UNIVERSITY OF COPENHAGEN
DEPARTMENT OF SCIENCE

Master Thesis

MSc in Environmental and Natural Resource Economics

A hard rain's a-gonna fall

A multiperiod difference-in-difference model for estimating the impact of ENSO on Peruvian MFIs

Supervisor: Micheal Friis Pedersen

Submitted on: 31 May 2022

Name of department: Department of Science

Author(s): Nicolas Jordi Aguilar Sandoval (Lwv662)

Title and subtitle: A hard rain's a-gonna fall: A multiperiod difference-in-difference model for estimating the impact of ENSO on Peruvian MFIs

Abstract: Extreme weather conditions are set to increase as a result of climate change. El Niño and the Southern Oscillation (ENSO) cycle influence global climate and manifests along the coasts of the Pacific Ocean in the form of droughts and heavy rains. Low-income households are affected directly through floodings and landslides, and indirectly through crop failures and broad disruptions to economic activity. Microfinance institutions (MFIs) in ENSO-exposed regions face the risk of broad-base defaults among borrowers, potentially dampening their ability to supply additional credit. This thesis evaluates the impact of ENSO in the portfolio of Peruvian MFIs using a multiperiod difference-in-difference (DiD) model, for two instances of the event. The results show that Peruvian MFIs have managed diversified away risk. Estimates for the strong ENSO of 1997-98 show a significant increase in problem loans; however, the more recent strong ENSO 2016-17 displays no increase in problem loans.

Supervisor: Michael Friis Pedersen

Submitted on: 31 May 2022

Grade:

Number of study units: 45 ECTS

Number of characters: 16.010

Table of Contents

Introduction

Natural disasters can significantly threaten financial institutions serving the poor. With the unfolding of climate change projected to increase the likelihood of extreme weather events, low- and middle-income countries reliant on primary economic activity are particularly exposed (Cai et al., 2014, 2021). Microfinance institutions (MFIs) require comprehensive risk assessment tools to gauge risks accurately. MFIs may either overestimate their vulnerability to natural disasters, unnecessarily curtailing credit, or underestimate it, at the cost of threatening long-term financial stability. In turn, adapting to a changing climate while insulating financial institutions serving low-income households, requires methodologies that enhance the evaluation of natural disaster risk. Although such methods already exist, continuous refinement and assessment is paramount given that climate projections remains extremely fluid.

Peru has proven to be a buoyant market for microfinance. MFIs began growing in the mid-1990s and expanded at breakneck speed after the turn of the century, largely thanks to market-friendly institutional reforms. As the market developed, more sophisticated financial products sprouted, including insurance packages for low-income households (Conger, Inga and Webb, 2009). Municipal *cajas* are the most common and significant form of MFI in Peru, and this thesis focuses on the impact of ENSO, i.e. El Niño, on their loan portfolios between 1994 and 2019.

From the various effects that ENSO has on Peru's economy, heavy rains can be one of the most devastating for local communities ,as they can led to flooding and landslides. The 1997-98 iteration of El Niño left half a million victims, and destroyed 135,000 homes while also leading to a cholera outbreak in the north of the country. The authorities estimated a USD 3.5 billion in damages(Agricultura (IICA) *et al.*, 2016). More recently, El Niño 2016-17 reached left more than a million victims (El Comercio, 2017), leaving and estimated USD 3.1 billion in damages. These two instances of ENSO have been the strongest in the last three decades, and are the focus of this thesis.

El Niño can especially affect *cajas* with large concentrations of clients in one area affected by ENSO, potentially denting their ability to supply fresh loans when a crisis struck. An unexpected increment of *bad loans* requires *cajas* to increase their provision, taking up resources and adding additional administrative costs, limiting the issuing of new loans. During a devastating ENSO episode, *cajas* should be able to increase lending rather than curtail it and for that a sound risk management is required.

Using an ARIMA model, Collier, Katchova, and Skees (2011) evaluated the impact of ENSO 1997-98 on the proportion of restructured loans in the portfolio of *caja* Piura and found the event led to a statistically significant increase. In the light of the limitations of that model, this thesis recreates that event study using a multiperiod difference-in-difference model. Fitted adequately, a DiD model isolates the impact of an event on the depend variable by control for time varying and constant factors. In brief, the research question for this thesis goes as follows: Can a difference-in-difference model be employed for evaluating the impact of ENSO on the level of restructured loans present in Peru's municipal *cajas?*

In practice, it requires finding a valid control group, that matches the treatment group in all but being affected by the event. The results obtained for ENSO 1997-98, are consistent with the literature that guided this study (Collier, Katchova and Skees 2011). For El Niño 2016-17 is not possible to fit the model because the correlation between ENSO and the dependent variable (PRL) disappears. In other words, the restructure loans for ENSO-exposed *cajas* show no increase as floodings and landslides ravaged the country. The reason is likely that *cajas* were able to reduce their exposure to the event in the past two decades through further client diversification and insurance.

The first section of this thesis presents the methodology employed, describes the nature of the tools and reviews literature and data. After that, the second section provides background on Peru and ENSO. Describing the main geographical divisions of the country while also going over the main events within the country's microfinance scene since the 1990s. In addition, a comprehensive description of ENSO and how it is measured is included. A clear picture of the nature and implications of the event is fundamental to understanding how it affects Peru's economy.

The third section presents the difference-in-difference (DiD) framework by first reviewing the simplest version of the model and its main assumptions. Given the nature of the problem, the more advanced multiperiod DiD model is employed in this thesis. A detailed description of its innerworkings and assumptions is provided in this section. The fourth section fits the data (Annex A, All CMAC data) to the model by dividing the *cajas* into treatment and control groups through criteria explicitly devised for this thesis. These two groups are at the core of the DiD framework;

hence establishing a proper procedure for selecting them is pivotal. Nevertheless, the chosen criteria for separating the data largely depend on the nature of the data itself and the characteristics of the problem at hand (Huntington-Klein, 2021a). The fourth section also presents a process for separating the data into treatment and control groups.

The fifth section presents the results estimated using the R software and the DiD package. Models are estimated for three affected regions, i.e. departments, and the models shown are those that best fit the assumptions. The sixth section pertains to the discussion of the results. Particularly regarding both iterations of ENSO, the limitations of the event, policy recommendations, and future research ideas. Lastly, section seven is a sensitivity analysis intended to assess how the estimations of the model change when one key parameter is tweaked.

1.Methodology

1.1. Literature review

The search for literature for this study began with ENSO, its relationship with the climate and its historical impact on Peru's economy. NOAA's website served as a starting point for finding new literature and deepening my understanding of El Niño. Notably, the research by Cai *et al.* (2014, 2021), which presents evidence of the increasing frequency of ENSO as climate change unfolds, primarily motivated the choice of this topic. The comprehensive overview of the event shown in this thesis was put together thanks to the descriptions presented in multiple papers and websites (Bjerknes, 1969; L'Hereux, 2014; Rojas, Li and Cumani, 2014; Cashin, Mohaddes and Raissi, 2017; Mcgregor and Ebi, 2018; NOAA, 2022).

At the outset, the idea was to study the impact of ENSO on farmers in Peru; however, comprehensive data on agricultural output by departments was not available. Note that *departments* are the largest political division of Peru's territory. As I was looking for another angle for the project, I stumbled across the paper by Collier, Katchova and Skees (2011), which evaluated the impact of the 1997-98 ENSO on an MFI lending portfolio (*Caja* Piura). This approach seemed feasible in terms of data availability. I proceeded to have a Zoom interview with Benjamin Collier, one of the paper's authors, to better understand the process behind his research. Collier was supportive and suggested that I evaluate whether a difference-in-difference model could be employed instead of the ARIMA model used in his study. The idea proved interesting as it showed potential for studying more recent iterations of ENSO.

Literature on the development of microfinance in Peru is presented in section 2 to provide context to the analysis (Ebentreich, 2005; Conger, Inga and Webb, 2009; Aguilar, 2013). Moreover, a closer look at the history of microfinance in Peru also shows how *cajas* have managed to diversified their ENSO-related risk through the years (Carmago and Furst Gonçalves, 2014; Collier, 2020). Meanwhile, papers and guides on the most straightforward designs of a DiD model were first reviewed to deliver a simpler picture of the logic behind it, together with its main assumptions (Gertler *et al.*, 2016; World Bank, 2018; Coleman, 2020; Perraillon, 2020; Huntington-Klein, 2021b).

Literature about the difference-in-difference (DiD) framework is broadly abundant, and websites and studies were reviewed to identify the general and particular details of the model (Lechner, 2011, 2011; World Bank, 2018; Coleman, 2020; Kahn-Lang and Lang, 2020; Perraillon, 2020; Huntington-Klein, 2021b). Papers utilizing DiD models to evaluate the impact of natural events were limited, and none of the found studies focused on Latin America. Most prominently, a paper on the impact of hurricane Sandy on market liquidity in the United States showed some similarities; however, again, the data proved too different from what is publicly available in Peru (Rehse *et al.*, 2019). Next, the more advanced multiperiod DiD framework, the one employed in the analysis, is described in conjunction with its specific assumptions (Callaway and Sant'Anna, 2021, 2022).

Lastly, official data from Peru's government and statistical institute were employed for various parts of the analysis, including the geographical and ecological background, macroeconomic snapshot, and other considerations done throughout the study (INEI, 2022).

1.2. Data review

This thesis employs time-series data of the monthly balance sheet of twelve municipal *cajas* operating in Peru from 1994 until 2022. The data is publicly available on the webpage of the Superintendency of Banking, Insurance and Pension Funds (SBS by its initials in Spanish)(SBS, 2022). From the dataset including the balance sheet of all *cajas*, the variables of used are: active loans, delayed loans and restructured loans (Annex A, Table 1). Following Collier, Katchova and Skees (2011), restructured credit is measured as a percentage of total credit, that way, it is feasible to compare *cajas* with different levels of outstanding credit. This variable is labeled the proportion of restructured loans (PRL) throughout the rest of this thesis.

A closer look at the PRL time series shows erratic data movement in the first (1994 and 1995) and later years (2020 and onwards). The front-end volatility in the data may imply some adjustments coinciding with the data becoming public. To avoid confusion, these years are dropped so the time series used for PRL effectively starts in 1996. Meanwhile, because the fallout of the COVID-19 pandemic is likely to blame for the extreme values in the later years, the time series ends in 2019 to avoid the pandemic disruptions on PRL.

Annual and monthly rainfall data at the department level, the largest political division of Peru's territory, is used to support the identification of ENSO. Monthly rainfall data was obtained from the database of SENAMHI, Peru's national meteorological and hydrological service (SENAMHI, 2022). There was no single value for monthly rainfall level for each department. Instead, SENAMHI provides access to rainfall data for all weather stations present in each department. To simplify the process, for each department of interest, three stations are selected and their results averaged to obtain an approximate value for monthly precipitation for each department. The calculations are done in Annex A, table 6. On the other hand, annual data was extracted from environmental reports published by the country's statistical institute (INEI, 2022).

Lastly, ONI data for the 3.4 and 1+2 regions is publicly available in the NOAA website. All data and calculation done in this thesis are available in Annex A, an excel file. Annex A is referenced multiple time throughout the explanation and fitting of the model. For estimating, R software and the DiD package were employed for structuring the different combinations of treatment and control groups, and also, for estimating the model. All code is available in Annex C.

1.2. Research approach

This thesis employs a multiperiod difference in difference model for estimating ENSO's impact on the percentage of restructured loans (PRL) for selected MFIs based in Peru. Literature on ENSO and the theory behind DiD models are employed as well as compressive time series data on multiple municipal MFIs. i.e. *cajas.* DiD models require that the available data is divided in treatment and control groups. The method for doing so mainly depends on the nature of the data. Here, a decision three method is employed for clustering each *cajas (i)* into groups. Two criteria are defined as branches for sorting the data into control and treatment group, ending up with a list of candidates (Figure 13 and 14). Next, different combinations for treatment and control group c are devised utilizing a matching process based on the available literature. The best model is found for each affected department, in the result section. Lastly a sensitivity analysis for evaluating how changing specific key parameters can alter the estimations of the multiperiod Did model.

2. Background

2.1. Peru: the land of the Incas

The country of Peru is located in western South America, in between the Equator and the tropic of Capricorn. Geographically, its land is endowed with vastly diverse ecosystems, primarily determined by the three main natural regions: coast, mountain range and rainforest—as reported by the government (INEI, 2022). The Pacific coast is characterized by a narrow strip of desserts and fertile valleys, which arise from the rivers flowing westwards from the Andes Mountains. Temperatures are generally warm and high in humidity, and northern areas experience higher temperatures almost all year round, with a typical short rain period between November and December. During El Niño years, however, rainfall can increase tenfold. The southern and central areas experience two marked seasons, winter, from April to October, and summer, from November to March (ESDAMIN, 2022; INEI, 2022).

Figure 1: Map of natural regions of Peru

Source: Google Earth (2022)

Turning to the mountain range region, the Andes Mountain dominates the landscape with several ecoregions on different altitude levels. In the north, the mountain range is lower and more humid, at the center, the highest and steepest points are found, while in the southern Andes are thicker, also known as the altiplano. The region experiences two regions: summer from April to October with sunny days, cold nights and low rain, and winter from November to March, with abundant rains. Meanwhile, the rainforest region is located to the east in the Amazon River basin, a vast and flat terrain covered by vegetation. Like the mountain range, it has two well-defined regions. From November to Match, winter is marked by abundant rains; while summer sees little rain from April to October. Humidity remains elevated throughout the year (ESDAMIN, 2022; INEI, 2022).

Figure 2: Map of Peru divided into departments

Source: Gobierno del Perú, (2022)

In terms of its economic structure, primary sector activity constitutes the lion-share of Peru's exports, similar to other countries in the region. As reported by the statistical institute, agriculture and fishing together with mining, represent about a fifth of Peru's output (INEI, 2022). Climate conditions play an essential role in the productive outlook of these activities, making Peru vulnerable to unexpected shocks in weather conditions such as ENSO. Notably, Peru is a leader in marine capture fisheries and a global producer of anchovy and derived products.

The most significant political division of Peru's territory is the Department, mentioned throughout this study. As seen in figure 2, the country is comprised of twenty-four departments. The bulk of Peru's population inhabits departments located in the natural coastal region (INEI, 2022; Gobierno del Perú, 2022). The departments studied have one or more *cajas* based in them.

2.2. Local MFIs and natural disasters risk

The advent of microfinance in Peru began in the 1990s, against the backdrop of the neoliberal advance in Latin-American during the wake of the Washington Consensus. The government of Alberto Fujimori introduced broad-based market-oriented policies to *unburden* the state and fuel private sector growth (Conger, Inga and Webb, 2009). As trade barriers and capital controls were dropped, Peru became an ideal candidate for microfinance, the latest trend in development economics at that time. Muhammad Yunus showed that microfinance could be used effectively to support poor households in India (Yunus, 1998), and those successes could be replicated elsewhere, including in Peru.

Overall, microfinance has shown mixed results in being an effective and inclusive tool for development. In Peru, however, there are signs of success. The microfinance business began growing in the mid-90s and accelerated at the turn of the century. By mid-2009, the average annual rate of growth of MFIs had been 19% for over two decades, and the country presented the most diversified industry in the global microfinance landscape (Conger, Inga and Webb, 2009). The *cajas municipales* studied in this thesis are among the largest players in the Peruvian microfinance market. These *cajas* are regulated institutions owned but not majority controlled by the municipal government; they receive deposits and specialize in micro and small enterprise loans. As the market matured, more financial services were introduced, including specialized credit lines and, insurance and microinsurance (Aguilar, 2013; Carmago and Furst Gonçalves, 2014).

In their inception, *cajas* were allowed to operate only within their home department. Against this backdrop, ENSO poses a significant risk to their lending portfolio because natural disasters result in spatially correlated losses (Collier, Katchova and Skees, 2011). Typically, financial institutions seek to diminish their exposure to idiosyncratic risk (e.g., health problems, unemployment, death of breadwinner) by increasing the number of borrowers. Idiosyncratic risk is uncorrelated between individuals, so a bank can mitigate this type of risk by increasing its client base. However, correlated risks cannot be diversified away by continued lending to members within the same community. The natural disaster risk posed by ENSO is a form of correlated risk for *cajas*, mainly if the bulk of their lending is concentrated in a vulnerable area (Collier, Katchova and Skees, 2011; Collier, 2020).

The ENSO of 1997-98 event took a toll on exposed *cajas* at a time when they ought to be increasing lending to aid affected households and support an economic recovery. The model used in this study assesses the event's impact on banks' balance sheets, particularly on restructured loans. A higher proportion of restructured loans limits an MFI's room for maneuvering through a crisis, stopping them from supplying much-needed relief credit. For this first iteration of ENSO, the model delivers satisfactory results, mainly because, at that time, *cajas* were exposed to significant correlated risks. However, in 2002 restrictions were lifted and *cajas* were allowed to operate outside their home department, reducing ENSO correlated risk by lending to households in less-exposed departments (Conger, Inga and Webb, 2009). As explored in the discussion, this change in regulation greatly influenced the potential for utilizing this model for later iterations of El Niño.

Besides expanding beyond ENSO-exposed departments, *cajas* have managed to mitigate natural disaster risks thanks to a dynamic insurance and microinsurance market. In 2007 the Superintendence of Banking and Insurance (SBS) approved its first microinsurance resolutions. It overhauled it in 2009, remarking the need to expand access to insurance across the country (Carmago and Furst Gonçalves, 2014). Research shows that in response to losses prompted by a natural disaster, lenders tend to contract credit, reducing loan allocation to bring it on par with a smaller equity capital base (Collier, 2020). However, having lenders contract lending during a natural disaster is counterproductive, given that additional credit is needed to prompt a recovery.

As it stands, the growing sophistication of Peru's microfinance market has enabled *cajas* to mitigate ENSO risk over the years. The opportunity to lend outside their home department coupled with the growth of insurance providers, has reduced the risk exposure of *cajas* to the event. That is essentially why the positive correlation between PRL and ENSO observed in 1997-98 is not present in the 2016-17 iteration of the event.

Before introducing the difference-in-difference model, the following section reviews the key dynamics of ENSO as a clear understanding of the event is fundamental to linking its impact to the economy.

2.3. El Niño and the Southern Oscillation (ENSO)

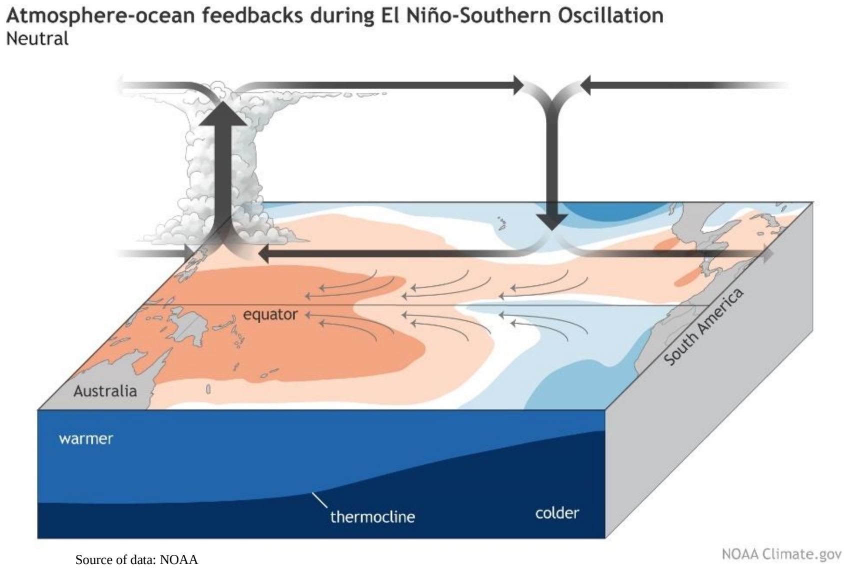
What is it?

The El Niño and the Southern Oscillation (ENSO) is a natural climate cycle that can affect global weather through changes in sea surface temperature (SST) and wind patterns across the tropical Pacific Ocean. Reflecting its complex nature, ENSO consists of two major components: the El Niño or ocean and the Southern Oscillation or atmospheric component (Mcgregor and Ebi, 2018). Its effect entails periodic fluctuations in ocean SST and changes in air pressure of the overlying atmosphere across the equatorial pacific sea that can have large-scale impacts on the global weather, including heavy rains and droughts with potentially devastating effects for local ecosystems and communities.

The oceanic component of ENSO has been documented for far longer than its atmospheric counterpart. Since the XVI century, Peruvian fishers understood the straining impact of unusually warm waters on fisheries that occasionally peaked around Christmas times, thus the name of the phenomenon: El Niño is Spanish for Christ Child, and it corresponds to the warm phase of the cycle (Agricultura (IICA) *et al.*, 2016). The cool phase counterpart, which involves lower SST, is called La Niña. In the absence of either warm or cool SST anomalies, the cycle is said to be in a neutral phase.

The discovery of the Southern Oscillation component of ENSO is often credited to H. Hidebrandsson. It refers to the atmospheric pressure variations between the western and eastern Pacific that occurs in tandem with SSTs variations, i.e. El Niño. Later on, Bjerknes (1969) conceptualized the link between El Niño and the Southern Oscillation as an ocean-atmosphere interaction, which led to the acronym ENSO (Mcgregor and Ebi, 2018). Nevertheless, the reason why ENSO does not include the word La Niña is that the term gained prominence around the 1980s, that is, after Bjerknes' coined the acronym (L'Hereux, 2014).

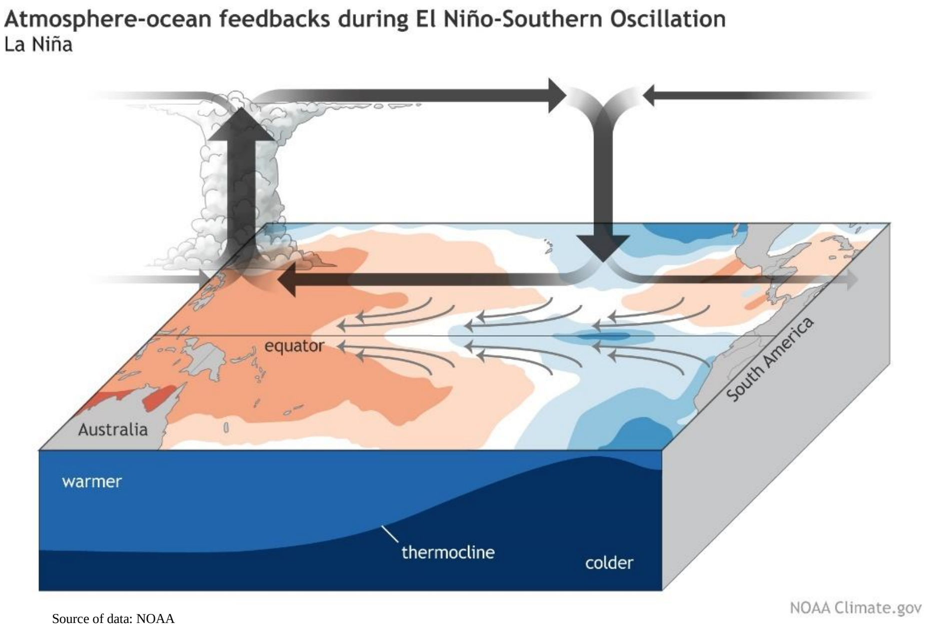
Figure 3: ENSO neutral phase



Source of data: NOAA

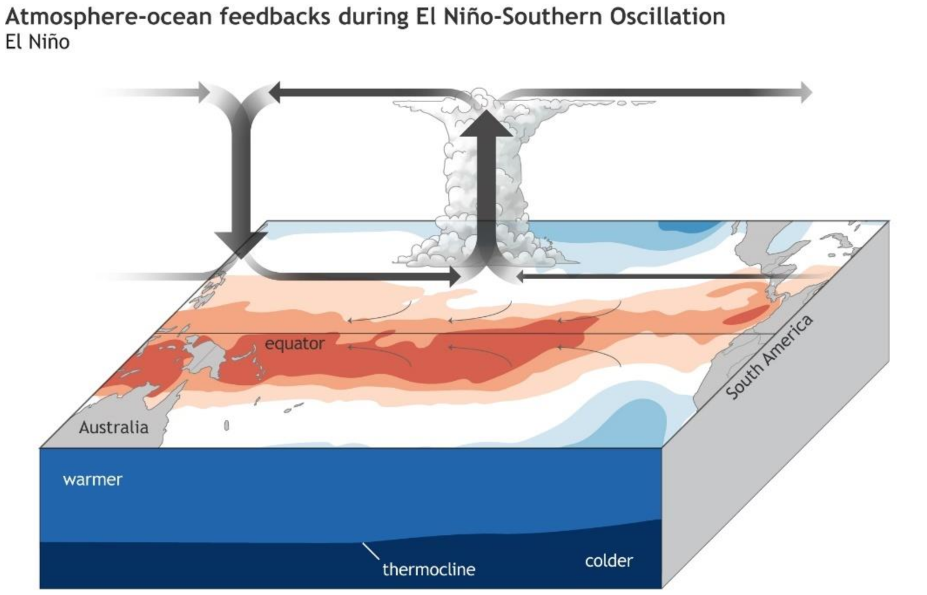
Turning to the dynamics of the cycle in the tropical Pacific, during the neutral phase, a surface low-pressure system develops in Indonesia and Northern Australia. In contrast, a high-pressure system builds up over Peru's coast. Consequentially, trade winds blow strongly from east to west, carrying warm surface waters westwards and bringing precipitations to Indonesia and Australia (Cashin, Mohaddes and Raissi, 2017). During La Niña or the cold phase of the cycle, the atmospheric conditions present in the neutral phase intensify. Westward trade winds strengthen, driving SST in the central and eastern tropical Pacific lower, while higher SST in the western pacific tend to increase rainfall over Indonesia (L'Hereux, 2014).

Figure 4: ENSO cold phase, i.e. La Niña



Source of data: NOAA

Figure 5: ENSO warm phase, i.e. El Niño



Source of data: NOAA

Meanwhile, in an El Niño or warm phase, air pressure falls in the central pacific and along the western coast of Latin America causing trade winds to be reduced and allowing the equatorial ocean current to flow from east to west, accumulating warm waters along the coastlines of Peru. As a result of higher SST, along the Peruvian coast, the thermocline[1] drops along the eastern tropical Pacific, causing the upwelling of cold, nutrient-rich deep water to weaken or stop altogether. Total phytoplankton mass decreases without the nutrients from the depth, thus limiting fish reproduction. At the same time, the increase in SST and weaker westward trade winds tend to allow a great cloud mass to move along the Pacific towards the western coast of North and South America, causing heavy rains and significantly increasing flooding risk in coastal regions (Agricultura (IICA) *et al.*, 2016; Cashin, Mohaddes and Raissi, 2017).

Typically El Niño and La Niña occur every two to seven years and tend to last between 12 to 18 months, while in extreme cases, the event can last beyond 24 months. At the outset, both phases manifest SST anomalies in the central and eastern Pacific around July. As the ENSO cycle progresses, SST continues to develop and reaches a peak around January-February of the following

[1] Defined by the NOAA as "the transition layer between the warmer mixed water at the surface and the cooler deep water below" (NOAA, 2022).

year. After that, a decay in SST anomalies is typically observed in the subsequent months from March to August (Mcgregor and Ebi, 2018).

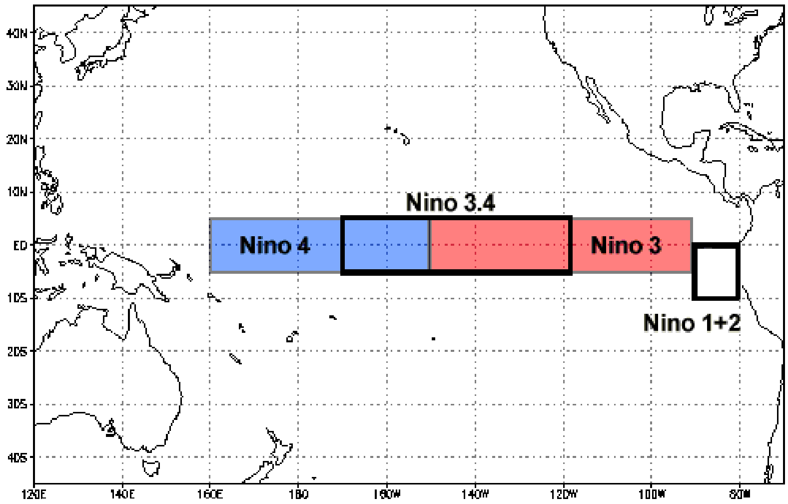
Despite their periodic episodes, ENSO phases do not follow a deterministic trend with constant intensity and fixed iterations. No two ENSO events are alike. Consequentially, a plethora of stochastic models has been employed by researchers to forecast the onset and intensity of the event. While predictions for the onset of warm and cold events are fairly accurate, intensity is harder to predict because of the randomness characteristic of atmospheric conditions (Rojas, Li and Cumani, 2014).

How is ENSO measured

Teleconnection indexes commonly describe the dynamics of specific forms of climate variability like ENSO. Typically, it is assumed that a teleconnection index captures in a single number a range of complex and specific atmospheric and/or ocean process interactions that give rise to a multifaceted form of climate variability, for a particular time frame (e.g. month, day, year). The plethora of existing ENSO indexes can be divided into atmospheric and oceanic, depending on the variables (Mcgregor and Ebi, 2018).

The Oceanic Niño Index (ONI) is the *de facto* standard used by the United States National Oceanic and Atmospheric Administration (NOAA), to identify the current phase of the cycle on a monthly basis (Rojas, Li and Cumani, 2014). The ONI is constructed as a three-month running average of SST anomalies—ending with the current month—estimated for three specific regions of the tropical Pacific ocean, as displayed in figure 6. For calculating the index, an SST anomaly is defined as a deviation from a 30-year mean SST, as shown in equation 1. ONI is after that estimated using equation 2, which takes the three-month rolling average of the SST anomaly.

Figure 6: ENSO regions



Source of data: NOAA

As defined by NOAA, the presence of El Niño (La Niña) is defined as five consecutive ONI values above (below) the threshold of +0.5°C (-0.5°C) in the Niño 3.4 region (Figure 6)(Lindsay, 2009; NOAA, 2022). Although ONI can be estimated for any of the regions shown in Figure 6, conventionally ONI is reported for the 3.4 regions. Nevertheless, there are limitations in the capacity of ONI to accurately estimate the presence of El Niño. The increase of SST must couple with atmospheric changes in order to unleash the reversal in tropical trade winds, otherwise El Niño may not occur (Williams and Null, 2015).

$$SST\ anomaly_i = current\ SST_i - 30\ year\ average\ SST \tag{1}$$

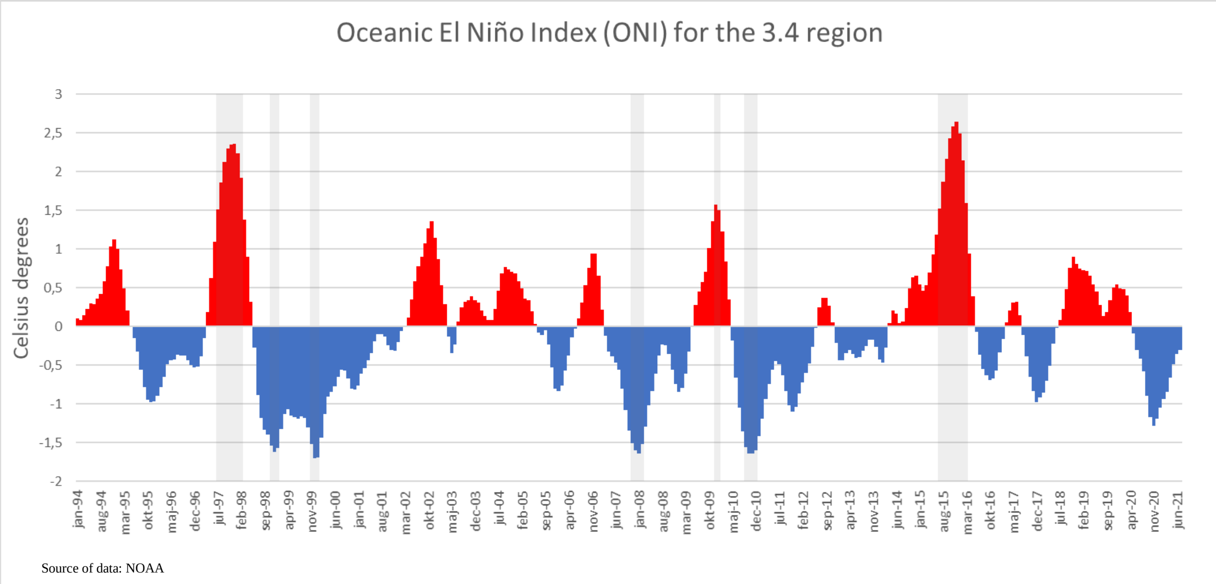
$$ONI_i = \frac{SST\ anomaly_{i-2} + SST\ anomaly_{i-1} + SST\ anomaly_i}{3} \tag{2}$$

$$for\ i = Jan, feb, mar \ldots$$

Williams and Null (2015) go further and use ONI to categorize El Niño and La Niña events according to their intensities. ONI values between ±0,5°C and ±1,0°C are labeled weak, above and between ±1,0°C and ±1.5°C are moderate, and above ±1,5°C are deemed strong. The proposed categories are useful for identifying the most devastating episodes of ENSO. It is reasonable to limit the analysis to strong iterations of the event since these are the most likely ones to have impacted regional lenders in the years ensuing the event. This study aims to evaluate the impact of El Niño on the lending portfolios of *cajas*; therefore, restricting the analysis to the periods where El Niño is strongest in the sample is a good place to start.

Figure 7 shows the ONI for the El Niño 3.4 region published by NOAA (2022). In red are the warm phases—i.e. El Niño—and in blue the cold phases—i.e. La Niña. The shadowed areas mark the periods when ONI exceeds the ±1.5°C threshold and represent strong ENSO iterations. In turn, there are three episodes of El Niño labelled as strong for the chosen time frame: 1997-1998, 2009-2010 and 2015-2016. Nevertheless, the one occurring in 2009-2010 was comparatively brief and softer than the two others and is hence left out of the analysis.

Figure 7: ONI for the 3.4 region

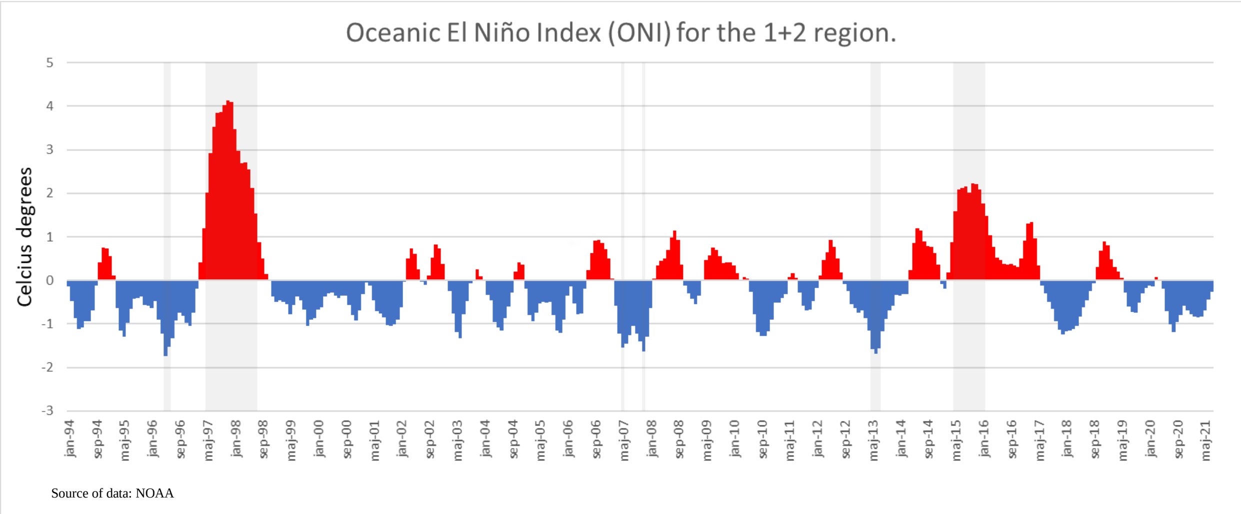


Although the standard is to estimate ONI using SST for the 3.4 region, NOAA also produces an ONI for the 1+2 region, which corresponds to the tropical pacific area next to the Latin-American western coast (Figure 6). Figure 8 plots the ONI for the 1+2 region, the shadow areas again represent the months where the index trespassed the *strong* threshold. One glaring difference between Figures 7 and 8 is the absence of high SST anomalies in 2009-2010 for the 1+2 region. This may suggest that the 2009-2010 El Niño had a milder impact on the Peruvian coast than other strong iterations of the event. Meanwhile, the 1997-1998 and 2015-2016 strong iterations of El Niño are reflected in both regions. Note that SST anomalies continue into 2017 in figure 8. This is an important element to consider because even though anomalies began showing in 2015, it was in 2016-2017 when Peru was struck by heavy rains and, consequently, flooding.

So far, the most relevant background information for this analysis has been presented. The key takeaway from this section is a basic overview of the country, the development of the local microfinance market and the dynamics of ENSO. The description of the ENSO phenomenon was detailed primarily due to the need to have a clear understanding of the ecological implications of the cycle to be able to link them to the broader economy. This is a personal topic of interest were further research could be done.

The next section of this thesis presents the model employed for estimating the impact of ENSO on the proportion of restructured loans on *cajas*' balance sheet. After a brief description of the simplest version of the difference-in-difference model, the more advanced multiperiod model is presented.

Figure 8: ONI for the 1+2 region



3. Difference-in-Difference model

3.1. Model overview: 2x2 DiD set-up

A difference-in-difference (DiD) model is a quasi-experimental approach used to compare changes in outcome over time between a population affected by an event or policy (treatment group) and a population unaffected by it (control group). This type of analysis is typically called event study in the literature, and it enables the estimation of causal inference even when randomized sampling is not possible (World Bank, 2018; Coleman, 2020; Huntington-Klein, 2021b).

The logic of the DiD is best described with an example: picture a government program aimed at boosting employment in a region; let us call it region A. A couple of years after implementing the program, researchers may be interested in assessing whether it impacted employment. Doing so is not as simple as comparing the employment level before and after the program's application, because there are likely other factors besides the program at play that influence the job market.

Imagine that next to region A sits region B, which is reasonably similar in sociodemographic and economic terms but was not subjected to the program. To evaluate the program's impact, a DiD model can be deployed with region A in the treatment group and region B as the counterfactual or control group. The idea is to estimate the before-and-after changes in outcomes (employment) between both groups. The difference in the before-and-after outcome for region A—the first

$$E[Y_{i1}|D_i = 1] - E[Y_{i0}|D_i = 1] = c_i + d_1 + \delta_1 - (c_i + d_0 + \delta_0) = d_1 - d_0 + (\delta_1 - \delta_0) \quad (4)$$
$$= d_1 - d_0 + \delta$$

$$E[Y_{i1}|D_i = 0] - E[Y_{i0}|D_i = 0] = c_i + d_1 - (c_i + d_0) = d_1 - d_0 \quad (5)$$

difference—controls for constant/time-invariant factors within the treatment group over time. However, there are still outside time-varying factors, such as energy prices, currency valuation, growth expectations, or even climatic events that are random in nature and thus impossible to fully capture without having to over parametrize the model.

One way to control for those outside time-varying factors is to use the first difference of region B and subtract it from the first difference of region A—obtaining the second difference. Region B was not enrolled in the program but was exposed to the same set of economic and environmental conditions, or so it is assumed because, as stated, both regions are closely similar. The first difference can be thus *cleaned* of outside time-varying factors that affect the outcome by subtracting from it the first difference of the control group (Gertler *et al.*, 2016; World Bank, 2018).

Perraillon (2020) provides a mathematical representation in equation three for modeling how the variable of interest, outcome Y_{it}, theoretically evolves over time:

$$Y_{it} = c_i + d_t + \delta D_{it} + \eta_{it} \quad (3)$$

Accordingly, *i* indexes represent the number of observations and *t* stands for time period. Meanwhile, *c* and *d* are variables while η_{it} is an unexplained random error. Hence, outcome, Y_{it}, depends on constant—time-invariant, fixed—factors at observation level, c_i, and on factors that depend on time, d_t, but not on unit of observation. Lastly, the treatment variable, D_{it} is a dummy representing whether the event is present at a certain time for the treatment group. Consequently, δ represents the magnitude of the event on outcome, Y_{it}. The next step in the DiD set-up is differentiation, for simplicity lets assume only two time periods:

Equation 4 represents the before-and-after for the treated group, while equation 5 is the before-and-after for the control group[2]. Note the presence of delta in equation 4, which corresponds to the impact of the event on outcome for the treatment group. On the other hand, equation 5 presents no delta because the control group is unaffected by the event.

Meanwhile, c_i are time-invariant and different across observations. These disappear during the first difference in both equations 4 and 5. As a result, we are only left with the time-varying factors $d_1 - d_0$, which are the same across equations by assumption[3].

Finally, by subtracting equation 5 from equation 4, $d_1 - d_0 + \delta - (d_1 - d_0) = \delta$; hence we have isolated the impact of the event, δ, on outcome, Y. This is the *second difference* part of the difference-in-difference process. Evidently, having a control group affected by exactly the same time-varying factor is impossible to find and there in lies the challenge for empirical applications.

Model assumptions

The validity of the DiD framework for modeling requires that three key assumptions are fulfilled (Lechner, 2011; Perraillon, 2020). Before proceeding to make estimations is necessary to test how well the data and event of the study satisfy these assumptions.

The first assumption is the Stable Unit Treatment Value Assumption (SUTVA), which requires consistency and no interference. The treatment or event studied must be well defined for consistency to be satisfied. When does El Niño start and for how long does it go on? The answer to this question must be the same for all group members. The no interference part of SUTVA assumes that the event's effect on one unit does not affect the outcome of any other unit.
Satisfying consistency requires that the length and starting point of El Niño is the same for every member of each group—treatment and control. The canonical DiD model of only two periods falls short in this study because not all members of the treatment group may be affected at the same

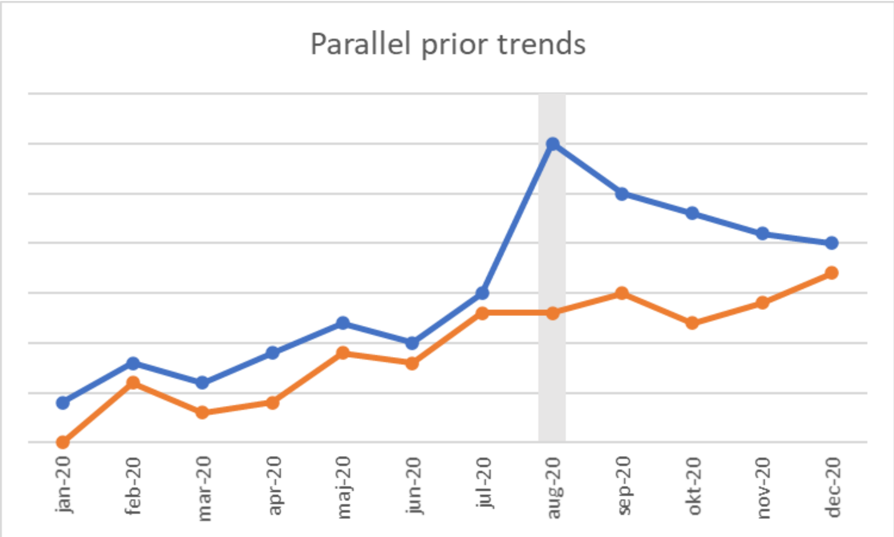
[2] Note that time-dependent factors, d_t , are assumed to affect all observations equally. For this reason we can operate with d_t across equations. This is a core assumption of the DiD model and is developed further in the next section.

[3] Assumption three parallel trends, described in the next section.

time by El Niño, even though the event's start can be traced down to one specific month. In the next section, the multiple time-period DiD model is presented to account for delays in treatment time and fulfill estimator consistency.

Meanwhile, SUTVA´s non-interference component poses additional challenges. It is likely that the studied *cajas* influence each other when it came to the correlated risks posed by El Niño. In other words, at the onset of an El Niño, one *caja* may wait to see what the others does before deciding on how much to restructure its own loan portfolio. Although it is not certain that this will happen, it cannot be ruled out.

Figure 9: Example of ideal parallel trends scenario



Source of data: own

The second assumption is exogeneity and for the context of DiD it states that the event must not influence the covariates of independent variables. This study does not account for independent variables to explain the effect of El Niño on restructured loans and therefore exogeneity plays a lesser role.

Third, the parallel trends assumption (PTA). It states that "no time-varying differences exist between the treatment and control groups" (World Bank, 2018). This means that the outcome for both groups—treatment and control—would have followed similar trends in the absence of the event. Evidently, this assumption cannot be proven because it is impossible to observe what the outcome would have been for both groups if the event had never taken place. Hence, the assumption entails constant bias. Figure 9 is an ideal scenario of PTA being beautifully fulfilled. In it, both time-series trend similarly until an event in August 2020 (shadowed area) causes them to diverge. Thus, the event's magnitude can be estimated using a DiD model because it can be assumed with confidence that, barring for the event, both time-series would have continued a similar path.

Although having an ideal parallel trend, as the one depicted in Figure 9, is very unlikely, researchers can test whether the PTA is plausible. Even if the series does not seem to follow the same trend at first glance, there may be an underlying pattern missed by the naked eye. In turn, tests have been developed to test for PTA, and for this study two of the most common ones will be used.

The first is the *prior trends* test, which looks at whether the treated and control groups had a similar trend before the event, as shown in figure 9. Graphing the time series for both groups and comparing changes in outcome for the pre-treatment period is the first place to start testing the PTA (World Bank, 2018; Perraillon, 2020; Huntington-Klein, 2021b). If both time series moved in parallel before the event happened, one gains confidence that they would have continued moving in tandem if El Niño had not occurred. If graphing does not provide a conclusive answer, *prior trends* can be tested statistically. Equation 6 presents a simple form of this test (Huntington-Klein, 2021):

$$Y = \alpha + \beta_1 Time + \beta_2 Time * Group + \varepsilon \qquad (6)$$

Using pre-treatment period data, $\beta_2 Time * Group$ enables the time trend to be different for each group. Thus, testing for $\beta_2 = 0$ is a good indicator of whether the trends are different. When prior trend test fails some researchers add *control for trends* by including the Time variable in the DiD model directly, instead of the time fixed effects, in an effort to salvage their research. That said, this practice can have the adverse effect of controlling away some of the treatment impact, especially if treatment effects get stronger or weaker over time (Wolfers, 2006).

Meanwhile, among other considerations regarding the test for prior trends parallel trends, Kahn-Lang and Lang (2020) make some general points about prior trends testing in their study on underage pregnancy. The most relevant for this study is that the PTA assumption tends to be more plausible when the treatment and control groups are similar in levels and not just trends. The same mechanism behind the difference in levels between both groups may also be affecting trends, they conclude. This is relevant for selecting the counterfactual for this study, considering that the levels in total portfolio value can diverge dramatically between *cajas*—given that some manage over ten times more credit than others.

Another test used for PTA is called the *placebo test*. It entails an additional DiD estimation using a *fake* treatment group. This means that the researcher takes data from a group unaffected by the event and uses it as the treatment group. Alternatively, the *fake* treatment group can also be data from the actual treatment group, but from before the event occurs. For instance, if the actual event occurred in January 2020, we use pre-January 2020 data only for the DID estimation and pretend that the event occurred, for example, in June 2019 (Gertler *et al.*, 2016; Huntington-Klein, 2021b).

Using the control and *fake* treatment groups, the DiD model should find a zero impact of the event on outcomes given that none of the groups was affected by it in the time frame studied. If it were statistically different from zero, the result would imply an underlying difference in trend between the two groups (*fake* treatment and control groups). In turn, this casts doubts on whether it can be assumed that the *real* treatment group can be assumed to have parallel trends in the absence of the event (Gertler *et al.*, 2016).

3.2. Multiple time period DiD set-up

The canonical DiD model described in the previous section considers two time periods: the first one where no policy—or event—has occurred and the second one where it has already happened. By the second time period the observations have either been treated or not. This structure poses limitations when it comes to El Niño because the observations—i.e. *cajas*—may be affected at different periods. Unlike a policy that affects financial institutions across the board starting on a specific date, El Niño occurs within a time frame and *cajas* can react to it at different times. For instance, a *caja* may act as soon as heavy rains are forecasted to occur as a result of ENSO, while other *caja* may react after or as rain is pouring. Defining *when* the adjustment of the credit portfolio occurs is a relevant piece of data, as well as the magnitude of the adjustment. Extending the DiD model to a multi-period setup allows for capturing both of these elements.

Callaway and Sant'Anna, (2021) present a unified framework for estimating average treatment effects in DiD specifications with multiple time periods. On this DiD setup, observations that are treated—or affected by the event—stay treated in all the following time periods; this is known as staggered treatment adoption. This multiple time period DiD setup is commonly used for evaluating policies or events with a staggered rollout, which means that observations are treated at different times. From a statistical point of view, a two-way DiD setup for staggered rollout leads to overlapping effects that can drastically reduce the accuracy of the estimators (Goodman-Bacon, 2021; Huntington-Klein, 2021b).

For the case of this study, a simplified version of Callaway and Sant'Anna's (2021) multiple time period DiD model is employed. *Simplified* because the specifications for allowing staggered rollout are not employed, i.e., all units of observation begin treatment in the same time period. The mathematical explanation of the model in the next section clarifies this further.

Meanwhile, this model has the added benefit of testing for PTA at the same time the DiD estimator is estimated. By having an estimator for all included time periods, one can test for *prior-trends* relatively easy. If the PTA holds, the DiD estimator for those time periods before the start of the event must be statistically equal to zero. In addition, having estimators for each time period *after* the start of the event enables researchers to evaluate how the effect evolves over time.

Model specific assumptions

Before fitting the multiperiod DiD model to the dataset it is necessary to go over the main variables and components that make it up. For this purpose this next sections reviews the main assumptions as described in Callaway and Sant'Anna's (2021). Note that the model possess features that go beyond the scope of this paper or that are simply not required due to the nature of this study. In turn, some model assumptions are not relevant or required, so the main focus is on the relevant ones.

Assumption 1 establishes staggered treatment, which states that no unit of observation is treated at $t = 1$ and that after a unit becomes treated, it remains treated in the following time periods T. From that starting point, define g as the time period when a unit becomes treated for the first time, for units that do not partake in the treatment $g = 0$. Denote $G_{i,g}$ as a binary variable equal to one when a unit is first treated in period g and define C to be a binary variable that is equal to one for units that do not participate in the treatment in any time period, i.e. $g = 0$.

From this point, the potential outcome framework is set up. In the case of this study, the potential outcome $Y_{i,t}$ corresponds to the first difference of the variable *restructured loans as a percentage of total loans* (PRL)—our variable of interest—as shown in equations 4 and 5. Define $Y_{i,t}(0)$ as unit i untreated potential outcome at time t if they remain untreated through the entirety of T—which basically corresponds to the first difference values for the units in the control group.

Meanwhile, for $g = 2, \dots, T$ define $Y_{i,t}(g)$ as the potential outcome experienced by unit i at time t if they were to become treated in time period g. The observed and potential outcomes are linked together through equation 7.

$$Y_{i,t} = Y_{i,t}(0) + \sum_{g=2}^{T} \left(Y_{i,t}(g) - Y_{i,t}(0)\right) * G_{i,g} \tag{7}$$

Equation 7 is used to estimate the potential outcome path for each unit. Observed outcomes equal untreated potential outcomes in all t for those units that do not participate in the treatment. In the case of units that are treated, observed outcomes are unit specific because they depend of g (Callaway and Sant'Anna's 2021).

Assumption 2 states random sampling, independent and identically distributed (*iid*). Here I stumble upon a curious matter. The entirety of the population of interest is already known and its data is readily available; that is, all *cajas* have their monthly balance sheet information published in Peru's SBS. Fitting the DiD model implies selecting which *cajas* to put on the treatment and control group—as done in the next section. As will be shown, the first *naïve* model is estimated using the entirety of the population, which is as close I get to iid sampling. Thereafter, treatment *cajas* are clustered according to their departments and control groups are sampled for each cluster. The results for this study present the impact of ENSO for each of these three clusters which are department of Piura, department of Ancash and department of Ica.

The bottom line is that because the total population of *cajas* is low, reducing the available data by sampling would lower the variance in the data making it unable for the model to produce estimates. Therefore, all available data is employed for fitting the model in the next section.

This study aims to estimate the average impact of ENSO on the proportion of restructured loans held by the *cajas*. Unlike Collier et al (2011) where only one *caja* is studied, the focus here is on a cluster of *cajas*. Consequently, the focus is to evaluate the impact of ENSO on each clusters, that is to say, the impact of ENSO on each department: Piura, Ancash and Ica. For this reason, the average treatment of effect (ATT) for each department is estimated. Equal weights are assigned to each caja for estimating ATT within each cluster. This is done for simplicity; however, a more complex model may adjust the weights assigned to each *caja* according to a criteria. This could be total portfolio value, for example, to make the results more *representative* of the risk influence of size.

Note that ATT is formulated in Equation 8 and represents the main building block of the model because it allows for estimating the average magnitude of the event on restructured loans.

$$ATT(g,t) = E\left[Y_t - Y_t(0)\ \middle|G_g = 1\right] \tag{8}$$

Assumption 3 allows for anticipation of treatment by introducing a new variable. Given that for this study we consider that the event begins on the first month that strong SST are reported, i.e. the first sign of a strong El Niño, no anticipation is required in the model. Next, two alternative assumptions are considered for imposing restrictions on the evolution of untreated potential outcomes.

According to assumption 4, conditional parallel trends are based on a *never-treated* group as the control group. Alternatively, assumption 5 relies on a *not-yet-treated* criterion for setting up the control group. Given that in this study all units of observation under treatment are treated at the same time, there are no observations that fit the *not-yet-treated* criteria and therefore the assumption 4 is the one employed here.

Lastly, assumption 6 deals with the overlap problem linked to having units of observation treated at different timeframes, which does not constitute an issue in the current study, given that treatment starts at the same time for all (Callaway and Sant'Anna's 2021).

By letting assumptions 1 – 4 and 6 hold, the group-time average treatment effect is non parametrically point-identified. Using an outcome regression, ATT for the never treated is shown in equation 9 (Callaway and Sant'Anna's 2021). Note that $\frac{G_g}{E[G_g]}$ is zero for all the period before the start of the event, and turn into a one for the treatment group once the event has started. In addition, notice that the difference estimation for all Y_t are calculated with respect to the last value before the start of the event, $Y_{g-\delta-1}$. Hence, the time period selected as the start of the event plays a pivotal role in the estimates of the model. Lastly, $m_{g,t,\delta}^{nev}(x)$ is equal to zero in this study because there are no other covariates included, while δ is also equal to zero because there is no anticipation.

$$ATT_{or}^{nev}(g,t;\delta) = E\left[\frac{G_g}{E\left[G_g\right]}\left(Y_t - Y_{g-\delta-1} - m_{g,t,\delta}^{nev}(x)\right)\right] \tag{9}$$

In the following section data and theory are brought together by fitting the model. This largely means selecting the *cajas* that will make it to the treatment and control group—i.e. our sample—from the universe of data—the total twelve *cajas* for which there is available data. This is a data funneling process in which I take the twelve *cajas* and separate them first by those affected by the event from those that are not affected. Next, the clusters of treatment *cajas* are set up, i.e. one treatment group for each *caja*, and the best control group for each is found[4]. Evidently, the aim is to find the combination that best fits our model assumption, and the focus here is on the model satisfying the parallel trends assumption.

[4] By best I mean the one that better fits the assumptions.

4. Model fitting

Applying any type of DiD model—two-period or multiperiod—requires a clear criterion for establishing control and treatment groups. The candidates for our treatment group should show signs of being affected by ENSO, while the *cajas* in the control group should not be affected by ENSO. The intuitive thought may be to separate the *cajas* based in departments close to the coast and the equator for the treatment group, and *cajas* based in the interior and southern departments for the control group. Collier also suggested this during an interview (2021).

However, this intuition must be corroborated with the data to accurately tailor treatment and control groups to fit the DiD model. Does the data match the hypothesis to some degree of certainty? The hypothesis is that the economic consequences of ENSO are reflected in the proportion of restructured loans (PRL) of affected *cajas*.

For the purpose of this thesis, two criteria are used for separating *cajas* in treatment and control groups. These are formulated as questions and the reader can think about it in the form of a decision tree. **Criteria 1:** Is the *caja's* home-department impacted by ENSO? And **Criteria 2**: does the *caja* react to the event with abnormal PRL? If both answers are *yes*, it is a fit for the treatment group, while if both answers are *no* it is a fit for the control group. *Cajas* with mixed responses (i.e. Y N, N Y) are discarded as "Unclear". Both criteria are applied to the data in the next section.

4.1. Data funnel: Criteria 1, ENSO and heavy rains

Since heavy rains and flooding are devastating consequences of a strong ENSO, using accumulated precipitation data seems like a valid way of separating the departments affected by the event from those that were not. The *cajas* present in the departments that faced extreme precipitation during the months of the event are candidates for the treatment group, while *cajas* based in unaffected departments are candidates for the control group.

Now, what does it mean to be affected—or not—by ENSO in terms of rains? In order to establish a consistent method for providing a binary answer to this question (Yes, its affected, or No, its not affected) I select the following process: Observe whether during the year of strong ENSO there were above average levels of rainfall, for each department. Annex A, Criteria 1, displays a table for annual accumulated rain data for 1996-2019 for all of Peru's departments using data from the local statistical institute (INEI, 2009, 2021).

To narrow down the number of departments, I select only those with cajas based on them. In the case of the department of Piura for example, three different cajas are operating: *caja* Sullana, *caja* Paita and *caja* Piura. All *cajas* are named after a city or region in their home department, where they hold the majority of their lending operations.

Figure 10: Rainfall (mm) for 1998 against the long-term trend by department

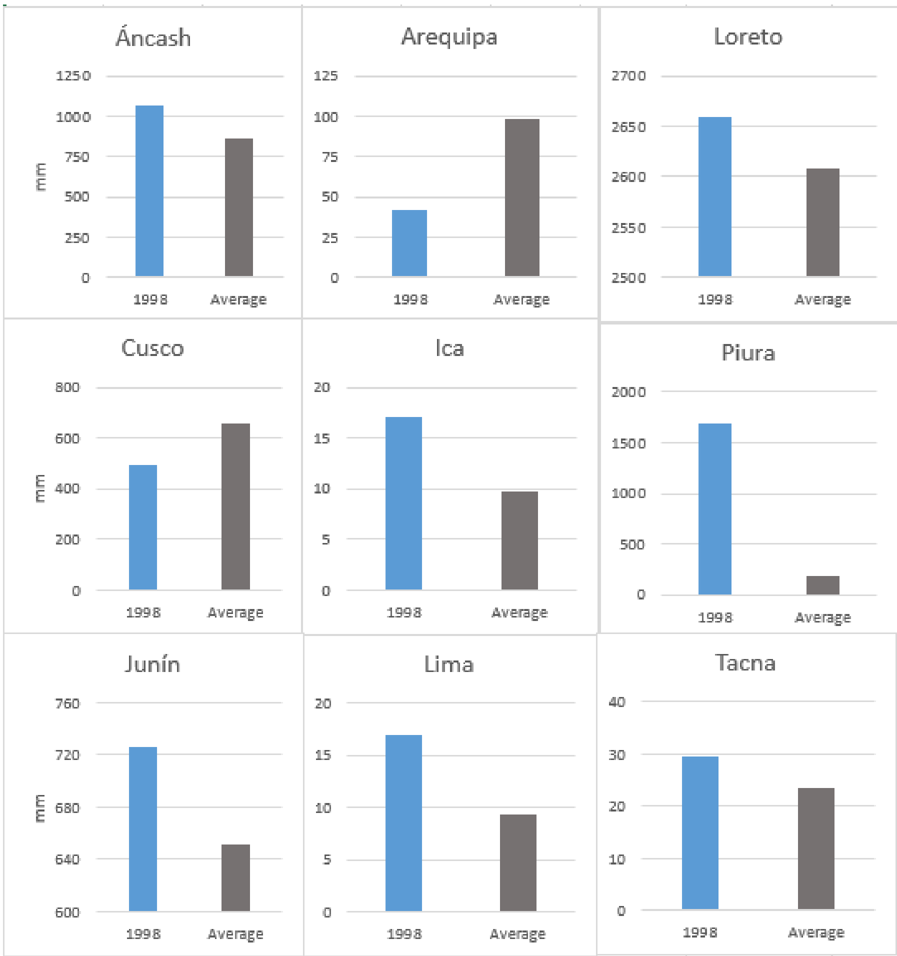
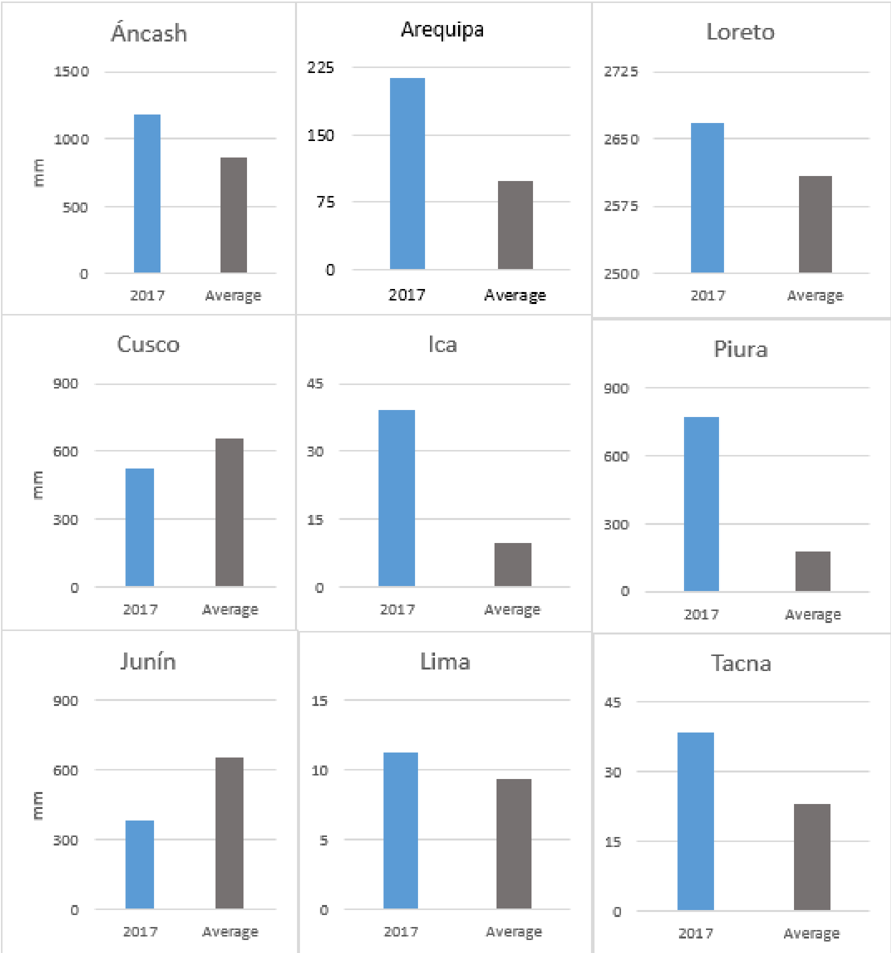


Figure 10 depicts the accumulated annual rain for the departments of interest during 1998, as El Niño unfolded in the Peruvian coast. A 24-year average (1996-2019) is added as long-term trend in rainfall and used as a benchmark for identifying the degree of mean deviation. Most glaring is the department of Piura, where rainfall in 1998 deviates significantly, providing evidence of the exposure of this department to ENSO. Evidently, this matches the meteorological observation linked to El ENSO and how its effects are felt more strongly in the regions closer to the Equator. The average 1996-2019 is stationary and is a valid benchmark for contrasting against the 1997-98 and 2016-17 events (Annex A, Criteria 1: "Average rainfall all departments").

Meanwhile, consider figure 11, which illustrates accumulated annual rainfall for the 2016-2017 El Niño against the same 24-year benchmark. Note how the deviation from the mean for the department of Piura is significantly lower than previously. The absolute rainfall value for 1998 in Piura was 1.686,8 mm, while for 2017, it was 777 mm; that is, rainfall in the 1997-1998 ENSO was close to one order of magnitude greater than for the 2016-2017 iteration of the event—table Y, annex A. Consequently, the impact of the latter iteration of ENSO likely had a milder effect on the *cajas* operating in the department of Piura.

Figure 11 Rainfall (mm) for 1998 against long-term trend by department



Criteria one aims to establish whether a department is affected by ENSO or not. Being affected implies high mean deviation. For this study, *cajas* with rainfall values above the 75th percentile in 1998 and 2017 are labelled as *affected* by both iterations of ENSO. Looking at table 2 - Criteria 1 in Annex A, values highlighted in blue are those in the upper 25th percentile of the time series, columns highlighted in yellow are the event years. Figure 12 summarizes the outcome of criteria 1, depicting which *cajas* experienced heavy rainfall in their home department during each iteration of ENSO.

Figure 12 : Outcome of criteria 1

Department	*Caja*	Rainfall 1998 above 75th percentile?	Rainfall 2017 above 75th percentile?
Áncash	CMAC Trujillo	Y	Y
	CMAC Del Santa	Y	Y
Arequipa	CMAC Arequipa	N	Y
Cusco	CMAC Cusco	N	N
Ica	CMAC Ica	Y	Y
Junín	CMAC Huancayo	N	N
Lima	CMCP Lima	Y	Y
Loreto	CMAC Maynas	N	N
Piura	CMAC Sullana	Y	Y
	CMAC Paita	Y	Y
	CMAC Piura	Y	Y
Tacna	CMAC Tacna	N	Y

Nevertheless, there are details to account for before jumping to label the data. Primarily because no two El Niños are the same. Take the department of Piura, where accumulated rainfall was an order of magnitude greater in 1998 than in 2017. Although both years saw rainfall with a high mean deviation, the degree of devastation was presumably higher in the 1998 iteration, at least for that department, and this should be considered. On the other hand, note that in 2017 a larger number of departments saw intense rainfall than in 1998. Coincidently, El Niño 2016-17 was called *El Niño costero*, in reference to the wider impact it had on departments close to the coast.

4.2. Data funnel: Criteria 2, the reaction of PRL to ENSO

The next criteria in the data funnel establish which *cajas* display a high mean deviation in their proportion of restructured loans (PRL) for the years of ENSO. In the case of aggregated rains, the long-term average (1996-2019) was valid as a benchmark because of the close stationarity of the time series (Annex A, Criteria 1). However, the long-term PRL mean (1996-2019) displays a more significant negative drift, indicating the *cajas* saw a decreasing PRL as time moved forward (Annex A, Criteria 2: Average PRL for all cajas).

Throughout the studied period (1996-2019), there have been significant developments in the world economy that have shacked banking in particular. The reduction in PRL in the latter years is coherent with tighter credit condition stemming from the fallout of the Great Financial Crisis. In practice, this means that *shorter* long-term PRL averages must be defined in order to evaluate which *cajas* present high mean deviation in PRL during ENSO.

Collier, Katchova and Skees, (2011) describes that *cajas,* and similar MFIs in Peru, are regulated under standards that follow the Basel regulatory framework. The capital requirements that MFIs must hold to manage their operational risk have evolved as new Basel frameworks have come into force (Conger, Inga and Webb, 2009; Ebentreich, 2005). As a result, it has an impact on the risk management strategy pursued by the cajas and likely influences their response to natural disaster risk management.

According to the Bank of International Settlements, (2014) there have been three BASEL frameworks during the studied time frame (1996-2019): BASEL I from 1988 to 2004, BASEL II from 2004 to 2010 and BASEL III, approved in late 2010 and so (2011-2019).

In this study, mean PRL for the duration of each Basel framework are used to identify deviation from the mean. That is, the PRL from 1997-98 for each individual *caja* is compare against mean PRL for 1996-2004, i.e. the Basel I period. Meanwhile, the PRLs for 2016 and 2017 are compared with mean PRL for 2011-2019, the Basel III period. This aids the analysis by providing a sensible way of identifying each *caja's* reaction to the event. Evidently, this study design is discussed later on; however, bearing in mind that the intention behind criteria one and two is just to allow a first segmentation of the data. Therefore, are intended to be slightly broad.

Criteria 2 in Annex A, shows highlighted in blue PRL values in the upper 25th percentile. These correspond to values with high mean deviation, just as was done in criteria 1. The columns in yellow correspond to the years of the event. The blue values in yellow columns are the values of interest for criteria 2. A *caja* is said to have reacted to ENSO if there is a value highlighted in blue on any of the event columns. That would mean that the *caja* in question increased its PRL during ENSO period.

Tables 13 and 14 show the outcome of both criteria. As it can be seen, only ENSO 1997-98 show a relatively balanced distribution in treatment and control groups, while ENSO 2016-2017 displays no candidates for the control group. The reason behind it is that, although departments were affected by ENSO, the PRL did not react to the increase in rainfall. In fact, it diminishes for some of the *cajas*. The obvious question here is why did PRL stopped reacting to ENSO? Have the *cajas* overcome El Niño-linked risks? The answers to these questions are presented and developed in the discussion. For now, let us apply the DiD model to ENSO 1997-98.

Figure 13: Outcome of criteria 1 and 2 for ENSO 1998

ENSO 1998				
Department	***Caja***	**Criteria 1:Rainfall 1998 above 75th percentile?**	**Criteria 2: PRL 1997 or 1998 above 75th percentile?**	**Group**
Áncash	CMAC Trujillo	Y	Y	Treatment
	CMAC Del Santa	Y	Y	Treatment
Arequipa	CMAC Arequipa	N	N	Control
Cusco	CMAC Cusco	N	N	Control
Ica	CMAC Ica	Y	Y	Treatment
Junín	CMAC Huancayo	N	N	Control
Lima	CMCP Lima	Y	N	Unclear
Loreto	CMAC Maynas	N	N	Control
Piura	CMAC Sullana	Y	Y	Treatment
	CMAC Paita	Y	Y	Treatment
	CMAC Piura	Y	Y	Treatment
Tacna	CMAC Tacna	N	N	Control

Figure 14: Outcome of criteria 1 and 2 for ENSO 2017

ENSO 2017				
Department	***Caja***	**Rainfall 2017 above 75th percentile?**	**PRL 2016 or 2017 above 75th percentile?**	**Group**
Áncash	CMAC Trujillo	Y	N	Unclear
	CMAC Del Santa	Y	N	Unclear
Arequipa	CMAC Arequipa	Y	Y	Treatment
Cusco	CMAC Cusco	N	Y	Unclear
Ica	CMAC Ica	Y	N	Unclear
Junín	CMAC Huancayo	N	Y	Treatment
Lima	CMCP Lima	Y	Y	Treatment
Loreto	CMAC Maynas	N	Y	Unclear
Piura	CMAC Sullana	Y	N	Unclear
	CMAC Paita	Y	Y	Treatment
	CMAC Piura	Y	N	Unclear
Tacna	CMAC Tacna	Y	Y	Unclear

4.3. Treatment and control group matching

Dividing the available *cajas* into treatment and control group candidates was the first segmentation of the data. Further divisions can be made for more accurate matching, i.e. increasing the likelihood of parallel trend assumption being fulfilled.

Huntington-Klein, (2021) presents a matching method based on selecting multiple variables as criteria for clustering our data. Here the observation made by Kahn-Lang and Lang, (2020) about evaluating levels of the data instead of only trends becomes highly relevant. From a research perspective, it makes sense to cluster together *cajas* with similar capital levels under management. The value of total outstanding loans differs greatly between *cajas*, in some cases by over one order of magnitude. There is reason to suspect that *cajas* administering similar capital levels will face similar risk constraints and level of diversification. Hence setting total loans under management as a matching criteria is arguably a good starting point for sampling.

In practical terms, this means that multiple models with diverse treatment and control group combinations are estimated. The six *cajas* in the control group pertain to three different departments: Ancash, Ica and Piura, these are our three clusters of data.

First, a naïve model is estimated using the entirety of both groups, but then each affected department is modelled separately and matched against viable control group combinations. From a study design perspective, it makes sense to evaluate each department separately as the *cajas* operating there may show more similar features, such as the degree of impact of ENSO, regulation, and economy.

Table 4 in Annex A depicts all the considered combinations of treatment and control group for which DiD models are estimated in the result section. The total credit in monetary value is computed for each group utilizing the dataset obtained from the SBS (Annex A, All CMAC data). The goal is to use control groups that are close in *level* to the treatment group, assuming that *cajas* operating with similar levels of aggregate loans in their portfolio are more likely to meet parallel trends.

In table 4 (Annex A), all the *closest* combinations are considered: eight for Piura, seven for Ancash and four for Ica, plus the naïve model with every candidate. These models are estimated to find the one that fits the parallel trend assumption best and from there on, find the average impact of ENSO on PRL. Although the objective is to find the best fit for parallel trends, the difference in total credit managed between both groups is also accounted for when choosing the best fit.

4.4. The starting point of El Niño 1997-1998

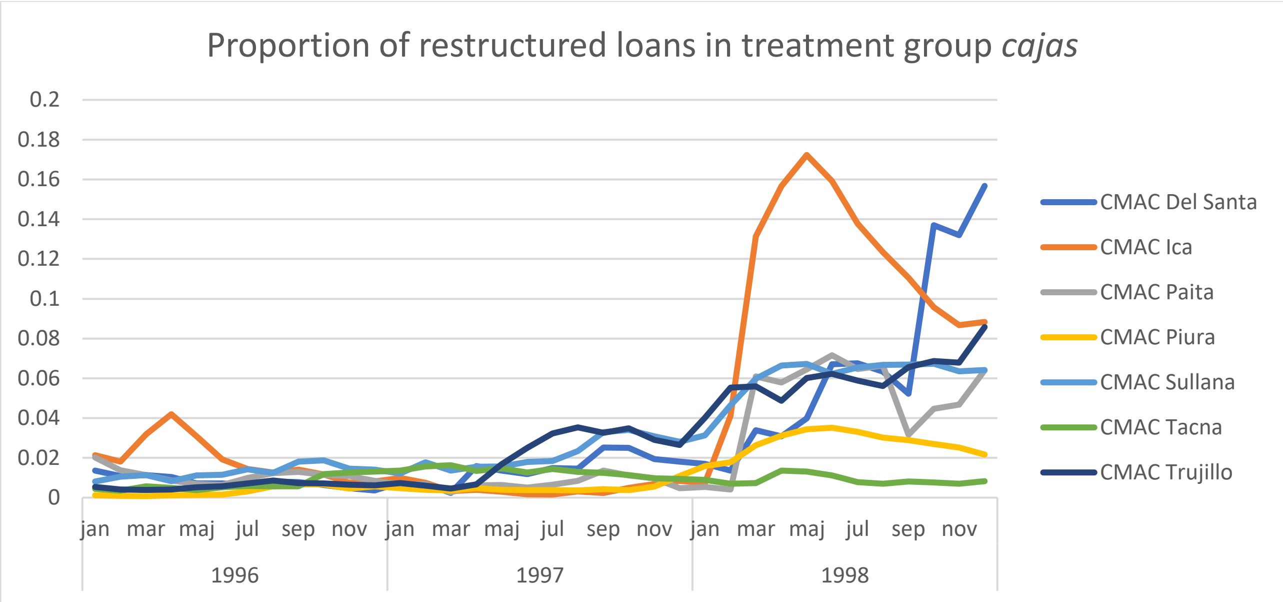
The last piece for the multiple period DiD model to work involves defining the start of the event, i.e. when do the *cajas* become *treated*? Although El Niño starts on the same month for all *cajas,* not all react at the same time to its impact. The DiD framework presented by Callaway and Sant'Anna, (2021) is interesting for studying the impact of El Niño on restructured loans because it provides estimates of how the impact of ENSO evolves over time. This makes testing for PTA relatively straightforward because it estimates *prior-trends* in the model output.

The last step is defining which time period, in this case in which month, does ENSO start. As we saw on equation 9, the starting time period, g, is crucial because all the differences for the months affected by the event are estimated with respect to value of period $g-1$.

One idea is to set the starting point on the first month a strong ONI value is reported, i.e. September 1997. Collier, Katchova and Skees, (2011) reported that *cajas* adapt in advance to the consequences of ENSO, but does mean that they look at ONI? Looking at ONI certainly provides a heads up; however, abnormal rainfall seems to be a more reliable measure of imminent disaster and the one preferred by the *cajas*, as the data shows.

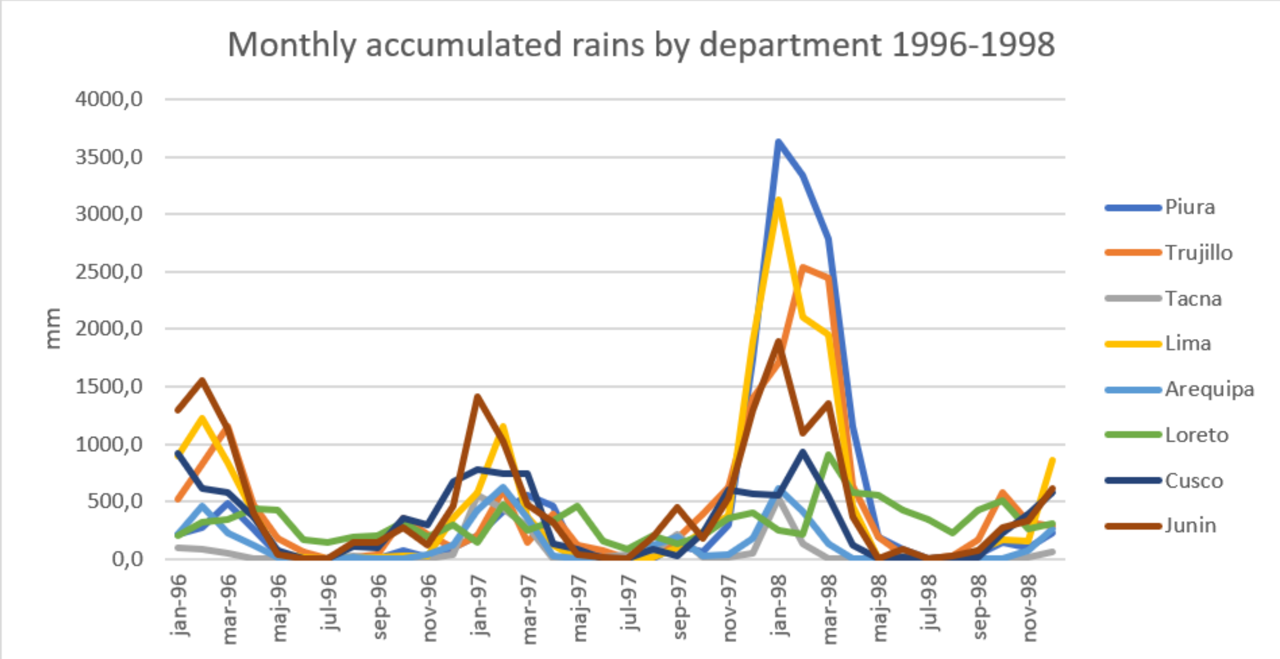
Figure 15 depicts the monthly evolution in PRL in the treatment *cajas*. Note that the bulk of the reaction occurs at the outset of 1998. This matches the peak rainfall, as displayed in Figure 16 (SENAMHI, 2022). The data implies that the *cajas* were forward-looking in the sense that they began restructuring loans as abnormal levels of rain began falling, preparing for the imminent consequences. This implies that ONI likely played no role in the *cajas* decision-making process.

Figure 15: Proportion of restructured loans in treatment groups *cajas*



Source of data: SBS

Figure 16: Accumulated rains by month for selected departments (SENAMHI)



Source of data: SENMAHI (2022)

In the light of the data, it seems sensible to select as the starting month of the event the month when heavy rain began to be reported. December 1997 appears to be a good match, while it also matches with the origins of El Niño, which, as was mentioned before, carries that name because the phenomenon tends to occur around Christmas.

In the R script (Annex C), the dataset introduced takes time period (*t)* 24 as the starting point of ENSO; the differences are estimated using period $g - 1$ as reference (equation 9). In turn, the column labeled G in Table 5 (Annex A), has a value of zero for control *cajas* and a value of 24 for treated *cajas*[5]. Lastly, the time-series ends in May 1998, when the event subsides according to the last strong ONI value (ONI, Annex A).

[5] The manual for the DiD package provided by Callaway and Sant'Anna, (2022) certainly helped understand the practical setup of the dataset for the software to read it.

5. Results

The multiperiod DiD model was estimated using the *did* R software package, with the instructions devised by Callaway and Sant'Anna, (2022). Restructured loans as a percentage of total loans (PRL) is the variable of interest and the time frame selected for studying the El Niño 1997-1998 starts in January 1996 and ends in May 1998. The reason for adding the entirety of 1996 is to have a larger period for testing prior parallel trends. The event begins on December 1997, which corresponds with time period 24, and ends on May 1998, i.e. time period 29, for all *cajas*. Remember the multiperiod DiD model assumes staggered rollout, meaning that once *cajas* become treated, they stay treated. All results are available in Annex B.

5.1. Naïve model

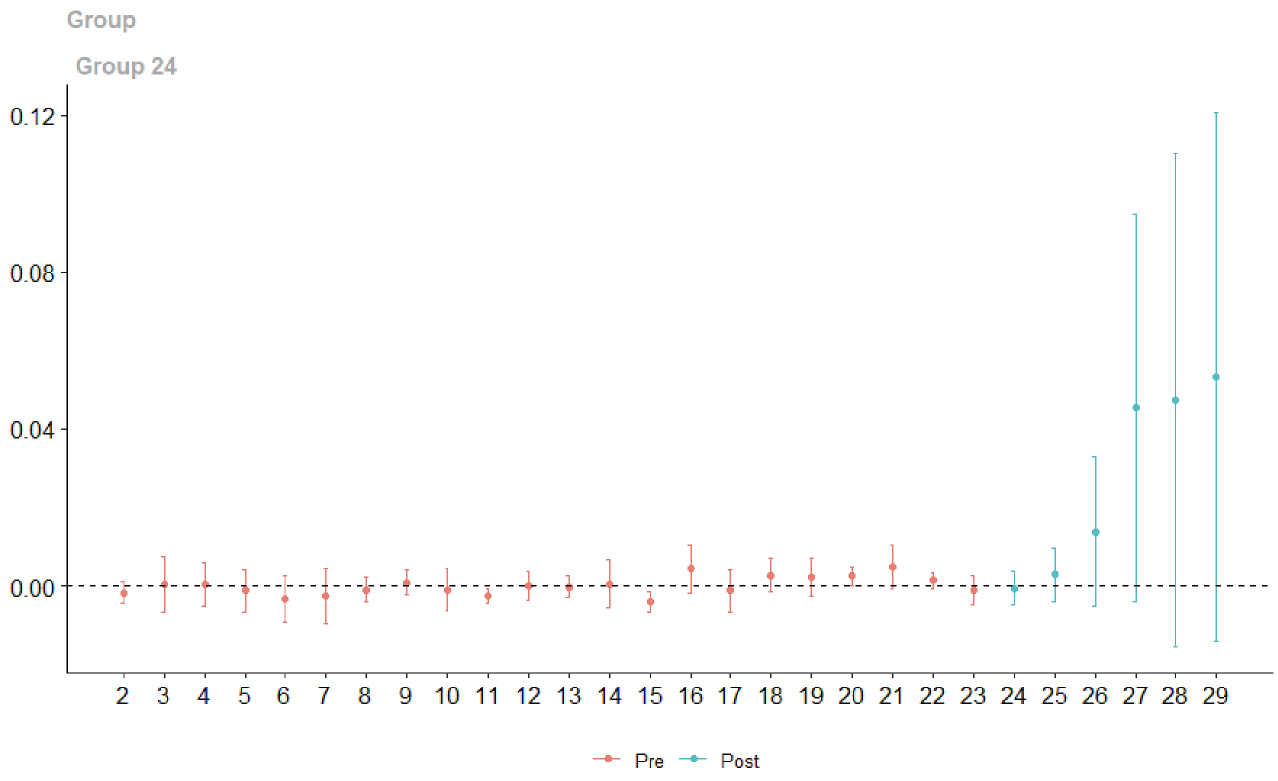
The first model estimated consists of all candidates for treatment and control groups based on criteria one and two (Figure 13). Figure 17 depicts the DiD estimation using the R code in Annex C and the dataset in Annex A. Pre values correspond to the second difference as estimated using equations 4 and 5, for the periods before the event's start. In an ideal parallel trend scenario, the second difference for all the pre-period is equal to zero, indicating that both groups presented parallel trends before ENSO.

For the naïve setup, the pre period difference remains statistically zero for all but three time periods (Annex B), as can be seeing by the 95% confidence interval attached to each value. These are periods 20, 15 and 11, and they are statistically different than zero only by a small margin. Now for how long back should δ_t be statistically equal to zero for the parallel trend assumption to be completely valid is a matter of discussion. For example, period 2 (February 1996) being statistically different than zero is less of a problem than period 22 being statistically different than zero. Generally, a researcher aims for the parallel trend assumption to be fulfilled in the periods immediately before the event (Goodman-Bacon, 2021; Huntington-Klein, 2021b).

Meanwhile, the post-period is estimated using equation 9. That is, taking period 23 as a benchmark for estimating the difference, $\delta_t^{post} = Y_t - Y_{g-\delta-1}$. Notice for period 23, parallel trends fits satisfactorily. On the other hand, none of the post periods is statistically different from zero, indicating no significant impact of ENSO on PRL. Yet a glance at figure 16 certainly reveals a deviation from the mean in the post period.

In the next sections the treatment group is divided by departments, clustering the data, and matched with the different control groups. By dividing into departments, the idea is to distill the event's impact by choosing a more accurate control group, i.e. closer in terms of total loans. The results for the best control group fit are presented.

Figure 17: Naïve model

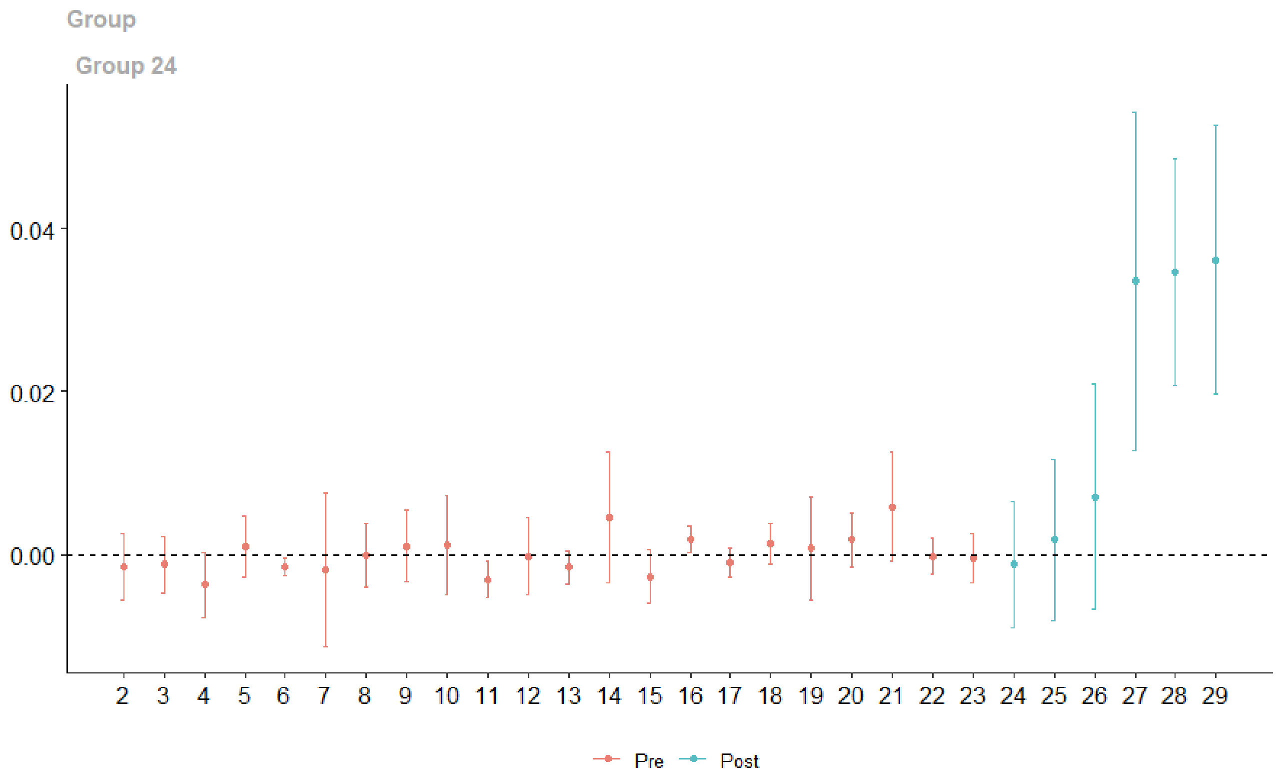


5.2. Piura

Using the *cajas* based in the department of Piura for the treatment group (Piura, Sullana and Paitas) and the combinations of the control group from table 4 (Annex A), eight models were estimated using R—results in Annex B. Control group 7 is the best match for Piura in terms of parallel trends, as only three time periods before the event are statistically different from zero. Meanwhile, looking at figure 18, the post-period displays a statistically significant increase in PRL in treatment *cajas* with respect to the control.

The DiD package in R has a function available to estimate the average treatment effect, giving one mean value for the event's impact on PRL. For model 7, the average treatment effect for the *cajas* in Piura corresponds to a 1.9%[6] increase in PRL during ENSO months ending May 1998, and is statistically different than zero with a 95% confidence interval of [1.53% - 2.21%] (Annex C).

Figure 18: Piura model 7



In terms of matching, the ratio of total credit between the treatment and control groups is 1,066 (Table 4, Annex A), indicating that both groups handle a similar volume of loans, in aggregate. As mentioned in the previous section, the literature indicates that PTA assumption tends to be more plausible when the treatment and control groups are similar in levels and not just trends (Kahn-Lang and Lang, 2020). The best model in terms of smallest difference in total credit between groups is number 2, with a ratio of 0,998 (Table 4, Annex A). However, model 2 performance was worst in parallel trends with five *pre* periods being statistically different from zero (Annex B).

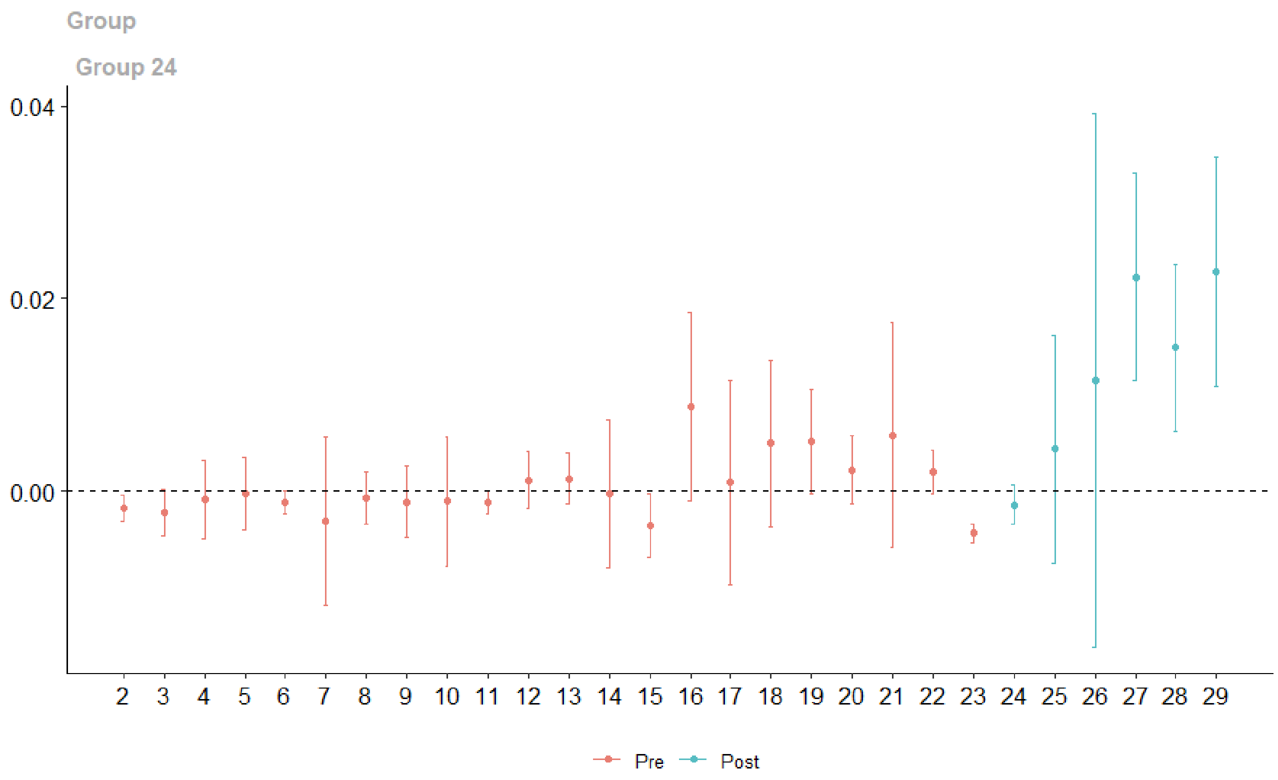
5.3. Ancash

In this experiment, *caja* Del Santa and Trujillo, the two *cajas* based in the department of Ancash, are placed in the treatment group. Seven different control groups are configured using total credit

[6] Estimated with the ATT function (Annex C)

under management for management matching. Control group 2 delivers the best fit in parallel trends, with only three values statistically different from zero in pre. The deviations are small and some occurred way before the event. Figure 19 depicts the model estimates as done previously. In terms of average aggregate treatment effect, the function yields a 1.2% increase in PRL for *cajas* subject to ENSO in Ancash, with a 95% confidence interval of [0.03% - 2.22%].

Figure 19: Ancash model 2



Meanwhile, the rest of the control groups deliver significantly worst parallel trend results. Moreover, as the sample control group gets smaller so does the variance in the data, making it impossible for the model to estimate confidence intervals.

5.4. Ica

Lastly, *caja* Ica is alone in the treatment group because it is the only *caja* based in the department of Ica. Control groups are created based on similar total credit under management. This approach poses a problem: *Caja* Ica is small in terms of total credit, consequently, the control group should be composed of one or two *cajas* tops. However, again, small groups make for bad modelling because of low variance. In fact, none of the four models yields satisfactory results in terms of parallel trends. A look at the results in Annex B reveals that almost all pre-periods depict values that are statistically different than zero.

5.5. Overview

Taking everything together figure 20 displays all the relevant results obtained in this study. The first average treatment effect column depicts the average impact of the event for the entire duration of the event, for period 24 to period 29. Meanwhile, the next three columns depicts only three post periods for which the Piura and Ancash model produce significant estimates. In turn, the last column estimates the ATT for only the periods that are statistically significant, that is, March 98, April 98 and May 98. Note that for the Naïve model, none of these months produces significant estimates, just as shown in Figure 17. Nevertheless, its overall ATT does yield an estimate that is statistically different than zero.

Figure 20: Results overview

Summary of DiD results					
Model	**Average treatment effect (ATT) for periods [24,29]**	**ATT March 98**	**ATT April 98**	**ATT May 98**	**ATT for periods [27,29]**
Naïve model	2,71%*	4,54%	4,74%	5,34%	4,87%
Piura model 7	1,87%*	3,35% *	3,46% *	3,62% *	3,47%*
Ancash model 2	1,24%*	4,04% *	2,35% *	3,45% *	3,28%*
* : Confidence bar does not reach zero, i.e. significant results.					

For comparison purposes, Figure 21 depicts the results obtained by Collier, Katchova and Skees, (2011) using an ARIMA model for estimating the impact of ENSO on PRL for caja Piura alone in 1997-98. While in the DiD framework one computes the average treatment effect between the members of the treatment group, the ARIMA model employed in that study produced results only for caja Piura, and cumulative total effects constitute the total impact of ENSO over that particular *caja*.

Figure 21: Collier et al. (2011) results

Summary of Collier et al. results for caja Piura	
Month	**Total effect on PRL**
December 1997	0,88%
January 1998	0,79%
March 1998	1,21%
April 1998	0,71%
Cumulative total effect	3,59%
Results are significant on the 99% level.	

6. Discussion

6.1. Overall results

For the ENSO 1997-98, the multiperiod DiD model delivers estimates that are largely in line with the findings of Collier, Katchova and Skees (2011). In their study, a cumulative 3,6% increase in the proportion of restructure loans (PRL) was estimated for *caja* Piura during the event, with the largest increase occurring on April 1998. Piura Model 7, which comprises *caja* Piura, Sullana and Paita, estimates an ATT of a 1,9% increase in PRL, which is somewhat off the Collier's results. Nevertheless, the DiD estimates come much closer when looking at the monthly values. Bear in mind that unlike with the ARIMA model where all significant estimates are summed up in the cumulative total effect value, for the DiD each monthly estimate is calculated with respect to period 23, and summing them up is not appropriate.

The last column of figure 20 averages only the statistically significant values obtained with the DiD model for the department of Piura and Ancash. For Piura, average treatment effect for significant months is 3,5%, which is only shy below the 3,6% estimated by Collier, Katchova and Skees (2011). One would not expect them to be equal, given that the DiD framework includes two additional *cajas*; however, the fact that the results are close provides evidence suggesting precision; i.e. two different methods arrive at similar results. Hence, while it can be said that the DiD model ranks high on precision—since estimates are fairly close—, determining if the model is accurate is more of a challenge because there may be underlying time varying effects that are not captured by the model. This could be changes on policy specifically as an emergency response to ENSO, for example.

In general, accuracy revolves around how close is the estimate from its *true* value. Evaluating accuracy would requires examining the estimates of the model when some parameters are changed. For this reason, the sensitivity analysis reviews how changing the start of the event affects the model's estimates for Piura. Meanwhile, the estimates of average treatment effect for Ancash is a 1,2% increase in PRL respectively. Unlike with Piura, no studies evaluating the impact of ENSO on PRL for this department were found.

In terms of parallel trends, the results are surprisingly good, particularly when using large treatment groups, like in the case of the naïve and Piura models. At the outset, my expectation was there would be fewer months that fit parallel trends. This is because, in this context, parallel trends implies that *cajas* face similar challenges in periods were there is no ENSO. This felt unlikely due to the diversity of the departments in terms of economic structure, social practices and geography. Nevertheless, the fact that only a handful of months deviate from PTA suggests that between 1996-98 PRL was a good proxy for assessing the impact of ENSO on a *caja*.

This thesis attempted to offer a different approach for evaluation the impact of ENSO on *cajas* than the ARIMA model used by Collier, Katchova and Skees, (2011). A key limitation from that study was the insignificance of the estimates for the control variables employed. During the interview I held with Benjamin Collier, he suggested that I made use of the data for all *cajas* out there, instead of only *caja* Piura like in his study. He also suggested that I use a DiD model for estimating the impact of ENSO; nevertheless, the selection of the specific multiperiod DiD model was a result of my own research.

In the light of the somewhat satisfactory parallel trend estimates, evidence suggests that the DiD model is a good fit for studying the impact of ENSO 1997-98 on the *cajas*. In addition, the specific multiperiod DiD model employed in this thesis shows potential for evaluating the impact of other types of natural catastrophes; hence it may be interesting to add it to the environmental economist toolkit.

6.2. What about ENSO 2016-17?

Readers may be disappointed with the absence of a model to estimate the impact of the 2016-17 ENSO on the *cajas*. As was shown with criteria one and two, no control groups can be established with confidence because no department saw normal rain levels and PRL during that period. Moreover, a closer look at figures 13 and 14 reveals that *cajas* that had experienced hardship in

1997-98 appeared fine in terms of PRL during 2016-17. The breakdown of the correlation between PRL and the ENSO for *cajas* like Piura, for example, likely linked to the development of the microfinance industry in Peru over the past two decades.

By allowing *cajas* to operate outside their home department and boosting access to insurance, regulators appear to have managed to reduce natural disaster risks. Big international banks, like Mapfre, entered the Peruvian insurance market, allowing for Peru's local risks to be diversified away by including them in large global portfolios (Carmago and Furst Gonçalves, 2014).

Against this backdrop, it looks as if *cajas* managed to successfully mitigate ENSO risk in the past few decades. *Caja* Piura increased its lending in 2017, as a response to ENSO which is exactly what is needed after a natural disaster in order to support the economic recovery. From the *cajas* perspective, it seems that progress has been made to cushion financial losses.

That said, the costs that ENSO continues to have on the population of affected departments is a different story. Of particular interest would be the impact of the El Niño on farmers and food security. The main hurdle for studying the impact of ENSO on farmers is obtaining comprehensive data. There are a number of studies utilizing micro-level farm panel data to assess how exposed farmers mitigate climate risks and the magnitude of impact that it has on their household (Witt and Waibel, 2009; Werners, Erdelyi and Supit, 2011). In the light the resource and time constraints, focusing on *cajas* was more adequate because of the extensive time-series data that is publicly available online. All told, there is plenty of room to broaden research on ENSO-related risks and their impact on the broad economy. Collier has continued his research on the impact of ENSO on Peru's economy, focusing on the microinsurance market on his latest publication (Collier, 2020). Nevertheless, data availability remains a key limitation for studying the impact of disastrous climate events in low- and medium-income countries.

The linkages between ENSO and Peru's economy run quite deep. On the one hand, heavy rains during an El Niño may lead to higher yields for dry farming crops, while at the same time dampening fishing output due to warmer SST. On the other hand, La Niña tends to cause the opposite: lower crop yields due to absent rains but larger fishing volumes due to lower SST (Tibbetts, 1996). The hypothesis on negative correlation between fishing and crop output due to ENSO seldomly appears in the literature. Yet, given the importance both activities for Peru's economy, evaluating whether this negative correlation exists, and its magnitude, is an interesting challenge for environmental economist. In finance, negative correlations between commodities are often exploited to mitigate portfolio risk. A country like Peru could mitigate risk by adjusting the resources it places on farming and fishing on ENSO years.

6.3. Limits of methods and analysis

Applying a DiD model required that three general assumptions were fulfilled to deliver reliable estimates. The first is SUTVA, which requires consistency and non interference. For consistency to be satisfied, the event must be well defined. This is exactly one of the tricky aspects of fitting the model: when does El Niño start? Moreover, the multiperiod model takes the period before the start of the event as the benchmark for estimating the average impact of treatment, i.e. period $g - 1$.

Defining when the event starts is exogenous to the model, different selections may yield different estimates. In the case of this study, December 1997 was selected as the start of the event because it coincided with the start of abnormal raining levels. Selecting this starting point showed good results in terms of parallel trends, particularly for the periods used as benchmarks (See figures in Results section). Hence SUTVA is largely fulfilled.

Turning to the second assumption, exogeneity. Since the model constructed in this study does not include other covariates as explanatory variables this assumption is fulfilled. Nevertheless, the reason why no time-varying explanatory variables were included was largely because in their study Collier, Katchova and Skees, (2011) found no significant explanatory variables. They used priced data on several commodities relevant to the region, coupled with inflation data, and found no significant effect of any of these on PRL for ENSO 1997-98. Price data was the most prominent candidate for including as a time-varying explanatory variable. However, detailed price and inflation data at the department level for Peru is not publicly available and using the country's general inflation level proved nonsignificant as an explanatory variable. Similarly, utilizing global commodity prices lead to nonsignificant estimators for Collier, Katchova and Skees, (2011).

The third assumption is parallel trends. This was broadly evaluated throughout the data funneling process and discussed together with the model results. The time frame went from January 1996 until May 1998, 29 time periods for which there are 28 estimates for each model (Annex B). From these 28 estimates, all corresponding to the period before the start of the event, i.e. period 24, are evaluated for parallel trends and, in an ideal scenario, all should be statistically equal to zero. The decision to include the entirety of 1996 was taken to broaden the spectrum and capture potential seasonality in the data. The best estimated model (Piura, Annex B) has three instances on which parallel trend is not fulfilled; that said, they are all statistically close to zero.

Is this enough to consider assumption three satisfied? I reckon it may be enough evidence, provided the results are taken for what they are: estimates chasing accuracy.

One last note on the assumptions pertains the specifics to the multiperiod DiD model, particularly assumption two, in which i.d.d. sampling is assumed. As mentioned in that section, given the small size of the population data, i.e. the number of *cajas*, sampling reduces the available population. Nevertheless, I still *sampled* the data when matching treatment and control groups. I selected several candidate control groups that seemed reasonable according to academic criteria (I matched them according to the difference in their total portfolio value). This may be considered some form of bias and is thus a limitation.

To better understand why the matching process incurs in bias consider the alternative of selecting control groups based on random sampling. For one cluster of treatment *cajas*, lets say department of Piura, one would have to randomly try each possible combination of the five available candidates for the control group to find the best matching model. This would imply first estimating a model using department of Piura and all five candidates in the control group. Then estimating all possible models for a combination of four candidates in the control group. Then all models for all combinations of three candidates in the control group and so on.

Although computing the number of combinations is feasible, it escapes the scope of the analysis. The bottom line is that via the matching procedure employed in this thesis, in principle, I reached control groups that have a higher likelihood of being representative, i.e. depicting accurate parallel trends. Perhaps the best fitting model is one where the control groups differ greatly in terms of total portfolio value from the treatment group. Because that is a possibility, albeit a small one, the matching process done in this thesis is a form of biased. This constitutes a limitation for this study. With enough resources and software knowledge, it should be possible to compute every possible model combination. Nevertheless, the results will likely be the same as those presented here.
Turning to the fitting of the model, the data separation process done with criteria one and two were devised for this study in particular. Given that no other application of difference-in-difference model was found for ENSO, deciding how to split the data was left as a design choice. Huntington-Klein, (2021b) broadly describes the requirements of the data selection process; however, its stated

how this is done is largely determined by the specific nature of the data being evaluated. As a result, I had to get creative and think about the way in which I could organize the different *cajas* into control and treatment group, through a process that is structured logically.

At the outset, I attempted to divide the data by putting *cajas* based in departments in the north and close to the coast in the treatment group, and *cajas* based in the interior and south in the control group. After estimating the DiD model using this data separation method, I realized that I was most likely falling into selection biased. Particularly because I was assuming that ENSO had no impact in *cajas* based in the south without a solid foundation to back that up. I decided to go back to the drawing board and start a data funneling process from scratch. Opting to develop criteria one and two to accurately discern which departments were exposed to ENSO through a decision three type of structure. Criteria one separates the departments facing heavy rains during the event, while criteria two highlights the *cajas* that saw abnormal reactions in their PRL due to the natural phenomenon. Thereafter I proceeded to match different control groups based on Kahn-Lang and Lang, (2020) observation about levels. The last steps involved selecting the date for the start of the event, which as mention before, follows no objective rule and central to the estimates.

The validity of this choice of data funneling is up for debate, yet the impression I got is that there is likely no one objectively accurate way of doing so. Nevertheless, bear in mind that the model's estimates will be largely influenced by the data selection process.

The most glaring limitation of the DiD framework employed in this thesis is its inability to estimate the impact of ENSO on *cajas* for most recent iterations of the event. Does this erode the value of the study? It depends. From a research perspective, it is interesting to evaluate which models work best to evaluate the impact of natural phenomenon on the economy, especially given the current climate change backdrop. Collier, Katchova and Skees, (2011) employed an ARIMA model, this thesis used a difference-in-difference model to reach a fairly close estimate—particularly when looking at the monthly estimates. Increasing the literature on the impact of natural disasters on the economy is paramount going forward, as climate risk rise. Future researchers can benefit from having a plethora of models and reference cases to draw from as they evaluate the evolving impact of climate change. More so, considering that it is not the model that fails on ENSO 2016-17 but rather that the data no longer reflects the impact of ENSO on that segment of the economy. The model may work effectively provided other proxy indicator is employed, e.g. agriculture output as previously mentioned. Further research may look at other areas of the economy affected by ENSO besides *cajas;* where the DiD framework could prove useful.

Lastly, pertaining to the multiperiod DiD model, Callaway and Sant'Anna, (2021) present it as a tool for evaluating staggered deployment of policy. For instance, they use it to assess the impact of minimum salary on employment for a number of states in the United States. The configuration of the model allows them to include into the treatment group states that implement a minimum wage at different time periods, and to see how employment evolves through time after the minimum wage comes into effect. You may have noticed that above all the figures shown in the Result section, it says *group 24*. The reason behind it is that period 24 is when ENSO begins for all *cajas*. However, in the minimum wage example presented before, one figure is estimated for each group, and groups are defined by the period on which the wage policy was implemented. In turn, the features of the DiD R library are thought primarily for policy analysis and careful considerations must be taken for implementing it in natural event impact studies.

6.4. Policy implications and further research

Looking at the results of the analysis, the main conclusion is that during the early development of microfinance in Peru *cajas* faced increases in PRL as a consequence of ENSO. As the market matured with insurance becoming more common and regulation allowing *cajas* to diversify their portfolio, the impact of ENSO on PRL was largely mitigated. Moreover, data shows that *cajas* in ENSO-exposed departments have actually being able to increase lending during the event, buttressing the recovery of the local economy.

Consequently, the availability of insurance and broader diversification appear to be effective methods to insulate MFIs from ENSO risks. Evidently, more evidence is needed to confirm this, particularly on insurance growth trends and client diversification. In case it is confirmed that these led to the reduction of risk exposure, these measures could likely be deployed in developing countries facing other types of natural disasters.

Meanwhile, another takeaway is that the focus on climate disaster impact should shift to the affected population and business rather than MFIs. Cajas play a central role in providing financial access to the poor and keeping them insulated from risks is relevant for financial stability. At the same time, however, studying the reaction of MFIs to ENSO is an indirect way of assessing the impact of the event on the population. Estimating the direct impact that El Niño has on farmers or households may broaden our understanding of vulnerabilities and allow policymakers to tailor regulation more effectively. As stated before, agricultural and fishing data is a tentative area to expand research. For centuries, local farmers in Peru have been dealing with ENSO, and long-running practices are being employed to overcome it or even benefit from it (Tibbetts, 1996).

7. Sensitivity analysis

One of the key questions remaining is how do slight changes in the DiD model parameters alter the estimates of the models. Of particular interest is selecting the period when ENSO 1997-98 starts. In the result section, the start of the event was set to December 1997, primarily because that date matched the start of heavy rains, while it is also the month that has been historically associated with the start of El Niño.

What would happen if instead of selecting December 1997, September 1997 is selected as the event's start? September 1997 is when strong ONI values are first reported (Annex A, Table 7) for the ENSO 3+4 region. A forward-looking *caja* might use ONI to gauge ENSO risks and restructure loans accordingly. Therefore, comparing the results for both stating dates is interesting to see how much of an impact the starting point plays on the estimates. Table 8 in Annex A presents the data set employed for the sensitivity analysis. Note that the only change with respect to the dataset used previously is that in column g, treatment *cajas* now have a value of 21 (i.e. September 1997) instead of 24 (December 1997).

Looking at figures 21 and 22, the results for using September 1997 as the starting date for the event yield fairly close estimates to when using December 1997. For all estimates but Ancash ATT March 98, the difference is only shy above half a percentage point. These results suggest that the impact of changing the starting date of the event is fairly limited. Nevertheless, its not clear which estimates are more accurate, i.e. closer to the *real impact* of ENSO on PRL. The results yield by using December 1997 as the starting point are closer to the result of the ARIMA model used by Collier, Katchova and Skees, (2011), supporting the argument that this starting point yields more accurate estimates.

Figure 21: Sensitivity analysis results

Summary of DiD results for sensitivity analysis					
Model	**Average treatment effect (ATT) for periods [24,29]**	**ATT March 98**	**ATT April 98**	**ATT May 98**	**ATT for periods [27,29]**
Naïve model	2,33%*	5,06% *	5,26%	5,86%	5,39%
Piura model 7	1,79%*	3,89% *	3,99% *	4,15% *	4,01%*
Ancash model 2	1,24%*	2,56% *	1,83%	2,62% *	2,34%
* : Confidence bar does not reach zero					

Figure 22: absolute difference between sensitivity results and presented results

Absolute difference between sensitivity and results					
Model	**Average treatment effect (ATT) for periods [24,29]**	**ATT March 98**	**ATT April 98**	**ATT May 98**	**ATT for periods [27,29]**
Naïve model	0,38%	0,52%	0,52 %	0,52 %	0,52%
Piura model 7	0,08%	0,54%	0,53 %	0,53 %	0,54%
Ancash model 2	0,00%	1,48%	0,52 %	0,83 %	0,94%

Conclusion

This thesis set out to answer whether a difference-in-difference model could be employed for evaluating the impact of ENSO on the level of restructured loans present in Peru's municipal *cajas?* The analysis shows that a DiD model can indeed be used with fairly satisfactory results; however, only for El Niños that occurred before *cajas* began diversification and insuring their portfolios, which can be traced back to the early 2000s. Restructured loans for municipal *cajas* located in departments affected by the event rose during the 1997-98 ENSO; making it possible for the DiD model to estimate the magnitude of the increase. The all-important assumptions behind the model are largely satisfied for this particular iteration of the event. All in all, the results estimated using the DiD framework are close to those obtained in previous studies, providing evidence on the accuracy of this study framework.

However, for later iterations of the event, utilizing proportion of restructured loans in the DiD model proves unfeasible because the correlation between this variable and the event broke down during the past two decades. More specifically, the proportion of restructured loans does not react to the strong El Niño of 2016-17, making it impossible to apply the DiD framework using PRL as the input variable. From this fact, it can be concluded that the proportion of restructured loans in affected *cajas* is no longer a valid indicator for measuring the impact of ENSO on the affected population. Nevertheless, the reason why proportion of restructured loans stops reacting to the events appears to be an increase in client diversification done by the *cajas* thanks to changes in regulation and the development of the insurance market. Together, these have insulated *cajas* against ENSO-linked risks, allowing them to aid affected households by increasing lending as the event unfolds. For policymakers, these are valuable lesson for limiting financial losses stemming from extreme weather events.

Meanwhile, the multiperiod DiD model employed in this thesis shows significant promise for evaluating the impact of extreme weather events on the population. Provided viable control groups are found, this model could be used effectively to assess the magnitude of a climate event on a particular variable. The key constraint for its application is data availability. Data is particularly limited in countries that are set to be the most affected by extreme weather. At the end of the day, this thesis aimed to broaden the literature of models being implemented to assess the impact of climate events, given the importance of expanding the economist's toolkit as.

References

Agricultura (IICA), I.I. de C. para la *et al.* (2016) ‘Boletín técnico : El fenómeno de “El Niño” en la agricultura de las Américas’. Available at: https://repositorio.iica.int/handle/11324/3041 (Accessed: 23 February 2022).

Aguilar, G. (2013) ‘Microfinanzas y crecimiento regional en el Perú’, *Economía Pontifica Universidad Católica*, XXXVI(Nº72), pp. 143–173.

Bank of International Settlements (2014) ‘History of the Basel Committee’. Available at: https://www.bis.org/bcbs/history.htm (Accessed: 20 April 2022).

Bjerknes, J. (1969) ‘ATMOSPHERIC TELECONNECTIONS FROM THE EQUATORIAL PACIFIC’, *Monthly Weather Review*, 97(3), pp. 163–172. doi:10.1175/1520-0493(1969)097<0163:ATFTEP>2.3.CO;2.

Cai, W. *et al.* (2014) ‘Increasing frequency of extreme El Niño events due to greenhouse warming’, *Nature Climate Change*, 4(2), pp. 111–116. doi:10.1038/nclimate2100.

Cai, W. *et al.* (2021) ‘Changing El Niño–Southern Oscillation in a warming climate’, *Nature Reviews Earth & Environment*, 2(9), pp. 628–644. doi:10.1038/s43017-021-00199-z.

Callaway, B. and Sant’Anna, P.H.C. (2021) ‘Difference-in-Differences with multiple time periods’, *Journal of Econometrics*, 225(2), pp. 200–230. doi:10.1016/j.jeconom.2020.12.001.

Callaway, B. and Sant’Anna, P.H.C. (2022) *Getting Started with the did Package*. Available at: https://bcallaway11.github.io/did/articles/did-basics.html (Accessed: 30 March 2022).

Carmago, A. and Furst Gonçalves, L. (2014) *Encouraging access to insurance in Peru: Reshaping the insurance environment for the underserved and unserved population*. Access to insurance initiative. Available at: https://a2ii.org/en/media/192/download.

Cashin, P., Mohaddes, K. and Raissi, M. (2017) ‘Fair weather or foul? The macroeconomic effects of El Niño’, *Journal of International Economics*, 106, pp. 37–54. doi:10.1016/j.jinteco.2017.01.010.

Coleman, T.S. (2020) ‘John Snow and Cholera: Revisiting Difference-in-Differences and Randomized Trials in Research’, p. 20.

Collier, B., Katchova, A.L. and Skees, J.R. (2011) ‘Loan portfolio performance and El Niño, an intervention analysis’, *Agricultural Finance Review*, 71(1), pp. 98–119.

Collier, B.L. (2020) ‘Strengthening Local Credit Markets Through Lender-Level Index Insurance’, *Journal of Risk and Insurance*, 87(2), pp. 319–349. doi:10.1111/jori.12277.

Conger, L., Inga, P. and Webb, R. (2009) *The Mustard Tree: A History of Microfinance in Peru – Instituto del Perú*. Universidad de San Martin de Porres. Available at: http://institutodelperu.pe/2009/08/01/the-mustard-tree-a-history-of-microfinance-in-peru/ (Accessed: 2 May 2022).

Ebentreich, A. (2005) ‘Microfinance Regulation in Peru: Current State, Lessons Learned and Prospects for the Future’, p. 13.

ESDAMIN (2022) ‘1.1.1 Características geográficas y demográficas del país’, *ESDA | Estudio de Desempeño Ambiental*. Available at: https://www.minam.gob.pe/esda/1-1-1-caracteristicas-geograficas-y-demograficas-del-pais/ (Accessed: 17 May 2022).

Gertler, P.J. *et al.* (2016) *Impact Evaluation in Practice, Second Edition*. Second. Washington, DC: World Bank. Available at: https://openknowledge.worldbank.org/handle/10986/25030 (Accessed: 11 March 2022).

Gobierno del Perú (2022) *Gobierno del Perú*. Available at: https://www.gob.pe/estado/gobiernos-regionales (Accessed: 17 May 2022).

Goodman-Bacon, A. (2021) ‘Difference-in-differences with variation in treatment timing’, *Journal of Econometrics*, 225(2), pp. 254–277. doi:10.1016/j.jeconom.2021.03.014.

Huntington-Klein, N. (2021a) *Chapter 14 - Matching | The Effect*. Available at: https://theeffectbook.net/ch-Matching.html (Accessed: 30 March 2022).

Huntington-Klein, N. (2021b) *Chapter 18 - Difference-in-Differences | The Effect*. Available at: https://theeffectbook.net/ch-DifferenceinDifference.html (Accessed: 8 March 2022).

INEI (2009) ‘Perú: Anuario de Estadísticas Ambientales, 2009’. Instituto Nacional de Estadísticas e Informatica. Available at: http://siar.minam.gob.pe/apurimac/documentos/peru-anuario-estadisticas-ambientales-2009 (Accessed: 16 April 2021).

INEI (2021) ‘Perú: Anuario de Estadísticas Ambientales 2021’. Instituto Nacional de Estadísticas e Informatica. Available at: https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1827/libro.pdf (Accessed: 16 April 2021).

INEI (2022) *PERÚ Instituto Nacional de Estadística e Informática*. Available at: https://www.inei.gob.pe/ (Accessed: 17 May 2022).

Kahn-Lang, A. and Lang, K. (2020) ‘The Promise and Pitfalls of Differences-in-Differences: Reflections on 16 and Pregnant and Other Applications’, *Journal of Business & Economic Statistics*, 38(3), pp. 613–620. doi:10.1080/07350015.2018.1546591.

Lechner, M. (2011) *The Estimation of Causal Effects by Difference-in-Difference Methods, University of St. Gallen Department of Economics working paper series 2010*. 2010–28. Department of Economics, University of St. Gallen. Available at: https://ideas.repec.org/p/usg/dp2010/2010-28.html (Accessed: 10 March 2022).

L’Hereux, M. (2014) *What is the El Niño–Southern Oscillation (ENSO) in a nutshell? | NOAA Climate.gov, NOAA*. Available at: https://www.climate.gov/news-features/blogs/enso/what-el-ni%C3%B1o%E2%80%93southern-oscillation-enso-nutshell (Accessed: 24 February 2022).

Lindsay, R. (2009) *Climate Variability: Oceanic Niño Index | NOAA Climate.gov*. Available at: https://www.climate.gov/news-features/understanding-climate/climate-variability-oceanic-ni%C3%B1o-index (Accessed: 3 March 2022).

Mcgregor, G. and Ebi, K. (2018) 'El Niño Southern Oscillation (ENSO) and Health: An Overview for Climate and Health Researchers', *Atmosphere*, 9, p. 282. doi:10.3390/atmos9070282.

NOAA (2022) *Equitorial Pacific Sea Surface Temperatures (SST) | El Niño/Southern Oscillation (ENSO) | National Centers for Environmental Information (NCEI)*. Available at: https://www.ncdc.noaa.gov/teleconnections/enso/sst (Accessed: 3 March 2022).

Perraillon, M.C. (2020) 'Week 9: Difference-in-differences II'. University of Colorado, Abschutz Medical Campus.

Rehse, D. *et al.* (2019) 'The effects of uncertainty on market liquidity: Evidence from Hurricane Sandy', *Journal of Financial Economics*, 134(2), pp. 318–332. doi:10.1016/j.jfineco.2019.04.006.

Rojas, O., Li, Y. and Cumani, R. (2014) *Understanding the drought impact of El Niño on the global agricultural areas: an assessment using FAO's Agricultural Stress Index (ASI)*. Rome: FAO (Environment and natural resources management series, 23).

SBS (2022) *Superintendencia de Banca, Seguros y AFP del Perú, SBSPerú*. Available at: https://www.sbs.gob.pe/ (Accessed: 25 May 2022).

SENAMHI (2022) *SENAMHI - Perú, Servicio Nacional de Meteorologia e Hidrologia del Peru*. Available at: https://www.senamhi.gob.pe/?p=descarga-datos-hidrometeorologicos (Accessed: 25 May 2022).

Tibbetts, J. (1996) 'Farming and fishing in the wake of El Niño: How does the periodic warming of the waters of the central Pacific relate to global climate change and food production?', *BioScience*, 46(8), pp. 566–569. doi:10.2307/1312984.

Werners, S., Erdelyi, E. and Supit, I. (2011) 'Use of Modern Portfolio Theory to Evaluate Diversification of Agricultural Land Use as an Adaptation to Climate Risks in the Tisza River Basin', in *Advances in Global Change Research*, pp. 371–383. doi:10.1007/978-94-007-0567-8_27.

Williams, J. and Null, J. (2015) 'What You Need to Know to Understand the Current El Niño', *Weatherwise*, 68(6), pp. 12–19. doi:10.1080/00431672.2015.1086238.

Witt, R. and Waibel, H. (2009) 'Climate risk and farming systems in rural Cameroon', p. 29.

Wolfers, J. (2006) 'Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results', *THE AMERICAN ECONOMIC REVIEW*, 96(5), p. 41.

World Bank (2018) *Difference-in-Differences - DIME Wiki*. Available at: https://dimewiki.worldbank.org/Difference-in-Differences (Accessed: 8 March 2022).

Yunus, M. (1998) *Banker To The Poor*. Penguin Books India.

Annex A

See attached excel file named Annex A.

Annex B

Model results, see detailed of treatment and control groups in Annex A, table 4.

Naive model

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0017	0.0011	-0.0044	0.0011	
24	3	0.0004	0.0029	-0.0067	0.0075	
24	4	0.0005	0.0023	-0.0052	0.0061	
24	5	-0.0012	0.0022	-0.0067	0.0043	
24	6	-0.0032	0.0024	-0.0091	0.0027	
24	7	-0.0024	0.0029	-0.0094	0.0047	
24	8	-0.0009	0.0013	-0.0040	0.0022	
24	9	0.0010	0.0013	-0.0021	0.0040	
24	10	-0.0010	0.0022	-0.0064	0.0045	
24	11	-0.0026	0.0008	-0.0044	-0.0007	*
24	12	0.0001	0.0015	-0.0035	0.0038	
24	13	-0.0003	0.0011	-0.0030	0.0025	
24	14	0.0005	0.0025	-0.0056	0.0067	
24	15	-0.0039	0.0011	-0.0065	-0.0013	*
24	16	0.0044	0.0025	-0.0016	0.0104	
24	17	-0.0012	0.0022	-0.0066	0.0041	
24	18	0.0028	0.0018	-0.0016	0.0072	
24	19	0.0024	0.0020	-0.0025	0.0072	
24	20	0.0025	0.0010	0.0001	0.0048	*
24	21	0.0048	0.0023	-0.0008	0.0104	
24	22	0.0014	0.0009	-0.0007	0.0035	
24	23	-0.0010	0.0015	-0.0047	0.0027	
24	24	-0.0005	0.0017	-0.0048	0.0038	

24	25	0.0029	0.0028	-0.0040	0.0097
24	26	0.0139	0.0078	-0.0051	0.0328
24	27	0.0454	0.0202	-0.0040	0.0947
24	28	0.0474	0.0258	-0.0155	0.1102
24	29	0.0534	0.0276	-0.0140	0.1208

Signif. codes: `*' confidence band does not cover 0

Control Group: Never Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

Piura models

<u>Model 1: *Cajas* in Piura against control group 1</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]
24	2	-0.0012	0.0015	-0.0048	0.0024
24	3	-0.0022	0.0013	-0.0053	0.0008
24	4	-0.0020	0.0017	-0.0060	0.0021
24	5	0.0011	0.0012	-0.0018	0.0040
24	6	-0.0013	0.0004	-0.0022	-0.0004 *
24	7	-0.0004	0.0031	-0.0076	0.0069
24	8	-0.0006	0.0015	-0.0042	0.0029
24	9	0.0021	0.0017	-0.0019	0.0062
24	10	-0.0004	0.0023	-0.0058	0.0051
24	11	-0.0026	0.0009	-0.0048	-0.0005 *
24	12	0.0000	0.0019	-0.0046	0.0045
24	13	-0.0022	0.0009	-0.0043	-0.0001 *
24	14	0.0021	0.0028	-0.0044	0.0087
24	15	-0.0036	0.0014	-0.0070	-0.0002 *
24	16	0.0027	0.0009	0.0006	0.0048 *
24	17	-0.0024	0.0016	-0.0063	0.0014
24	18	0.0021	0.0012	-0.0007	0.0049

24	19	0.0010	0.0018	-0.0033	0.0053	
24	20	0.0028	0.0014	-0.0006	0.0062	
24	21	0.0062	0.0025	0.0004	0.0120	*
24	22	0.0003	0.0009	-0.0018	0.0024	
24	23	0.0001	0.0015	-0.0034	0.0036	
24	24	-0.0005	0.0031	-0.0079	0.0068	
24	25	0.0024	0.0029	-0.0044	0.0093	
24	26	0.0085	0.0061	-0.0060	0.0229	
24	27	0.0346	0.0065	0.0193	0.0499	*
24	28	0.0355	0.0057	0.0220	0.0490	*
24	29	0.0372	0.0073	0.0201	0.0544	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Never Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 2: Cajas in Piura against control group 2</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0013	0.0025	-0.0078	0.0052	
24	3	-0.0027	0.0015	-0.0066	0.0011	
24	4	-0.0008	0.0013	-0.0041	0.0025	
24	5	0.0007	0.0013	-0.0027	0.0042	
24	6	-0.0016	0.0004	-0.0026	-0.0006	*
24	7	-0.0012	0.0033	-0.0098	0.0073	
24	8	-0.0010	0.0017	-0.0055	0.0035	
24	9	0.0023	0.0019	-0.0026	0.0072	
24	10	0.0004	0.0026	-0.0063	0.0071	
24	11	-0.0028	0.0010	-0.0054	-0.0002	*
24	12	0.0000	0.0020	-0.0051	0.0051	
24	13	-0.0025	0.0010	-0.0051	0.0002	

```
   24   14   0.0020     0.0033      -0.0066      0.0107
   24   15  -0.0040     0.0014      -0.0077     -0.0003 *
   24   16   0.0029     0.0011       0.0001      0.0057 *
   24   17  -0.0028     0.0018      -0.0075      0.0018
   24   18   0.0026     0.0010       0.0000      0.0053
   24   19   0.0025     0.0014      -0.0012      0.0062
   24   20   0.0031     0.0015      -0.0008      0.0071
   24   21   0.0059     0.0022       0.0001      0.0116 *
   24   22   0.0003     0.0010      -0.0023      0.0029
   24   23   0.0003     0.0012      -0.0029      0.0035
   24   24  -0.0002     0.0029      -0.0077      0.0074
   24   25   0.0028     0.0022      -0.0030      0.0087
   24   26   0.0087     0.0068      -0.0089      0.0263
   24   27   0.0344     0.0061       0.0186      0.0501 *
   24   28   0.0348     0.0044       0.0234      0.0461 *
   24   29   0.0361     0.0064       0.0196      0.0527 *
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Not Yet Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
NULL
```

<u>Model 3: Cajas in Piura against control group 3</u>

```
Group-Time Average Treatment Effects:
 Group Time ATT(g,t) Std. Error [95% Simult.  Conf. Band]
   24    2  -0.0013     0.0024      -0.0069      0.0043
   24    3  -0.0021     0.0016      -0.0057      0.0016
   24    4  -0.0018     0.0013      -0.0047      0.0012
   24    5   0.0007     0.0014      -0.0025      0.0039
   24    6  -0.0018     0.0004      -0.0027     -0.0010 *
   24    7  -0.0022     0.0040      -0.0113      0.0068
   24    8   0.0001     0.0016      -0.0034      0.0036
   24    9   0.0013     0.0017      -0.0025      0.0052
```

24	10	0.0003	0.0035	-0.0077	0.0083	
24	11	-0.0033	0.0009	-0.0054	-0.0012	*
24	12	-0.0004	0.0026	-0.0063	0.0054	
24	13	-0.0018	0.0013	-0.0047	0.0011	
24	14	0.0036	0.0039	-0.0052	0.0125	
24	15	-0.0031	0.0013	-0.0061	-0.0001	*
24	16	0.0030	0.0011	0.0006	0.0054	*
24	17	-0.0011	0.0009	-0.0031	0.0008	
24	18	0.0021	0.0010	0.0000	0.0043	
24	19	0.0021	0.0016	-0.0016	0.0057	
24	20	0.0026	0.0013	-0.0004	0.0055	
24	21	0.0053	0.0022	0.0002	0.0104	*
24	22	-0.0001	0.0009	-0.0022	0.0020	
24	23	0.0000	0.0013	-0.0029	0.0030	
24	24	-0.0007	0.0031	-0.0077	0.0063	
24	25	0.0025	0.0041	-0.0068	0.0118	
24	26	0.0080	0.0065	-0.0068	0.0229	
24	27	0.0338	0.0086	0.0141	0.0535	*
24	28	0.0328	0.0058	0.0196	0.0459	*
24	29	0.0345	0.0073	0.0179	0.0511	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 4: Cajas in Piura against control group 4</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0016	0.0024	-0.0075	0.0042	
24	3	-0.0017	0.0018	-0.0061	0.0028	
24	4	-0.0022	0.0013	-0.0053	0.0009	
24	5	0.0003	0.0016	-0.0036	0.0042	
24	6	-0.0021	0.0004	-0.0030	-0.0011	*

24	7	-0.0043	0.0044	-0.0149	0.0063	
24	8	-0.0005	0.0019	-0.0051	0.0041	
24	9	0.0009	0.0018	-0.0034	0.0052	
24	10	0.0036	0.0028	-0.0032	0.0104	
24	11	-0.0034	0.0009	-0.0056	-0.0012	*
24	12	-0.0002	0.0035	-0.0086	0.0083	
24	13	-0.0016	0.0016	-0.0054	0.0022	
24	14	0.0056	0.0039	-0.0037	0.0149	
24	15	-0.0029	0.0013	-0.0059	0.0001	
24	16	0.0019	0.0008	0.0000	0.0038	*
24	17	-0.0010	0.0012	-0.0039	0.0019	
24	18	0.0020	0.0010	-0.0003	0.0043	
24	19	0.0037	0.0008	0.0018	0.0055	*
24	20	0.0020	0.0019	-0.0026	0.0065	
24	21	0.0051	0.0031	-0.0023	0.0126	
24	22	-0.0004	0.0009	-0.0026	0.0018	
24	23	-0.0002	0.0013	-0.0033	0.0029	
24	24	-0.0008	0.0031	-0.0082	0.0066	
24	25	0.0024	0.0041	-0.0074	0.0122	
24	26	0.0070	0.0065	-0.0087	0.0226	
24	27	0.0326	0.0086	0.0119	0.0534	*
24	28	0.0328	0.0058	0.0190	0.0467	*
24	29	0.0334	0.0073	0.0159	0.0509	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 5: Cajas in Piura against control group 5</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]
24	2	-0.0015	0.0034	-0.0095	0.0065

24	3	-0.0027	0.0018	-0.0070	0.0016	
24	4	-0.0007	0.0018	-0.0049	0.0034	
24	5	0.0005	0.0013	-0.0026	0.0035	
24	6	-0.0017	0.0005	-0.0028	-0.0006	*
24	7	-0.0023	0.0040	-0.0116	0.0071	
24	8	-0.0017	0.0021	-0.0068	0.0033	
24	9	0.0023	0.0021	-0.0026	0.0071	
24	10	0.0026	0.0023	-0.0027	0.0080	
24	11	-0.0026	0.0012	-0.0055	0.0003	
24	12	0.0004	0.0024	-0.0052	0.0060	
24	13	-0.0026	0.0015	-0.0061	0.0010	
24	14	0.0028	0.0039	-0.0063	0.0119	
24	15	-0.0042	0.0013	-0.0072	-0.0011	*
24	16	0.0022	0.0008	0.0004	0.0040	*
24	17	-0.0033	0.0023	-0.0087	0.0021	
24	18	0.0027	0.0010	0.0003	0.0052	*
24	19	0.0037	0.0007	0.0021	0.0053	*
24	20	0.0029	0.0016	-0.0009	0.0068	
24	21	0.0060	0.0027	-0.0005	0.0124	
24	22	0.0003	0.0013	-0.0028	0.0033	
24	23	0.0002	0.0013	-0.0027	0.0032	
24	24	-0.0001	0.0029	-0.0068	0.0067	
24	25	0.0028	0.0028	-0.0037	0.0093	
24	26	0.0083	0.0068	-0.0078	0.0243	
24	27	0.0338	0.0066	0.0183	0.0494	*
24	28	0.0355	0.0053	0.0230	0.0480	*
24	29	0.0359	0.0066	0.0203	0.0516	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 6: Cajas in Piura against control group 6</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0010	0.0014	-0.0044	0.0024	
24	3	-0.0018	0.0015	-0.0054	0.0019	
24	4	-0.0016	0.0019	-0.0064	0.0031	
24	5	0.0016	0.0011	-0.0013	0.0045	
24	6	-0.0010	0.0003	-0.0018	-0.0002	*
24	7	0.0021	0.0006	0.0007	0.0035	*
24	8	-0.0001	0.0017	-0.0044	0.0041	
24	9	0.0030	0.0016	-0.0010	0.0070	
24	10	-0.0023	0.0015	-0.0061	0.0015	
24	11	-0.0025	0.0010	-0.0051	0.0001	
24	12	-0.0012	0.0019	-0.0058	0.0034	
24	13	-0.0019	0.0011	-0.0046	0.0009	
24	14	0.0001	0.0021	-0.0051	0.0053	
24	15	-0.0041	0.0014	-0.0077	-0.0006	*
24	16	0.0028	0.0011	0.0001	0.0054	*
24	17	-0.0024	0.0021	-0.0077	0.0029	
24	18	0.0022	0.0014	-0.0015	0.0058	
24	19	0.0001	0.0019	-0.0046	0.0048	
24	20	0.0032	0.0015	-0.0005	0.0068	
24	21	0.0059	0.0022	0.0003	0.0115	*
24	22	0.0007	0.0008	-0.0013	0.0027	
24	23	0.0000	0.0013	-0.0033	0.0033	
24	24	-0.0006	0.0034	-0.0091	0.0078	
24	25	0.0027	0.0043	-0.0082	0.0136	
24	26	0.0090	0.0060	-0.0060	0.0241	
24	27	0.0349	0.0088	0.0129	0.0570	*
24	28	0.0364	0.0062	0.0208	0.0520	*
24	29	0.0393	0.0079	0.0195	0.0590	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

Model 7: Cajas in Piura against control group 7

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0014	0.0017	-0.0056	0.0027	
24	3	-0.0012	0.0015	-0.0047	0.0024	
24	4	-0.0037	0.0017	-0.0077	0.0003	
24	5	0.0011	0.0015	-0.0026	0.0048	
24	6	-0.0015	0.0004	-0.0025	-0.0005	*
24	7	-0.0019	0.0039	-0.0113	0.0075	
24	8	-0.0001	0.0016	-0.0040	0.0039	
24	9	0.0011	0.0018	-0.0032	0.0054	
24	10	0.0012	0.0025	-0.0048	0.0073	
24	11	-0.0030	0.0009	-0.0052	-0.0008	*
24	12	-0.0002	0.0020	-0.0049	0.0045	
24	13	-0.0015	0.0008	-0.0035	0.0005	
24	14	0.0046	0.0033	-0.0035	0.0126	
24	15	-0.0026	0.0014	-0.0060	0.0007	
24	16	0.0019	0.0007	0.0003	0.0036	*
24	17	-0.0009	0.0007	-0.0027	0.0008	
24	18	0.0014	0.0010	-0.0011	0.0038	
24	19	0.0008	0.0026	-0.0055	0.0071	
24	20	0.0019	0.0014	-0.0014	0.0052	
24	21	0.0059	0.0028	-0.0008	0.0126	
24	22	-0.0002	0.0009	-0.0024	0.0020	
24	23	-0.0004	0.0012	-0.0034	0.0026	
24	24	-0.0012	0.0032	-0.0089	0.0065	
24	25	0.0019	0.0041	-0.0080	0.0117	
24	26	0.0071	0.0057	-0.0066	0.0209	
24	27	0.0335	0.0086	0.0127	0.0543	*
24	28	0.0346	0.0058	0.0207	0.0485	*
24	29	0.0362	0.0069	0.0196	0.0527	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 8: Cajas in Piura against control group 8</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0012	0.0024	-0.0072	0.0047	
24	3	-0.0030	0.0013	-0.0061	0.0001	
24	4	-0.0022	0.0020	-0.0070	0.0026	
24	5	0.0011	0.0014	-0.0023	0.0044	
24	6	-0.0013	0.0005	-0.0025	-0.0001	*
24	7	-0.0009	0.0031	-0.0084	0.0067	
24	8	-0.0012	0.0017	-0.0053	0.0028	
24	9	0.0019	0.0017	-0.0022	0.0061	
24	10	-0.0004	0.0029	-0.0074	0.0066	
24	11	-0.0024	0.0010	-0.0049	0.0001	
24	12	0.0012	0.0016	-0.0027	0.0050	
24	13	-0.0029	0.0006	-0.0045	-0.0014	*
24	14	0.0025	0.0033	-0.0055	0.0104	
24	15	-0.0035	0.0013	-0.0066	-0.0003	*
24	16	0.0030	0.0010	0.0005	0.0055	*
24	17	-0.0032	0.0017	-0.0073	0.0009	
24	18	0.0021	0.0014	-0.0013	0.0055	
24	19	0.0005	0.0021	-0.0044	0.0055	
24	20	0.0030	0.0015	-0.0006	0.0065	
24	21	0.0070	0.0021	0.0018	0.0121	*
24	22	0.0004	0.0010	-0.0021	0.0028	
24	23	0.0004	0.0013	-0.0028	0.0035	
24	24	-0.0003	0.0030	-0.0076	0.0070	
24	25	0.0022	0.0037	-0.0069	0.0113	
24	26	0.0087	0.0066	-0.0073	0.0247	

24	27	0.0352	0.0083	0.0150	0.0555	*
24	28	0.0358	0.0056	0.0222	0.0494	*
24	29	0.0372	0.0071	0.0199	0.0544	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

Ancash models

<u>Model 1: Cajas in Ancash against control group 1</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0019	0.0008	-0.0057	0.0020	
24	3	-0.0032	0.0004	-0.0054	-0.0011	*
24	4	0.0006	0.0018	-0.0078	0.0090	
24	5	-0.0008	0.0019	-0.0098	0.0082	
24	6	-0.0015	0.0005	-0.0039	0.0010	
24	7	-0.0045	0.0040	-0.0236	0.0147	
24	8	-0.0014	0.0010	-0.0061	0.0033	
24	9	-0.0011	0.0023	-0.0119	0.0098	
24	10	-0.0001	0.0011	-0.0053	0.0052	
24	11	-0.0013	0.0007	-0.0046	0.0021	
24	12	0.0016	0.0008	-0.0022	0.0054	
24	13	0.0007	0.0013	-0.0052	0.0067	
24	14	-0.0003	0.0046	-0.0223	0.0216	
24	15	-0.0041	0.0023	-0.0150	0.0069	
24	16	0.0091	0.0068	-0.0234	0.0415	
24	17	0.0001	0.0053	-0.0251	0.0252	
24	18	0.0056	0.0061	-0.0235	0.0348	
24	19	0.0069	0.0022	-0.0036	0.0174	

24	20	0.0026	0.0016	-0.0052	0.0103	
24	21	0.0056	0.0091	-0.0377	0.0490	
24	22	0.0021	0.0013	-0.0042	0.0083	
24	23	-0.0040	0.0002	-0.0050	-0.0030	*
24	24	-0.0009	0.0007	-0.0042	0.0024	
24	25	0.0048	0.0088	-0.0374	0.0469	
24	26	0.0119	0.0211	-0.0892	0.1130	
24	27	0.0222	0.0073	-0.0130	0.0573	
24	28	0.0141	0.0038	-0.0043	0.0324	
24	29	0.0213	0.0058	-0.0066	0.0492	

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 2: Cajas in Ancash against control group 2</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0018	0.0006	-0.0031	-0.0005	*
24	3	-0.0023	0.0010	-0.0047	0.0001	
24	4	-0.0008	0.0018	-0.0049	0.0033	
24	5	-0.0003	0.0016	-0.0040	0.0034	
24	6	-0.0011	0.0005	-0.0024	0.0001	
24	7	-0.0032	0.0037	-0.0119	0.0055	
24	8	-0.0007	0.0012	-0.0034	0.0020	
24	9	-0.0012	0.0016	-0.0049	0.0026	
24	10	-0.0011	0.0029	-0.0078	0.0056	
24	11	-0.0012	0.0005	-0.0025	0.0000	
24	12	0.0011	0.0013	-0.0019	0.0041	
24	13	0.0013	0.0011	-0.0014	0.0039	
24	14	-0.0003	0.0033	-0.0080	0.0075	
24	15	-0.0036	0.0014	-0.0069	-0.0003	*
24	16	0.0087	0.0042	-0.0011	0.0185	

24	17	0.0009	0.0046	-0.0098	0.0115	
24	18	0.0049	0.0037	-0.0037	0.0136	
24	19	0.0051	0.0023	-0.0003	0.0105	
24	20	0.0021	0.0015	-0.0014	0.0057	
24	21	0.0058	0.0050	-0.0059	0.0174	
24	22	0.0020	0.0010	-0.0002	0.0043	
24	23	-0.0044	0.0004	-0.0054	-0.0034	*
24	24	-0.0014	0.0009	-0.0035	0.0006	
24	25	0.0043	0.0051	-0.0074	0.0161	
24	26	0.0115	0.0119	-0.0163	0.0393	
24	27	0.0222	0.0046	0.0114	0.0330	*
24	28	0.0149	0.0037	0.0062	0.0235	*
24	29	0.0228	0.0051	0.0109	0.0348	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 3: Cajas in Ancash against control group 3</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0027	0.0005	-0.0033	-0.0021	*
24	3	-0.0034	0.0002	-0.0037	-0.0031	*
24	4	-0.0020	0.0004	-0.0026	-0.0014	*
24	5	-0.0021	0.0016	-0.0043	0.0000	
24	6	-0.0024	0.0001	-0.0026	-0.0023	*
24	7	-0.0126	0.0009	-0.0137	-0.0114	*
24	8	-0.0022	0.0001	-0.0023	-0.0020	*
24	9	-0.0043	0.0004	-0.0048	-0.0039	*
24	10	0.0067	0.0005	0.0060	0.0074	*
24	11	-0.0019	0.0003	-0.0024	-0.0015	*
24	12	0.0045	0.0003	0.0041	0.0049	*
24	13	0.0004	0.0011	-0.0011	0.0019	

24	14	0.0076	0.0003	0.0072	0.0079	*
24	15	-0.0017	0.0012	-0.0034	-0.0001	*
24	16	0.0082	0.0042	0.0025	0.0138	*
24	17	0.0014	0.0046	-0.0047	0.0076	
24	18	0.0047	0.0037	-0.0003	0.0097	
24	19	0.0091	0.0015	0.0071	0.0112	*
24	20	0.0008	0.0013	-0.0010	0.0026	
24	21	0.0061	0.0050	-0.0007	0.0128	
24	22	0.0007	0.0009	-0.0005	0.0019	
24	23	-0.0043	0.0001	-0.0044	-0.0042	*
24	24	-0.0013	0.0004	-0.0019	-0.0007	*
24	25	0.0034	0.0051	-0.0034	0.0103	
24	26	0.0091	0.0119	-0.0070	0.0252	
24	27	0.0202	0.0046	0.0140	0.0265	*
24	28	0.0107	0.0031	0.0065	0.0149	*
24	29	0.0149	0.0040	0.0095	0.0203	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 4: Cajas in Ancash against control group 4</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0022	0.0007	-0.0035	-0.0009	*
24	3	-0.0037	0.0004	-0.0046	-0.0029	*
24	4	0.0008	0.0021	-0.0033	0.0048	
24	5	-0.0013	0.0016	-0.0045	0.0018	
24	6	-0.0016	0.0006	-0.0028	-0.0003	*
24	7	-0.0065	0.0045	-0.0153	0.0022	
24	8	-0.0029	0.0006	-0.0040	-0.0018	*

24	9	-0.0012	0.0023	-0.0057	0.0034	
24	10	0.0034	0.0025	-0.0015	0.0082	
24	11	-0.0009	0.0008	-0.0024	0.0006	
24	12	0.0030	0.0012	0.0007	0.0052	*
24	13	0.0001	0.0011	-0.0021	0.0023	
24	14	0.0010	0.0049	-0.0084	0.0105	
24	15	-0.0043	0.0025	-0.0091	0.0005	
24	16	0.0082	0.0042	0.0000	0.0165	*
24	17	-0.0012	0.0046	-0.0102	0.0077	
24	18	0.0058	0.0037	-0.0014	0.0131	
24	19	0.0087	0.0015	0.0057	0.0117	*
24	20	0.0024	0.0024	-0.0023	0.0071	
24	21	0.0062	0.0050	-0.0035	0.0160	
24	22	0.0020	0.0018	-0.0015	0.0054	
24	23	-0.0039	0.0003	-0.0044	-0.0035	*
24	24	-0.0005	0.0009	-0.0022	0.0012	
24	25	0.0046	0.0051	-0.0052	0.0145	
24	26	0.0114	0.0119	-0.0119	0.0346	
24	27	0.0217	0.0046	0.0127	0.0307	*
24	28	0.0153	0.0062	0.0032	0.0274	*
24	29	0.0208	0.0080	0.0052	0.0363	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 5 Cajas in Ancash against control group 5</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0019	0.0009	-0.0038	-0.0001	*
24	3	-0.0028	0.0005	-0.0038	-0.0018	*
24	4	-0.0008	0.0009	-0.0026	0.0010	
24	5	-0.0009	0.0018	-0.0046	0.0027	

24	6	-0.0018	0.0004	-0.0027	-0.0009	*
24	7	-0.0064	0.0045	-0.0156	0.0027	
24	8	-0.0002	0.0014	-0.0031	0.0027	
24	9	-0.0026	0.0013	-0.0052	0.0001	
24	10	-0.0001	0.0051	-0.0103	0.0101	
24	11	-0.0020	0.0003	-0.0027	-0.0013	*
24	12	0.0017	0.0021	-0.0025	0.0059	
24	13	0.0012	0.0012	-0.0011	0.0036	
24	14	0.0023	0.0039	-0.0057	0.0102	
24	15	-0.0027	0.0014	-0.0055	0.0002	
24	16	0.0095	0.0042	0.0010	0.0180	*
24	17	0.0020	0.0046	-0.0072	0.0113	
24	18	0.0050	0.0037	-0.0025	0.0124	
24	19	0.0063	0.0031	0.0001	0.0125	*
24	20	0.0018	0.0016	-0.0013	0.0050	
24	21	0.0053	0.0050	-0.0048	0.0154	
24	22	0.0014	0.0012	-0.0009	0.0038	
24	23	-0.0042	0.0001	-0.0044	-0.0041	*
24	24	-0.0014	0.0004	-0.0023	-0.0006	*
24	25	0.0043	0.0051	-0.0060	0.0145	
24	26	0.0111	0.0119	-0.0130	0.0351	
24	27	0.0217	0.0046	0.0123	0.0310	*
24	28	0.0112	0.0031	0.0049	0.0175	*
24	29	0.0186	0.0055	0.0075	0.0298	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 6 Cajas in Ancash against control group 6</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0021	0.0008	-0.0037	-0.0006	*

24	3	-0.0015	0.0015	-0.0043	0.0014	
24	4	-0.0037	0.0012	-0.0060	-0.0013	*
24	5	-0.0004	0.0025	-0.0053	0.0045	
24	6	-0.0013	0.0009	-0.0029	0.0004	
24	7	-0.0059	0.0049	-0.0154	0.0036	
24	8	-0.0004	0.0013	-0.0029	0.0020	
24	9	-0.0029	0.0011	-0.0050	-0.0009	*
24	10	0.0013	0.0040	-0.0064	0.0090	
24	11	-0.0015	0.0007	-0.0028	-0.0002	*
24	12	0.0021	0.0018	-0.0015	0.0056	
24	13	0.0016	0.0018	-0.0018	0.0051	
24	14	0.0037	0.0029	-0.0019	0.0093	
24	15	-0.0020	0.0012	-0.0044	0.0004	
24	16	0.0079	0.0042	-0.0002	0.0161	
24	17	0.0023	0.0046	-0.0065	0.0112	
24	18	0.0038	0.0037	-0.0034	0.0109	
24	19	0.0044	0.0035	-0.0025	0.0112	
24	20	0.0008	0.0013	-0.0017	0.0034	
24	21	0.0062	0.0050	-0.0035	0.0158	
24	22	0.0013	0.0010	-0.0006	0.0032	
24	23	-0.0049	0.0005	-0.0058	-0.0040	*
24	24	-0.0022	0.0009	-0.0039	-0.0005	*
24	25	0.0032	0.0051	-0.0066	0.0130	
24	26	0.0097	0.0119	-0.0134	0.0328	
24	27	0.0213	0.0046	0.0123	0.0303	*
24	28	0.0140	0.0048	0.0046	0.0233	*
24	29	0.0211	0.0080	0.0057	0.0365	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 7 Cajas in Ancash against control group 7</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0015	0.0003	-0.0059	0.0029	
24	3	-0.0019	0.0012	-0.0169	0.0132	
24	4	-0.0005	0.0024	-0.0309	0.0300	
24	5	0.0004	0.0009	-0.0116	0.0123	
24	6	-0.0007	0.0003	-0.0043	0.0029	
24	7	0.0000	0.0008	-0.0097	0.0096	
24	8	-0.0002	0.0017	-0.0223	0.0219	
24	9	-0.0001	0.0010	-0.0130	0.0128	
24	10	-0.0037	0.0022	-0.0317	0.0244	
24	11	-0.0010	0.0007	-0.0096	0.0076	
24	12	0.0000	0.0008	-0.0105	0.0104	
24	13	0.0015	0.0015	-0.0177	0.0207	
24	14	-0.0029	0.0013	-0.0200	0.0142	
24	15	-0.0042	0.0020	-0.0292	0.0208	
24	16	0.0089	0.0042	-0.0446	0.0624	
24	17	0.0007	0.0045	-0.0566	0.0579	
24	18	0.0050	0.0021	-0.0219	0.0319	
24	19	0.0037	0.0031	-0.0353	0.0427	
24	20	0.0026	0.0016	-0.0173	0.0225	
24	21	0.0057	0.0050	-0.0579	0.0693	
24	22	0.0025	0.0008	-0.0074	0.0124	
24	23	-0.0045	0.0005	-0.0114	0.0025	
24	24	-0.0015	0.0009	-0.0125	0.0096	
24	25	0.0046	0.0016	-0.0158	0.0250	
24	26	0.0123	0.0020	-0.0132	0.0378	
24	27	0.0229	0.0005	0.0163	0.0295	*
24	28	0.0163	0.0041	-0.0353	0.0678	
24	29	0.0255	0.0031	-0.0133	0.0642	

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

Ica models

Model 1 Caja in Ica against control group 1

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0026	0.0003	-0.0029	-0.0022	*
24	3	0.0116	0.0012	0.0100	0.0132	*
24	4	0.0100	0.0024	0.0068	0.0133	*
24	5	-0.0098	0.0005	-0.0105	-0.0092	*
24	6	-0.0123	0.0003	-0.0127	-0.0120	*
24	7	-0.0053	0.0004	-0.0058	-0.0048	*
24	8	-0.0036	0.0019	-0.0062	-0.0010	*
24	9	0.0021	0.0010	0.0007	0.0034	*
24	10	-0.0052	0.0032	-0.0096	-0.0009	*
24	11	-0.0040	0.0011	-0.0054	-0.0025	*
24	12	0.0012	0.0011	-0.0002	0.0027	
24	13	0.0008	0.0009	-0.0004	0.0020	
24	14	-0.0044	0.0013	-0.0062	-0.0026	*
24	15	-0.0053	0.0013	-0.0070	-0.0036	*
24	16	0.0018	0.0009	0.0005	0.0030	*
24	17	-0.0043	0.0023	-0.0073	-0.0012	*
24	18	0.0006	0.0011	-0.0009	0.0020	
24	19	-0.0016	0.0022	-0.0046	0.0014	
24	20	0.0028	0.0009	0.0017	0.0040	*
24	21	0.0009	0.0007	0.0000	0.0018	
24	22	0.0040	0.0004	0.0034	0.0045	*
24	23	0.0033	0.0005	0.0026	0.0040	*
24	24	0.0020	0.0009	0.0008	0.0031	*
24	25	0.0008	0.0008	-0.0003	0.0019	
24	26	0.0364	0.0010	0.0350	0.0377	*
24	27	0.1266	0.0003	0.1263	0.1270	*

24	28	0.1506	0.0036	0.1457	0.1554	*
24	29	0.1652	0.0015	0.1631	0.1673	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 2 Caja in Ica against control group 2</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]
24	2	-0.0025	NA	NA	NA
24	3	0.0104	NA	NA	NA
24	4	0.0125	NA	NA	NA
24	5	-0.0103	NA	NA	NA
24	6	-0.0126	NA	NA	NA
24	7	-0.0057	NA	NA	NA
24	8	-0.0044	NA	NA	NA
24	9	0.0028	NA	NA	NA
24	10	-0.0050	NA	NA	NA
24	11	-0.0039	NA	NA	NA
24	12	0.0014	NA	NA	NA
24	13	0.0002	NA	NA	NA
24	14	-0.0057	NA	NA	NA
24	15	-0.0063	NA	NA	NA
24	16	0.0024	NA	NA	NA
24	17	-0.0056	NA	NA	NA
24	18	0.0016	NA	NA	NA
24	19	0.0005	NA	NA	NA
24	20	0.0037	NA	NA	NA
24	21	0.0006	NA	NA	NA
24	22	0.0042	NA	NA	NA
24	23	0.0038	NA	NA	NA
24	24	0.0028	NA	NA	NA

24	25	0.0016	NA	NA	NA
24	26	0.0374	NA	NA	NA
24	27	0.1269	NA	NA	NA
24	28	0.1501	NA	NA	NA
24	29	0.1643	NA	NA	NA

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NUL

<u>Model 3: Caja in Ica against control group 3</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0013	0.0019	-0.0066	0.0040	
24	3	-0.0021	0.0014	-0.0061	0.0020	
24	4	-0.0018	0.0013	-0.0055	0.0019	
24	5	0.0007	0.0013	-0.0029	0.0044	
24	6	-0.0018	0.0004	-0.0030	-0.0006	*
24	7	-0.0022	0.0041	-0.0139	0.0095	
24	8	0.0001	0.0015	-0.0041	0.0043	
24	9	0.0013	0.0016	-0.0032	0.0059	
24	10	0.0003	0.0054	-0.0152	0.0158	
24	11	-0.0033	0.0005	-0.0047	-0.0020	*
24	12	-0.0004	0.0025	-0.0076	0.0067	
24	13	-0.0018	0.0011	-0.0051	0.0015	
24	14	0.0036	0.0039	-0.0074	0.0147	
24	15	-0.0031	0.0013	-0.0069	0.0007	
24	16	0.0030	0.0012	-0.0003	0.0063	
24	17	-0.0011	0.0009	-0.0036	0.0013	
24	18	0.0021	0.0007	0.0001	0.0042	*
24	19	0.0021	0.0017	-0.0029	0.0070	

24	20	0.0026	0.0013	-0.0012	0.0063	
24	21	0.0053	0.0022	-0.0010	0.0116	
24	22	-0.0001	0.0009	-0.0027	0.0025	
24	23	0.0000	0.0013	-0.0036	0.0037	
24	24	-0.0007	0.0031	-0.0094	0.0080	
24	25	0.0025	0.0041	-0.0091	0.0141	
24	26	0.0080	0.0065	-0.0104	0.0265	
24	27	0.0338	0.0086	0.0092	0.0583	*
24	28	0.0328	0.0058	0.0162	0.0493	*
24	29	0.0345	0.0083	0.0108	0.0583	*

Signif. codes: `*' confidence band does not cover 0

Control Group: Not Yet Treated, Anticipation Periods: 0

Estimation Method: Doubly Robust

NULL

<u>Model 4: Caja in Ica against control group 4</u>

Group-Time Average Treatment Effects:

Group	Time	ATT(g,t)	Std. Error	[95% Simult.	Conf. Band]	
24	2	-0.0024	0.0002	-0.0026	-0.0022	*
24	3	0.0127	0.0010	0.0114	0.0140	*
24	4	0.0080	0.0021	0.0052	0.0108	*
24	5	-0.0094	0.0004	-0.0099	-0.0089	*
24	6	-0.0123	0.0004	-0.0129	-0.0118	*
24	7	-0.0050	0.0004	-0.0056	-0.0045	*
24	8	-0.0019	0.0002	-0.0021	-0.0016	*
24	9	0.0010	0.0003	0.0007	0.0014	*
24	10	-0.0071	0.0010	-0.0085	-0.0056	*
24	11	-0.0045	0.0004	-0.0050	-0.0040	*
24	12	0.0005	0.0003	0.0002	0.0009	*
24	13	0.0017	0.0003	0.0013	0.0021	*
24	14	-0.0031	0.0011	-0.0045	-0.0017	*
24	15	-0.0041	0.0005	-0.0048	-0.0033	*

```
   24   16   0.0021     0.0011        0.0005      0.0036 *
   24   17  -0.0020     0.0002       -0.0023     -0.0017 *
   24   18  -0.0004     0.0009       -0.0016      0.0008
   24   19  -0.0038     0.0014       -0.0057     -0.0019 *
   24   20   0.0021     0.0007        0.0011      0.0031 *
   24   21   0.0005     0.0007       -0.0003      0.0014
   24   22   0.0036     0.0001        0.0035      0.0037 *
   24   23   0.0029     0.0005        0.0022      0.0035 *
   24   24   0.0011     0.0006        0.0004      0.0019 *
   24   25   0.0002     0.0008       -0.0008      0.0012
   24   26   0.0357     0.0010        0.0343      0.0371 *
   24   27   0.1265     0.0003        0.1261      0.1269 *
   24   28   0.1487     0.0021        0.1460      0.1515 *
   24   29   0.1646     0.0018        0.1621      0.1671 *
---
Signif. codes: `*' confidence band does not cover 0

Control Group:  Not Yet Treated,  Anticipation Periods:  0
Estimation Method:  Doubly Robust
NULL
```

Annex C

R code attached to this thesis. Must copy the data set from Annex A using the clipboard function, that is already written in the code.