative Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		meanTAVG			sd_TAVG_growth	
$PositiveExposure_c \times$	0.526***		0.483***	0.0794***		0.0763***
$El\ Nino_t$	(0.0194)		(0.0198)	(0.0100)		(0.0103)
$NegativeExposure_c \times$		-0.461***	-0.351***		-0.0426***	-0.0252***
$El\ Nino_t$		(0.0197)	(0.0200)		(0.00855)	(0.00881)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	108,761	108,761	108,761	108,752	108,752	108,752
Adj. R sq.	0.949	0.949	0.949	0.597	0.597	0.597
Mean Dep. Var.	12.86	12.86	12.86	1.674	1.674	1.674

Notes:

Table A18: Alternative Exposure

VARIABLES	(1)	(2) log_loans	(3)	(4)	(5) HPI2000	(6)
$PositiveExposure_c \times$	-0.123***		-0.118***	-0.0136***		-0.0132***
$El\ Nino_t$	(0.0174)		(0.0177)	(0.00221)		(0.00226)
$NegativeExposure_c \times$		0.0637***	0.0386*		0.00661**	0.00377
$El\ Nino_t$		(0.0199)	(0.0202)		(0.00315)	(0.00322)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	91,591	91,591	91,591	77,708	77,708	77,708
Adj. R sq.	0.916	0.916	0.916	0.893	0.893	0.893
Mean Dep. Var.	10.46	10.46	10.46	1.094	1.094	1.094

Notes:

List of Variables used in the LASSO estimation

1. sc = Securities;
2. bkprem = Equipment and premises;
3. ore = Other real estate;
4. intan = Intangibles and goodwill;
5. liab = Total liabilities;
6. dep = Total deposits;
7. eqtot = Total equity;
8. rwajt = Riskweighted assets;
9. rbct1j = Tier 1 (core) capital ;
10. intinc = Total interest income;
11. ilndom = Interest income from domestic loans;
12. ilnfor = Interest income from foreign loans;
13. eintexp = Total interest expense;

14. edepdom = Interest expense from deposits ;
15. efrepp = Interest expense from fedfunds and repos (liabilities);
16. nonii = Noninterest income;
17. epremagg = Expenses on premises and fixed assets;
18. ideoth = Noninterest, operating expenses;
19. idpretx = Net income before taxes;
20. eqcdiv = Cash dividends to equity holders;
21. noij = Net operating income;
22. lnlsnet = Loans and leases, net ;
23. lnatres = Loans and leases loss allowances;
24. lnlsgr = Loans and leases, gross;
25. idlnls = Loans and lease financing receivables of the institution, including unearned income;
26. lnre = Loans secured primarily by real estate, whether originated by the bank or purchased;
27. lnci = Commercial and industrial loans;
28. lndepac = All loans (other than those secured by real estate), including overdrafts, to banks, other depository institutions;
29. scus = Total US Treasury securities plus US Government agency and corporation obligations;
30. scrdebt = Total debt securities, both domestic and foreign at amortized cost and fair value, excluding nonaccrual debt securities;
31. lndepcb = Total loans to commercial banks located in the U.S. and acceptances of such banks;

32. lnrenr4 = Amount of currently outstanding loans secured by nonfarm nonresidential properties with original amounts less than \$1,000,000 held in domestic offices;

33. lnrenr1 = Amount of currently outstanding loans secured by nonfarm nonresidential properties with original amounts of \$100,000 or less held in domestic offices;

34. lnrenr2 = Amount of currently outstanding loans secured by nonfarm nonresidential properties with original amounts of more than \$100,000 through \$250,000 held in domestic offices;

35. depdom = The sum of all domestic office deposits, including demand deposits, money market deposits, other savings deposits and time deposits;

36. idtrcomb = Total transaction and nontransaction accounts of commercial banks and other depository institutions;

37. trn = The sum of the following accounts held in domestic offices: demand deposits, NOW accounts, Automated Transfer Service (ATS) accounts and telephone or preauthorized transfer accounts;

38. ddt = Total demand deposits included in transaction accounts held in domestic offices;

39. uc = The unused portions of commitments to make or purchase extensions of credit;

40. ucloc = Unused commitments for revolving, openend lines secured by 14 family residential properties;

41. p3asset = Total assets past due 30 through 89 days and still accruing interest;

42. p3re = Total loans secured by real estate past due 30 through 89 days and still accruing interest;

43. p3ci = Total commercial and industrial loans past due 30 through 89 days;

44. nimy = Net interest margin as percentage of asset;

45. roa = return on assets;

46. insdep = Amount ($) of deposit accounts of $100,000 or less held in domestic offices and in insured branches in Puerto Rico and U.S. territories and possessions or, if missing Beginning September 2009, amount of deposit accounts of $250,000 or less (excluding retirement= accounts) held in domestic offices and in insured branches in Puerto Rico and U.S;

47. ntlnls = Net chargeoffs: Total loans and leases chargedoff (removed from balance sheet because of uncollectibility), less amounts recovered on loans and leases previously charged-off.);

48. chcoin = Currency and coin held in domestic offices;

49. lncon = Loans to individuals;

50. chus = Balances due from depository institutions in U.S.;

51. chfrb = Balances due from FRB;

52. chbal = Total cash and balances due from depository institutions.