The impact of a drought on financial stability: evidence from Argentina[*]

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Abstract

We assess the impact of a drought on credit, risk and bank performance in Argentina, using credit registry data at the bank-firm level. We estimate difference-in- difference panel data models to measure whether the drought in 2022-23 had an impact on credit to firms and non-performing loans, controlling for banks and borrowers' features. We identify borrowers exposed to the shock as companies carrying out activities that suffered most from the drought: producers and exporters of soybean, corn and wheat. Our findings suggest that credit to firms exposed to the drought was 7 p.p. y-o-y lower (when measured at the bank-firm level) and 10 p.p. y-o-y lower than to firms not exposed to the event (in real terms in both cases). Non-performing loans (NPLs) to exposed firms increased close to 8 p.p. more than to unaffected firms. When considering staggered impact of the drought across firms, credit growth was even lower, while NPL increase was comparable. Credit supply decreased more to firms in sectors affected by the drought (by around 3 p.p.); it may have been influenced by regulation. But higher overall estimates suggest that factors other than regulation and those accounted for in firm and bank controls, individual and time fixed effects, were at play to reduce credit –namely the drought. We also look at bank performance following the drought, comparing banks which were more or less exposed to affected firms: their credit, liquidity, and NPLs. We find no significant differences in credit and NPLs for banks more exposed to the drought, weighted by credit size. Our results indicate that the drought had significant individual impacts on firms credit and their ex post risk, but no discernible systemic effect on banks.

JEL classification codes: C23, G21, E44

Key words: physical risks, credit registry data, difference-in-difference panel data models

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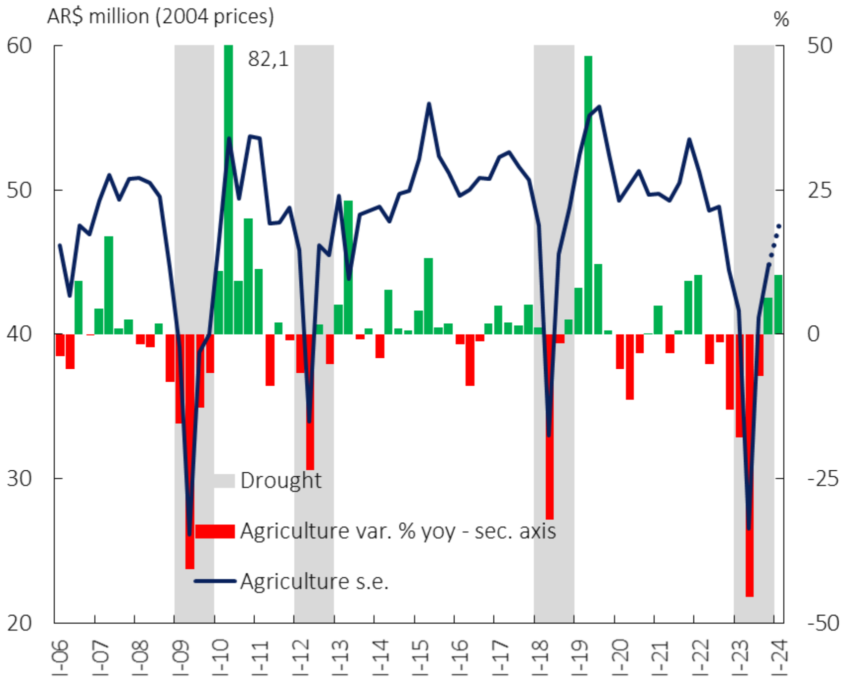
I. Introduction

As a commodity-exporting country, Argentina is subject to risks from weather events – that is, physical risks, in contrast to those stemming from mitigation or adaptation actions, called transition risks. Physical risks may weigh on households, firms, governments and their assets (including financial ones); they comprise weather events such as floods, droughts, hurricanes and extreme rainfall.

In Argentina, severe droughts have taken place in recent years, with adverse consequences on exports and growth. Critical episodes occurred in 2009, 2012, 2019 and 2022-23 (figure 1). The latest one stands out as it was the first time since 1988-89 that the *La Niña* phenomenon, which in Argentina translates into droughts, extended for three years. Starting in early 2022, droughts hampered agricultural production, exports and tax revenues (export taxes carry a significant share of revenues). Lack of rainfall affected the most fertile areas, such as those in the provinces of Buenos Aires, Santa Fe, Córdoba, San Luis and Entre Ríos: wheat production plummeted, while soybean and corn sowing was substantially delayed; this also took its toll on fruit production and cattle stock. Adverse weather conditions persisted and worsened into 2023, with droughts and early frosts that weighed heavily on the soybean and corn harvests. Agricultural GDP fell by 3% in 2022 and plummeted by 24% in 2023, involving a recession for the economy at large: GDP fell by 1.6 in 2023.

Figure 1. Argentina: droughts and agricultural GDP



What was the impact on the financial system? Simulations by BCRA (2023) suggest a limited one. Using the Central Bank of Argentina's credit registry (*Central de Deudores*), the exercise considers companies that export soybean, wheat and corn. They amounted to 17% of credit to the private sector by the third quarter of 2023; and their non-performing loan ratio was about 5,5%, compared to 3% of the whole banking system. The exercise then simulates the impact of three alternative scenarios of NPL increase on banks' regulatory capital position: simulations suggest little impact, as the position's excess over regulation stands at between 280% and 290%, and falls to 220% under the assumption that no companies in this segment will repay as committed –still, this shows that banking capital is more than double what is required by regulation.

In this paper, we go beyond simulation and aim to assess to what extent credit and non-performing loans were affected by the 2022-23 drought in Argentina, both at the firm and bank levels. We employ a difference-in-difference approach, using credit registry panel data on lending from banks to firms. We look at credit granted by banks to firms in the agricultural export sector (employing the sample indicated above) and to those in other sectors, before and after the drought; we include bank characteristics and, where possible, firm characteristics as well as individual and time controls. In addition, we look at each bank-firm observation's classification in terms of loan repayment (from regular to non-performing or delinquent). A similar approach is employed by Reinder et al (2021) to assess the effects of the 2010-2011 La Niña on the Colombian banking system (where they look at change in banks' provisions), and by Azañedo et al. (2025) to analyze the impact of climate risks on the local financial system, they find that increased exposure to climate shocks (droughts and floods) leads to higher loan provisions and a tightening of credit conditions in Perú, reflecting the elevated risk perceived by banks.

In order to ascertain any financial stability repercussions, we also look at bank performance following the drought, comparing banks which were more or less exposed to affected firms: their credit, liquidity, and non-performing loans. We assess whether exposure to affected firms leads to changes in financial system soundness, weighting banks by the size of their credit.

Our approach is related to works that look at how credit to firms changes depending on rainfall (in the regions where firms operate), extreme temperatures or fires, controlling by bank and firm-specific characteristics and macroeconomic factors. They also consider non-performing loans. Rodríguez Novoa (2022) and Oliveira (2022) analyze how changes in rainfall affect bank loan provisions in Colombia and Brazil, respectively: the former finds that lower than average rainfall increases bank loan provisions due to higher credit risk in affected regions; the latter, that extreme deviations in rainfall, both excess and shortage, lead to a rise in loan provisions and a contraction in a credit supply.

Brei et al. (2019) study the effect of hurricanes in the Caribbean using a panel data regression with a hurricane index to measure shocks. They find that after a hurricane, banks face deposit withdrawals and respond by reducing credit supply and resorting to liquid assets, though they do not observe increased loan defaults. In contrast, Branch et al. (2024) examine Bahamas, finding that hurricane increase loan default rates while decreasing credit supply. Alvarado et al. (2024) find that credit risk increases with rainfall in Costa Rica. Aguilar-Gómez et al. (2022) investigate how extreme temperatures influence delinquency rates in Mexico, their results show that extreme heat leads to higher delinquency rates, particularly for firms in temperature sensitive sectors.

Physical risks have also been analyzed in developed financial systems. Brown et al. (2021) study severe winter weather in the U.S., showing that firms respond by increasing credit line withdrawals, while banks adjust terms such as limits and interest rates. Koetter et al. (2019) analyze the response of banks in Germany to the Elbe floods of 2013. They find that local banks not directly affected by the flood increased their lending by 3% to firms in the affected areas, enabling a 16% rise in borrowing by these firms, without significant increases in credit risk or evidence of rent extraction. Alvarez-Roman et al. (2024) examine the impact of wildfires on banks in Spain. They find that wildfires lead to a reduction in credit supply, particularly by outsider banks, while local banks reduce lending less due to better access to soft information. This differential response does not result in higher non-performing loans.

In turn, all these works are part of a broader strand of literature on physical risks, the macroeconomy and the financial system, a survey of which would largely exceed the scope of this note. Noy (2009) highlights the immediate negative effects of disasters on macroeconomic indicators such as GDP and human capital, while also suggesting that with proper management, long-term recovery is possible. When it comes to the financial sector, Klomp (2014) finds that disasters tend to increase the probability of bank failures, especially in cases where financial regulation is weak and the economy is underdeveloped. This is particularly relevant for Argentina, as economic vulnerabilities may exacerbate the effects of the drought on banks' balance sheets. Moreover, Keerthiratne and Richard (2017) show that both households and businesses tend to increase their debt levels significantly after a natural disaster, with this effect being more pronounced in poorer countries. This finding aligns with our focus on firms in the agricultural sector, as we may see an uptick in credit demand following the drought. Gallagher and Hartley (2017), in their analysis of the financial consequences of Hurricane Katrina, note temporary increases in delinquency rates and credit card usage, which could serve as a parallel to the rise in non-performing loans we anticipate in the aftermath of the drought in Argentina.

The rest of the paper is organized as follows. Section II explains what basic descriptive statistics of the financial system tells us, and what basic meteorological data indicate about the episode under study. Section III describes our micro data sample and its information. Section IV presents the econometric model and its main results for credit and risk. Section V deals with bank performance; section VI summarizes further robustness checks. We conclude with the next steps and points for further research (section VII).

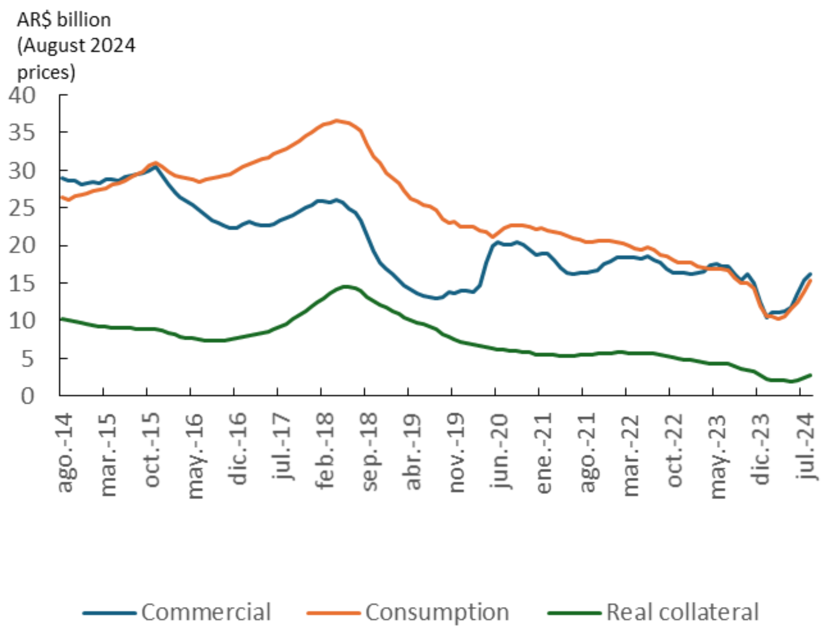
II. What aggregate data show

II.1 The financial system

In Argentina, the financial system is small, short-term and transactional; and it is largely bank-based. As a result of successive macroeconomic crises, savings in Argentina are channeled largely outside the financial system. By mid-2024, credit to the private sector was 5.7% of GDP, while the average for the past decade was 10.1%. This low level of credit is not due to recent cyclical episodes but reflects a structural trend since at least the early 2000s: credit in Argentina has remained stagnant while in other Latin American countries it has consistently grown.

Following the impact of the 2018-19 balance of payment crisis, credit in Argentine pesos to the private sector has posted a downward trend (Figure 2). However, the behaviour differs between credit to firms and households (commercial lines tend to correspond to the former, and consumption and collateral lines to the latter). Commercial credit grew countercyclically in 2020, due in large part to measures taken to counteract the effects of the pandemic. From February to October 2020, commercial credit grew by 45% in real terms, while total credit grew by 13% in the same period. But the former stagnated throughout 2021 and 2022, and then fell.

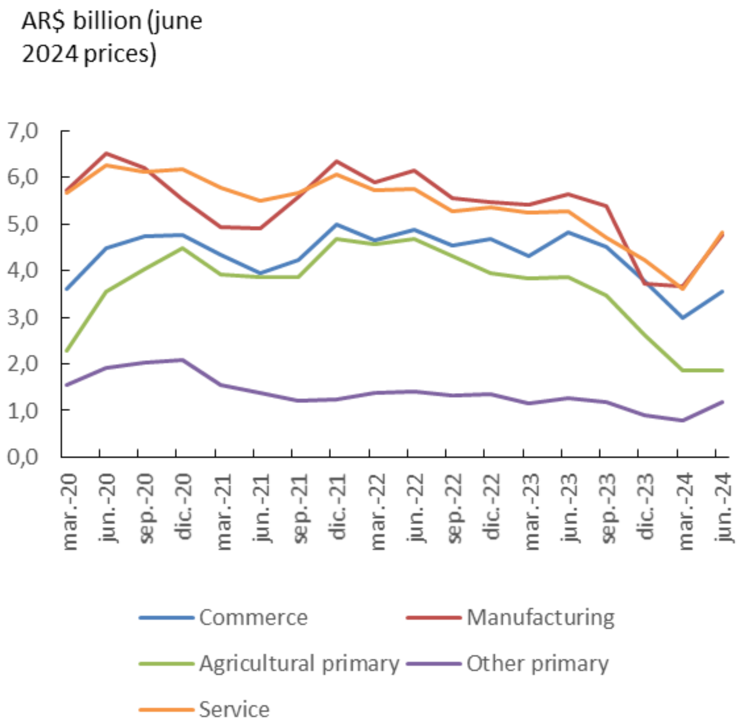
Figure 2. Credit in AR pesos to the private sector



These dynamics took place in a context of stagnating economic activity and accelerating inflation. GDP fell by 9,9% in 2020, recovered to 10,4% in 2021, grew by 5.2% in 2022, and then contracted by 1.6% in 2023. Inflation accelerated from 36,1% in 2020 to 50,9% in 2021, 94,8% in 2022 and 211,4% in 2023 (annual change in CPI).

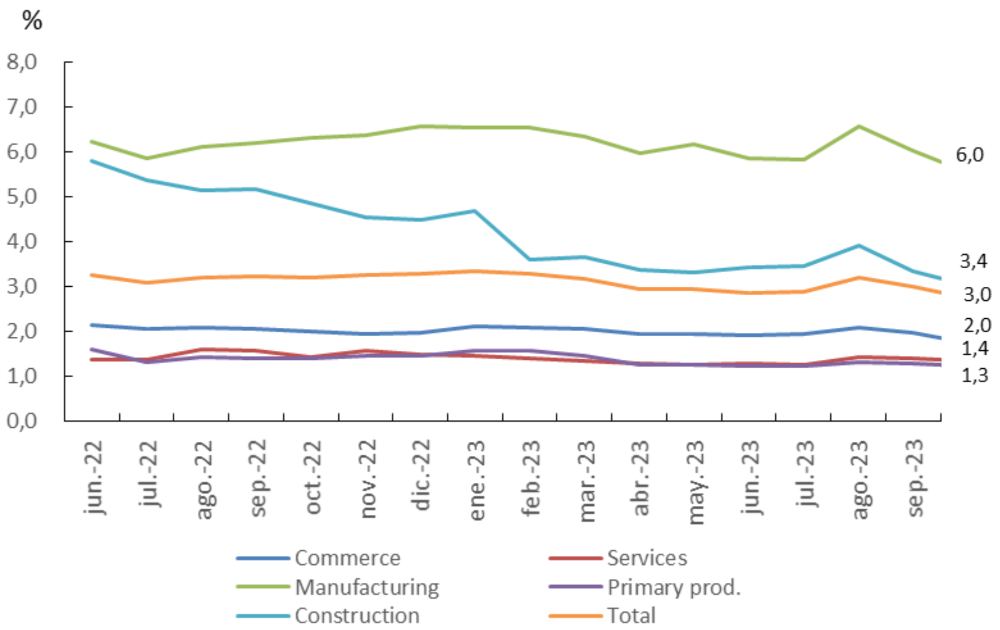
On top of this, the drought that affected Argentina between 2022 and 2023 had heterogeneous effects across sectors. Between September 2022 and September 2023, total credit to companies in local currency fell by 8.4%, but credit to primary production (agriculture, cattle and farming, etc.) doubled that figure: it dropped by 17.5%, with credit to services being the second most affected (-10.6%). Aggregate data suggest that the sector affected by the drought was hit harder than the rest of the sectors in response to the shock.

Figure 3. Loans by sector



The Argentine financial system is generally characterized by low non-performing loans (NPLs). By late 2023, the total NPL ratio was 3.0%. NPL in the primary sector stood at 1.3%, lower than the system average. Analyzing how the drought affected NPL in the system, there seems to be no differential response of NPLs in the primary sector or any other sector.

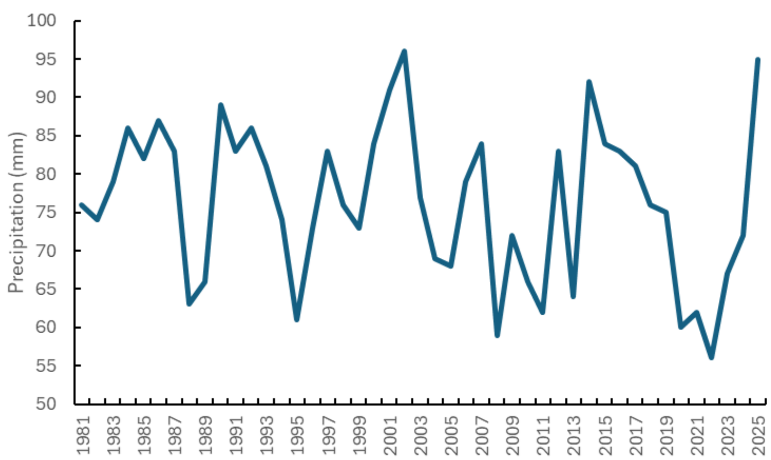
Figure 4. Non performing loans by sector



II.2 The 2022-2023 drought

In 2022, average annual precipitation (rainfall) in Argentina was the lowest on record since 1981 (figure 5). Indeed, the three years from 2020 to 2022 were the driest ones in recorded history. The central region of the country (that includes the *pampa húmeda*, where the most fertile land lies) suffered the driest conditions in sixty-two years. During 2022, the drought increased its severity: while the area affected by dry conditions were 55 million hectares in February, it more than doubled to over 140 million hectares in September.

Figure 5. Argentina: yearly average precipitation

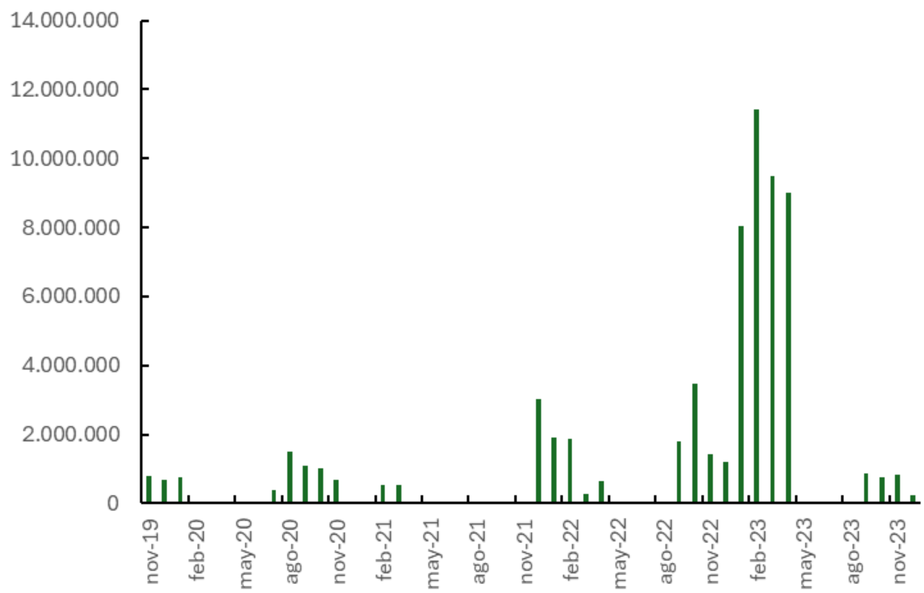


Source: IDB.

Drought conditions are determined by a combination of factors: rainfall, soil humidity, vegetation, hydrology (rivers) and impact on livestock and farming. Indeed, in September 2022 the level of such conditions increased to from “moderate“ to “severe” in 53 departments in the center of the country, taking an initial toll on wheat production with 1.8 million hectares affected (affected cultivation areas are estimated by a combination of: a) moderate and severe drought conditions; b) mediocre, poor or very poor production estimates); population at risk also went from zero in the previous month to over 1 million people. Affected surface, which had been zero in July and August, increased by a factor of 6 between September 2022 and January 2023 (figure 6). Drought also extended to other crops such as corn and soybean, first delaying the sowing and later slashing the harvest.

By February 2023, the drought already entailed “extreme physical severity”: in the so called “core zone” of agricultural production, soil humidity was at four-decade lows, with a hard impact on summer sowing (mainly soybean). In that month, surface under severe conditions increased by 19 million hectares: this meant a worsening of already affected areas, dealing a major blow on livestock, farming and population. Crop yields reached historical lows as reported by producers. While the peak in affected areas was reached in February, moderate and severe drought conditions in areas of the core zone were recorded until October 2023.

Figure 6. Agricultural production: area affected by the drought (moderate and severe)



Source: based on reports by *Dirección Nacional de Riesgo y Emergencia Agropecuaria (DNRyEA).*

III. What micro data show

Financial institutions regulated and supervised by the Central Bank of Argentina (BCRA) inform monthly outstanding credit balances of their debtors since 1996; this rich credit registry data is compiled and published by BCRA as *Central de Deudores*. Informing institutions include: banks (public, private domestic, foreign and branches), non-banking financial institutions (domestic and foreign), and credit companies (*cajas de credito*). Information provided by financial institutions *to Central de Deudores* comprises both debtor identification and credit characteristics. The former include whether it is physical or law person, its residency, whether it belongs to the private or public sector, its main economic activity, if it is a small or medium-sized enterprise, and whether it is a commercial or consumption debtor. Information on credit includes: amount in national currency (AR$); type of loan (overdraft, promisory note, pledge, mortgage, personal, credit card, among others); loan performance as classified by the lending institution, i.e. if it is performing or non-performing, ranked from 1 (normal) to 6 (write-off); guarantees; provisions; interest rate; maturity. It should be noted, however, that not all information is available for the whole database since its inception, as informational requirements have changed over time, and not all institutions inform the complete required set continuously.

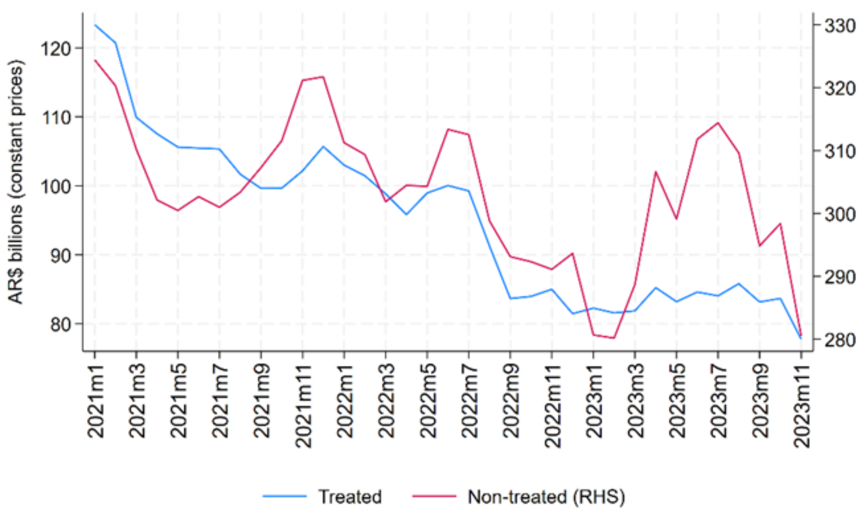
As of June 2024, there were over 15 million debtors of the financial system, of which 269.000 are law persons. The latter are typically taken to be companies; still, some of the physical persons in debt borrow for their small or medium sized companies. In what follows, we focus on companies as law persons.

As a first approximation to identifying debtors affected by droughts, we consider non-financial firms in the credit registry data based on three criteria: a) whether they are exporters of soybean, wheat and corn, as identified by tax records from the Argentina tax collection agency (AFIP); b) whether they export cereals or oilseeds and sell their proceeds in the local foreign exchange market, according to BCRA's records; c) whether their main activity declared in the credit registry data is agriculture and livestock. Companies that meet either of the three criteria are included in our sample as debtors that have been affected by adverse weather condition ("treated"). The rest of companies in the credit registry are considered as unaffected and part of the control group ("non-treated"). This is admittedly a crude and preliminary approach (the alternative would be to count on geolocalized data of both weather conditions and credit, which at this point we do not have; more on this later).

What do the data show? During 2022, when the drought started, outstanding credit to treated companies fell more, in real terms, than to non-treated ones; and in 2023, while outstanding credit to non-treated companies recovered substantially, treated companies credit stagnated (Figure 7, panel a). Indeed, treated companies credit decrease was more than double that of non-treated ones by end 2022; and, by mid-2023, once the full impact of the drought had been felt, non-treated companies growth was basically null, as compared to a 15% fall in real terms for treated companies. This is to say our micro data also suggests that companies in sectors more exposed to the drought saw their credit decrease substantially more than credit to companies less likely to have been affected by this weather event.

Figure 7. Credit registry data: companies affected and unaffected by the drought

(a) Outstanding credit to companies (in real terms).



(b) Credit to companies: change in real terms, Y-O-Y

IV. Econometric methodology and results

In order to assess whether the drought had any impact on credit at the bank-firm level, we employ a difference-in-difference approach. We take the whole set of relationships between financial institutions and non financial private sector firms in the Argentine financial system between January 2022 and November 2023. We then split the set in two groups: a) bank-firm relationships belonging to sectors affected by the drought, as defined following the three criteria outlined in section III; b) unaffected bank-firm relationships.

We take September 2022 as the date of impact of the drought, as at this point affected areas of agricultural production went from zero to almost 2 million hectares and increasing from that point onwards (section II.2). Basic descriptive statistics of the sample are summarized in Table 1 and annex 2. The table shows: mean and number of observations of the whole sample and of its partition in treated and non-treated firms, for both bank-firm level and firm-level data; and how each group faired in terms before and after the date of initial impact of the drought. We can see differences between treated and non-treated groups for the whole sample; and also that these widened sharply following the impact of the drought.

Table 1. Bank lending to firms, 2022-2023: descriptive statistics

Period	Statistics	Firm - Bank	
2022m1 - 2023m11	Mean	-6,212	
	Observations	5.769.804	
		Non treated	Treated
2022m1 - 2023m11	Mean	-5,073	-9,992
	Observations	4.433.698	1.336.106
2022m1 - 2022m8	Mean	-4,768	-3,713
	Observations	1.445.122	454.850
2022m9 - 2023m11	Mean	-5,221	-13,232
	Observations	2.988.576	881.256

Period	Statistics	Firm	
2022m1 - 2023m11	Mean	0,419	
	Observations	4.018.709	
		Non treated	Treated
2022m1 - 2023m11	Mean	1,765	-4,564
	Observations	3.163.625	855.084
2022m1 - 2022m8	Mean	1,109	3,067
	Observations	1.037.573	291.098
2022m9 - 2023m11	Mean	2,085	-8,502
	Observations	2.126.052	563.986

IV.I Credit growth

We employ panel data, difference-in-difference model. The basic regressions are as follows:

$$\begin{aligned}\Delta\, Credit_{{if}_t} &= \beta_0 + \beta_1 SHOCK_t + \beta_2 bank\ controls_{it} + \beta_3 firm\ controls_{ft} + \beta_5 D_{if} \\ &\quad + \beta_6 month_t + v_{ift}\end{aligned}$$

Where the dependent variable is the year-over-year (y-o-y) percentage change in real credit granted by bank *i* to firm *f* in month *t*, excluding outliers (values of the dependent variable in the upper 10th percentile). $SHOCK_t$ is a dummy variable defined as follows: it takes the value 1 for bank-firm relationships in the group affected by the drought since September 2022, and zero otherwise. We also include bank and firm controls: the former are each bank's liquidity ratio and return on equity; the latter, each debtor's classification according to the financial institutions they operate with. There are also time and bank-firm fixed effects. See annex I for data definitions and sources.

We estimate difference-in-difference panel data models for either a) bank-firm or b) firm-level data, and go from baseline to more complete specifications. For bank-firms, Model (1) is our baseline, a standard DID specification with time and bank-firm fixed effects. Model (2) includes bank and firms controls; model (3) includes all controls but excludes outliers of bank controls (values of liquidity ratios and ROE in the 1st and 99th percentiles). Using firm-level data (ie. aggregating credit granted to each firm by all banks), model (4) is our baseline, with time and firm-fixed effects; model (5) adds firm controls. Residuals are clustered by bank-firms (models 1-3) and by firms (models 4-5).

Results suggest a significant impact of the 2022-2023 drought on credit growth for the affected firms. The average treatment effect on the treated (ATET) is negative and highly significant across all presented models, indicating a contraction in credit following the drought for the companies most exposed to it (Table 2).

At the firm-bank level, results indicate that the drought reduced credit growth by approximately 7.8 to 7.4 percentage points (p.p.) y-o-y. with a marginal decrease in the effect's magnitude as more explanatory variables are added. In all cases, the effect is statistically significant at the 1% level.

When the analysis is performed at the firm level, an even stronger effect is observed. The drought reduced credit growth by 10.9 to 10.7 p.p. y-o-y. Once again, all coefficients are significant at the 1% level.

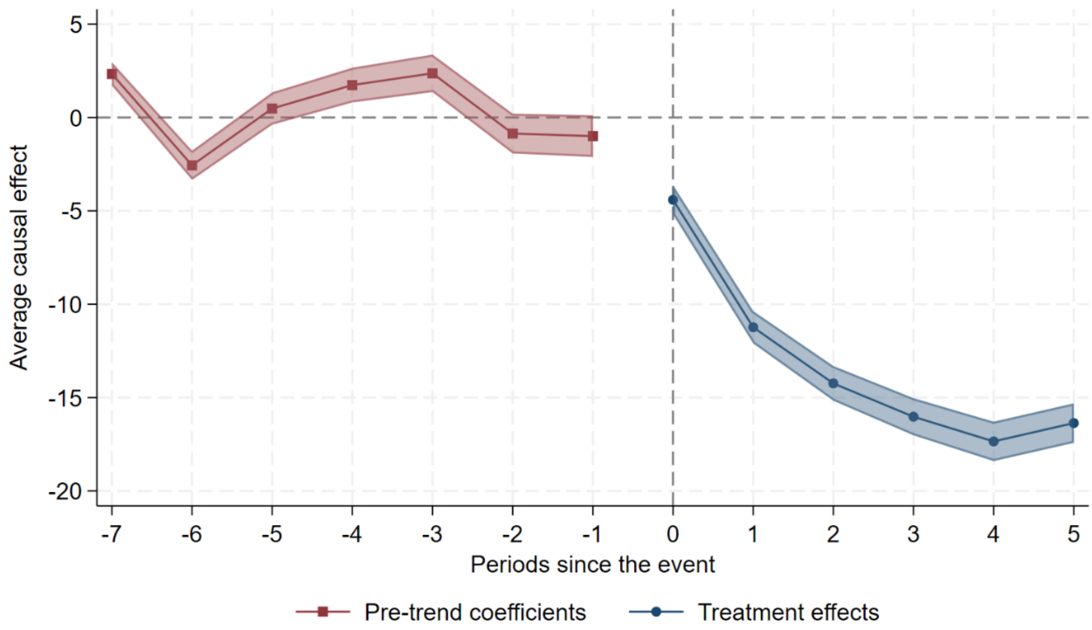
Table 2.
Credit growth following the impact of the drought starting in September 2022

	Dependent variable: credit growth (YoY%)				
	Firm - Bank			**Firm**	
	(1)	(2)	(3)	(4)	(5)
ATET	-7.7527***	-7.3911***	-7.3818***	-10.9500***	-10.6713***
	[0.3752]	[0.3755]	[0.3847]	[0.4783]	[0.4786]
Individual fixed effects	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES
Banks and firms controls	NO	YES	YES	NO	YES
Observations	5.769.804	5.769.804	5.599.509	4.018.709	4.018.709

Standard errors in brackets. Residuals clustered by bank-firms (1-3) and firms (4-5).
* p<0.10, ** p<0.05, *** p<0.01

In this type of models, a key concern is whether anticipation effects can be ruled out, and the assumption of paralell trends is satisfied. While checking the latter would actually demand testing a counterfactual, a number of alternatives have been developed. We employ here the imputed difference-in-difference estimator by Borusyak et al. (2024), which allows to estimate an "event study"-like coefficient of interest with leads and lags with respect to the date of impact. When we do so, we find significant differences between estimated coefficients before and after the drought starated affecting agricultural production. In the two months immediately prior to that impact, the estimated coefficient is zero; and it is close to that value in the preceding three moonths --and actually not different from zero five months before the impact (figure 8). Following the start of the impact of the drought, the coefficient turns negative and significant. Based on this evidence, we can rule out anticipation effects (or "pre-trends") for the purpose of our study, while assuming that the paralell trend assumption holds to a significant extent.

Figure 8. Pre-trend test: "event study"-type coefficients, before and after impact (September 2022)



IV.2 Credit risk (delinquency)

We go on to gauge the impact of the drought on credit risk, by looking at the change in non-performing loans (instead of total credit):

$$\Delta NPL_{{if}_t} = \beta_0 + \beta_1 SHOCK_t + \beta_2 bank\ controls_{it} + \beta_3 firm\ controls_{ft} + \beta_5 D_{if} + \beta_6 month_t + v_{ift}$$

Where the dependent variable is now the of the y-o-y change in non performing loans (NPLs) granted by bank i to firm f in month t (excluding outliers defined as in section IV.1); NPLs are delinquent loans as classified by banks (in situations 3, 4, 5 and 6: from arrears exceding 90 days to write-offs). The dependent variables are defined as in the previous subsection.

We also run the models for bank-firm and firm-level data: a baseline (standard DID, model 6); including bank and firm controls (model 7)); excluding outliers of bank controls. Models (8) and (9) are estimated using firm-level data (baseline and with firm controls, respectively). Residuals are clustered by bank-firms.

Results indicate the NPLs of bank-firms in activities exposed to the drought increased some 8.7 to 9.5 p.p. y-o-y more than those of firms not exposed (data at the bank-firm level); whereas for firms in sectors exposed to the drought, the rise in NPL was almost 5 p.p. more than for firms not exposed (data at the firm level), but this is not significant at conventional levels.

Table 3

NPLs' growth following the impact of the drought starting in September 2022

	Dependent variable: NPL credit growth (YoY %)				
	Firm - Bank			Firm	
	(1)	(2)	(3)	(4)	(5)
ATET	8.7056***	8.7651***	9.4514***	5.0489	5.0130
	[2.8235]	[2.8199]	[3.0141]	[4.0826]	[4.0781]
Individual fixed effect	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES
Banks and firms controls	NO	YES	YES	NO	YES
Observations	*112.057*	*112.057*	108.668	106.881	106.881

Standard errors in brackets. Residuals clustered by bank-firms (6-8) and firms (9-10).
* p<0.10, ** p<0.05, *** p<0.01

IV.3 Credit supply

One may wonder whether the decrease in growth was due to supply or demand factors. In order to identify supply, we restrict the sample to firms operating with multiple banks (Khwaja and Mian, 2008): in a firm-fixed effect setting, this allows to test whether a firm borrowing from two different banks experiences a larger decline in lending from one of them (that has suffered a shock to its liquidity supply); as the comparison is across banks for the same firm, the firm-fixed effect absorbs demand shocks specific to firms.

We estimate our models for credit growth (as defined in section IV.1) on this subsample of firms that work with more than one bank (Table 4). We consider bank-firm relationships for a baseline difference-in-difference specification (model 11) and including bank and firm controls (model 12): credit supply decreased following the drought, at an average rate that was 3,4 p.p. lower (y-o-y in real terms) for firm-bank relationships that were more exposed to the event. In order to include firm fixed effects for multiple firms, we employ high-dimensional fixed effects (models 13 and 14). For firms that were more exposed to the drought (summing up all credit they received), credit went down some 4 p.p. more than for non-treated firms. All results continue to be significant at a 1% level.

Table 4.

Credit supply growth following the impact of the drought starting in September 2022 (firms with multiple banks)

	Dependent variable: credit growth (YoY %)			
	DiD Panel		**HDFE**	
	(11)	(12)	(13)	(14)
ATET	-3.4254*** [0.4943]	-3.3811*** [0.4945]	-4.1298*** [0.4771]	-4.0478*** [0.4779]
Bank-firm fixed effect	YES	YES	YES	YES
Time controls	YES	YES	YES	YES
Bank and firms controls	NO	YES	NO	YES
Firm FE	NO	NO	YES	YES
Observations	*3.207.743*	*3.207.743*	3.197.819	3.197.819

Standard errors in brackets. Residuals clustered by bank-firms
* p<0.10, ** p<0.05, *** p<0.01

Identifying the impact on credit supply exceeds an analytical interest, as it may help us do away with possible confounding factors. Indeed, as from September 2022, the Central Bank of Argentina put in place regulations that entailed a higher lending interest rate for relatively large soybean producers: firms that kept stocks of soybean higher than 5% of their produce were charged a minimum lending interest rate set at 120% over the central bank policy rate. This regulation was in place until June 2024; thus, it coincides with the period that we identify as following the treatment (January 2023-December 2023). Other regulations were in place that entailed differential capital requirements for lending to firms that kept soybean stocks over 5%: but these were implemented in 2020 and unchanged during our sample period. Still, credit to soybean producers represents around 20% of our treated sample, so this could explain only part of the decrease in supply.

There were also regulations that could affect demand: since 2019, big exporting firms were limited in their access to credit in local currency. Above a certain threshold, they required BCRA approval to obtain such credit. This threshold was updated (increased) in June 2022. The marginal effect was to actually ease the regulatory constraint on big exporting firms, so –if anything- this should mean higher credit demand. In turn, since July 2022, soybean exporters had access to a differential exchange rate in order to sell the produce from their exports; there were complementary regulations concerning their deposit accounts. This meant a marginal easing effect on producers and an income effect; so it could mean, for part of our sample, lower incentives to demand credit.

Our interpretation of the results is as follows. Credit supply to firms exposed to the drought fell on average 3-4 p.p. more than to less exposed firms (as found in models 11-14). This may have been either due to the weather shock (as banks reduced credit to affected firms in view of their lower liquidity, for instance) or to the regulation change (as banks charged higher interest rates to larger exporting firms, which would amount up to 20% of credit in the treated group ;see annex III). Overall credit fell on average 8% more in firms exposed to the shock vis-à-vis untreated ones, due to both demand and supply factors. Hence, we can conjecture that factors other than regulation and those accounted for in firm and bank controls, individual and time fixed effects, were at play to reduce credit -the most salient one being the drought. A back-of-the-envelope calculation would suggest that, conditional on its impact being correctly identified, the drought entailed 6 p.p. lower credit y-o-y for firms that were exposed to it; this would be a conservative estimate of demand factors -a baseline to which part of the supply impact may be added.

Why would firms actually decrease demand in the presence of an adverse shock? Standard intertemporal optimization behaviour indicates that following a temporary decrease in revenues, firms should increase their demand for credit. Indeed, this is in keeping with findings for the US and Germany (see section I). However, this argument applies in the absence of credit frictions; when firms are rationed in credit markets, a negative shock to their revenues (and equity) typically means lower ability to collateralize, and hence lower access to credit. We consider the latter explanation squares better with the situation of Argentine firms, operating in an extremely shallow financial market and with very low credit penetration. (Higher or lower credit can also result in advanced systems: as pointed out by Brown et al., 2021, negative profitability shocks can lead to less use of credit lines due to covenant violations and bank monitoring, or higher use via a liquidity management mechanism).

There could be another explanation, yet to be explored: in 2023, both the national government and provinces affected by the draught declared "agricultural emergency", ; this envolved measures to support producers affected by the draught, including tax relief (at the national level) and local measures. While we have not quantified this impact, the amounts involved (around AR$ 13 billion in 2023, 13% of the Agricultural and Production Ministry budgets) do not appear particularly significant. The marginal effect on credit demand should be negative, so we leave for further work to factor this into the analysis.

A separate word goes to the macroeconomic situation. During the period, inflation was mounting, activity was falling, policy and market interest rates were increasing. All this is absorbed by time fixed effects (as they vary over time but not over individuals), but potential interactions of macroeconomic controls with banks or firms could be explored.

IV.4 Staggered impact of the drought

One natural concern with our analysis is that the drought may not have affected all firms at the same time. Indeed, available information indicates that certain crops were affected before others: the so called *cosecha fina* (wheat, oats, barley, rye) went through harsher conditions by around the third quarter of 2022, while the *cosecha gruesa* (corn, soybean) faced such conditions in a stark and definite way only in early 2023. Our database allows to identify the main activity of firms based mostly on what they declare to banks; they typically indicate whether their main product or crop. In addition to this, part of our database is based on tax data that classifies producers in soybean, wheat and corn. This is certainly an imperfect way of identifying firms' activities, as they may have more than one product, or their statement may not currently reflect their main output. It still is our best approximation to whether they were affected sooner or later by the drought. Roughly 40% of our sample is identified as producing wheat and other cosecha fina crops, and the rest are mostly producers of soybean, corn, or are not identified with the information currently available

To account for heterogeneity in the timing of impact across firms, we estimate staggered difference-in-difference panel data models following Borusyak et al. (2024). We take timing of the impact for wheat and other *cosecha fina* cereals to be September 2022, and for soybean, corn and the rest of the products, January 2023 (a date when all agricultural production was affected). We first consider credit growth: we continue to find that credit to affected firms was lower than to unaffected ones, in both statistical and economic terms (table 5); indeed, considering that the drought impacted different crops at different times suggests higher estimates of its likely impact on credit. We now find that, at the bank-firm level, credit was 11 p.p. y-o-y lower for firms belonging to sectors more exposed to the drought; at the firm level, the difference reaches almost 14 p.p..

Table 5.
Credit growth to firms following the staggered impact of the drought, 2022-23

	Dependent variable: credit growth (YoY %)				
	Firm-bank			**Firm**	
	(1)	(2)	(3)	(4)	(5)
ATET	-11.385*** [0.3778]	-10.983*** [0.3786]	-11.149*** [0.3871]	-13.936*** [0.4849]	-13.653*** [0.4852]
Individual fixed effect	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES
Banks and firms controls	NO	YES	YES	NO	YES
Observations	5.707.384	5.707.384	5.543.472	3.993.197	3.993.197

Standard errors in brackets.
* p<0.10, ** p<0.05, *** p<0.01

We then turn to ex-post credit risk as evidenced by non-performing loans (table 6). We find that NPLs increased more in firms belonging to affected sectors, at the bank-firm level The coefficient is similar to that found without considering differences in the timing of impact across firms.

Table 6

NPLs' growth following the staggered impact of the drought in 2022-23

	Dependent variable: NPL credit growth (YoY %)		
		Firm - Bank	
	(6)	(7)	(8)
ATET	5.7136** [2.3160]	5.1363** [2.3169]	6.2367*** [2.1055]
Individual fixed effect	YES	YES	YES
Time controls	YES	YES	YES
Banks and firms controls	NO	YES	YES
Observations	110.294	110.294	108.668

Standard errors in brackets. Residuals clustered by bank-firms (6-8)
* p<0.10, ** p<0.05, *** p<0.01

For further robustness checks, we run models with the timing of impact in January 2023 for all firms, and continue to find that credit growth decreased and NPLs increased more in affected firms. We also find comparable impacts on credit supply

V. Banks and financial stability

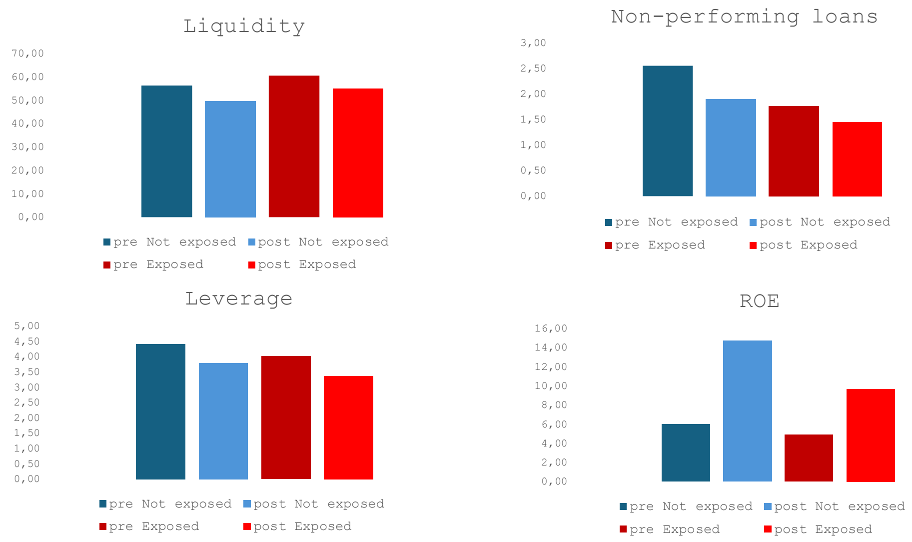
The preceding sections have shown a significant impact of the drought on credit and risk of individual firms and bank-firm relationships; but one may wonder whether there was any systemic impact. Were conventional financial soundness indicators affected? To this end, we look at banks' exposure to firms affected by the weather event, and compare key performance indicators such as leverage, liquidity, profitability and non-performing loans.

For the financial system as whole, average exposure to affected firms (as defined in section III) was 15%, with a 15% standard deviation. As a first step in the analysis, we consider banks whose outstanding credit to affected firms exceeded 25% during 2022-

2023. These are 12 banks which account for around 52% of outstanding credit balances in our sample; they comprise those institutions whose exposure to affected firms is above the 75% percentile of the distribution.

Median leverage, liquidity, profitability and non-performing loans decreased for both more exposed and less exposed banks (we consider median values as they are less influenced by outliers). As could be expected, liquidity decreased less in exposed banks, while leverage decreased more. As exposed banks lent more to affected firms, and these accessed less credit, it seems straightforward to find that their leverage was lower (and their liquidity higher). Along similar lines, ex post risk in exposed banks decreased less than in non-exposed ones. And profitability virtually doubled in exposed banks, but it almost tripled in lesser exposed ones. Both groups of banks went in the same direction, but exposed ones seem to have suffered somewhat more.

Figure 6. Banks' leverage, liquidty, profitability and non performing loans: exposed vs not exposed to firms affected by the drought.



In order to test whether these possibly differential reactions were significant, we estimate panel data difference-in-difference models at the bank level. We exclude outliers (values of the dependent variables in the upper 10th percentile). We first look at whether exposed banks' credit to firms was different than non-exposed ones, following the same steps as in section IV (table 7). We defined exposed banks as those described in the preceding paragraphs. We estimate models with time and bank effects (model 12 in table 7) and also bank and firm controls (model 13). We find no significant difference between both group of banks, on average, at 5% significance levels (the difference is significant only at 10% levels, and the coefficient, as expected, is negative).

Table 7
Banks' credit, liquidity and NPLs following the impact of the drought in September 2022

	Dependent variable: credit growth (%)		**Dependent variable: liquidity**		**Dependent variable: NPL credit growth**	
	Bank		**Bank**		**Bank**	
	(12)	(13)	(14)	(15)	(16)	(17)
ATET	-5,5246 [10,0542]	-7,5340 [9,7710]	15,6074* [8,6575]	13,8123* [7,6406]	69,1883 [48,9449]	84,3601 [57,2005]
Individual fixed effect	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES
Additional controls	NO	YES	NO	YES	NO	YES
Observations	*1.351*	1.351	1.363	1.363	1.166	1.166

Standard errors in brackets.
* p<0.10, ** p<0.05, ***p<0.01

We also look at whether exposed banks' liquidity differed from that of non-exposed ones (table 7). There is a positive difference on average between both groups in the baseline adn full specifications (model 14 and 15), but only significant at 10% levels. As expected, the difference is positive: exposed banks accumulated on average more liquidity (as they are lending less), but we do not find this to be significant.

Finally, we look at whether ex-post risk as evidence by non-performing loans increased more in exposed banks (table 7, models 16 and 17). NPLs are the average for each bank in the sample. We find no significant difference between both groups of banks (with or without bank and firm controls).

Since our main concern in this section is with a systemic event, we perform the same exercises but weighting banks according to their size. We weight them by their average lending to firms in 2022-2023. Once again, we consider banks that lent more to firm exposed to the drought, compared to those who lent less. And estimate difference-in-difference panel data models to compare both groups along three dimensions: credit growth, liquidity and non-performing loans. As usual, the baseline specification is with time and bank fixed effects, while a second one includes bank and firm controls. Results are summarized in table 8.

Once we weight banks by the size of their lending over the sampling period, we find no statistically significant differences between exposed and non-exposed banks when it comes to credit (models 18 and 19), and to non-performing loans (models 22 and 23). Exposed banks also had more liquidity, at a 5% level of significance (models 20 and 21).

Table 8
Banks' credit, liquidity and NPLs following the impact of the drought, 2022-23, weighted by banks outstanding credit

	Dependent variable: credit growth (%)		**Dependent variable: liquidity**		**Dependent variable: NPL credit growth**	
	Bank		**Bank**		**Bank**	
	(18)	(19)	(20)	(21)	(22)	(23)
ATET	-9,7588 [7,3163]	-9,2061 [6,6945]	4,0763** [1,7921]	4,0727** [1,8426]	0,0230 [13,4860]	6,0243 [14,3164]
Individual fixed effect	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES
Additional Controls	NO	YES	NO	YES	NO	YES
Observations	*1.351*	1.351	1.423	1.423	1.166	1.166

Standard errors in brackets.
* p<0.10, ** p<0.05, ***p<0.01

Our results point in the direction that credit, liquidity and NPLs at the bank level were not significantly affected by the drought. Whereas at the average firm and bank-firm level we have found a significant impact (sections III and IV), there is hardly any such impact at the bank level, either on average or weighting by their size. This is consistent with the view that the drought was not a financial stability event in Argentina (BCRA, 2023): it weighed substantially on individual firms, but this did not translate into bank peformance either at the financial institution or systemic level. To be sure, the drought entailed a recession for the economy at large, and aggregate credit fell, but: a) banks that had lent more to firms affected by the drought did not show different credit or NPL performance than those that had lent less; b) aggregate financial system soundness indicators did not worsen, with capital and liquidity buffers staying at comfortable levels. Our findings provide systematic evidence (a) to underpin expert judgement or anecdotal evidence (b).

VI. Further robustness checks

We have already shown that qualitative results hold if we assume a staggered impact of the drought. It could be argued that the drought properly speaking started later , when there was no doubt that conditions had irreversibly turned against agricultural production; we mean "irreversibly" as in such productions, sometimes a dry season is soon interrupted by rainfall, and production takes place. By January 2023, drought conditions had worsened in this way. We run the same models as in sections IV and V, but changing the date of impact to January 2023, and so we look at: change in credit growth, change in credit supply, change in NPL growth, from the point of view of bank-firm and pairs and firms. And we assess the impact on banks, looking at changes in liquidity, credit growth and NPLs, both for the average bank and for banks weighted by credit size. All qualitative results hold: credit growth decreased for the average affected bank-firm and firm following the impact of the drought, and so did credit supply; NPLs grew more for affected bank-firms and firms; and the bank level, credit decreased and NPLs increased, especially for banks weighted by credit size; while there was an impact on liquidity but only at the 10% significance level. Results are presented in annex VI.

VII. Concluding remarks

We aim at estimating the impact of the 2022-23 drought on commercial credit growth and credit risk in Argentina at the bank-firm level. Using credit registry data that covers the universe of Argentine firms indebted to the financial systema under BCRA regulation and supervision, we estimate difference-in-difference panel data models. We look at: I) firms and bank-firm relationships; II) banks.

I) Our database allows us to identify companies that were more or less exposed to the drought based on whether they are producers and/or exporters of the crops that were more or less affected. Our control group is the rest of the companies. We enquire whether a) credit growth and b) non-performing loans changed following the drought in treated vis-a-vis non treated companies. We also identify changes credit in supply.

We find that:

- credit suffered, as firms more exposed to the drought saw their credit decrease by around 7 p.p. y-o-y in real terms at the bank-firm level and around 10 p.p. at the firm level.
- Ex-post credit risk increased. Non-performing loans of firms more exposed to the drought increased by around 8 p.p. y-o-y more than that of other firms (at the bank-firm level) and close to 5 p.p. at the firm level (but the latter coefficient was not statistically significant).
- Credit supply decreased more to firms in sectors affected by the drought (by around 3 p.p.). Supply might have been influenced by other factors, such as regulation in place during the same period of the drought.

But higher overall estimates (including supply and demand), suggest an effect that worked through credit demand, most likely linked to the drought -with a baseline estimate of 7 p.p. lower credit y-o-y. We conjecture that as the drought worsened firms' prospects and net equity, they reduced their demand for credit. To this, supply factors unrelated to regulation but related to the drought could be added (not higher in size than 3 p.p.).

When considering a staggered impact of the drought, results for credit and NPLs continue to show significant values, and are actually higher in size.

Our results are averages for bank-firm relationships and firms in our sample. In order to capture systemic effects potentially relevant for financial stability, we turn to the following exercise.

II) While the average firm was hit in terms of credit and risk, we look at how banks fared in the face of the drought. We find that, on average and weighting by bank credit stock size:

- banks more exposed to the drought did not lent significantly less to firms;
- and they were not significantly more risky than banks that lent less to exposed firms (ex post risk as reflected in NPL growth).
- Banks that lent more to firms exposed to the drought accumulated more liquidity up to a 5% level of significance.

These findings provide some statistical evidence for ruling out a financial stability event. This complements both expert judgement and anecdotal evidence, according to which there was no such event (BCRA, 2023).

Our strategy is, at best, an acceptable first step toward identification of weather events' impact, based on companies' activities. But other approaches are feasible and desirable.

We plan to extend the analysis in two ways. The first one is by improving the current approach. The first step is to deal, where possible, with potentially confounding factors, controlling for central bank and fiscal measures takent during the estimation period. We also plan to incorporate other bank and (if possible) firm controls, and their possible interaction with macroeconomic variables. We would also like to extend the period of analysis to account for other droughts in recent decades.

The second way is by changing the identification strategy and basing it in the geographical area where businesses operate. The latter is especially demanding since location is included in our credit registry data, but it refers to companies' headquarters, not necessarily to the place where actual operations are carried out; we will have to adapt georeferences to indicate actual business operations. Moreover, we need to employ weather data at regional level. We may incorporate these changes depending on data availability.

Finally, our results could be contrasted with those of other countries based on comparable exercises. In a follow-up project, we may run baseline models as the ones presented here, around relevant weather events in other jurisdictions. We may then perform a meta-regression analysis in order to obtain general results for Latin America and the Caribbean (see Gambacorta and Murcia Pabón, 2020, for an illustration). We expect then to obtain more robust and general findings on how weather events impact financial stability in our region.

References

Aguilar-Gomez, S., Gutierrez, E., Heres, D., Jaume, D. and Tobal, M. (2022): "Thermal Stress and Financial Distress: Extreme Temperatures and Firms' Loan Defaults in Mexico", Working Papers 148, Red Nacional de Investigadores en Economía (RedNIE), August.

Alvarado, I., Barquero, J. and Sancho, C. (2024): "Assessment of the Banking Sector's Exposure to Hydrometeorological Events in Costa Rica," presented at the Fourteenth Annual BIS CCA Research Conference, Central Bank of Colombia, December.

Alvarez-Roman, L., Mayordomo, S., Vergara-Alert, C. and Vibes, X. (2024): "Climate risk, soft information and credit supply", Banco de España, Working paper No. 2406.

Azañedo, P.L., L.A. Casaverde, D.A. Casiano and J. Lupú (2025): "Delinquency rate in the Peruvian agro-export sector in the context of the El Niño Phenomenon: Firm-level evidence for the period 2013–2019," *Latin American Journal of Central Banking*, in press.

BCRA (2023): "Una aproximación al impacto de los riesgos climáticos físicos sobre el sistema financiero local", *Apartado* 4 in *Informe de Estabilidad Financiera*, December.

BCRA (2024): *Informe sobre Bancos*, June.

Borusyak, K., Jaravel, X. and Spiess, J. (2024): "Revisiting event study designs: robust and efficient estimation," *Review of Economic Studies,* 91, 3253-3285.

Branch, S., Dames, L., Rolle, N., Ward, L. and Wright, A. (2024): "Estimating the Impact of a Climatic Shock on Credit Supply and the Probability of Default in The Bahamas," presented at the Fourteenth Annual BIS CCA Research Conference, Central Bank of Colombia, December.

Brei, M., Mohan, P. and Strobl, E. (2019). "The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean." The Quarterly Review of Economics and Finance, 72, 232–239:

Brown, J. R., Gustafson, M. T., and Ivanov, I. T. (2021): "Weathering Cash Flow Shocks". *The Journal of Finance*, 76(4), pp. 1731-1772.

Gambacorta, L. and Murcia-Pabón, A. (2020): "The impact of macroprudential policies in Latin America: An empirical analysis using credit registry data", Journal of Financial Intermediation, Volume 42

Khwaja, A, and A Mian (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market." *American Economic Review*, 98 (4): 1413–42**.**

Koetter, M., Noth, F., and Rehbein, O. (2019): "Borrowers under Water! Rare Disasters, Regional Banks, and Recovery Lending." *Journal of Financial Intermediation*, 39, 101310.

Oliveira, G. R. (2022): "Effects of climate on bank default", Revista Brasileira de Climatologia 21, pp. 106-123, June.

Reinders, H. J., Regelink, M. G. J., Calice, P. and Uribe, M. E. (2021): "Not-So-Magical Realism : A Climate Stress Test of the Colombian Banking System". *Equitable Growth, Finance and Institutions Insight Washington, D.C. : World Bank Group, September.*

Rodriguez Novoa, D. (2022): "Do weather shocks affect banks' loan portfolio? Evidence from Colombia". MA dissertation, *Universidad del Rosario*.

Annex I. Data description and sources

Variable	Description	Source
Consumer price index	National CPI, monthly index (base: 2016=100)	INDEC
Credit ift	Outstanding credit of bank b to firm i, monthly data, deflated by CPI	Central de deudores BCRA
Return on equity	Return on bank equity (annual nominal rate), monthly data	Informacion de entidades financieras BCRA
Liquidity	Coverage ratio of deposits and call loans taken with quickly realizable assets, monthly data	Informacion de entidades financieras BCRA
Agricultural GDP	Agricultural GDP, quarterly (AR$ million 2004 prices)	INDEC
Credit in AR pesos to the private sector	Credit in AR pesos to the private sector, monthly seasonally adjusted (AR$ billion august 2024 prices)	BCRA
Loans by sector	aggregate credit by sector, quarterly (AR$ million june 2024 prices)	BCRA
Non performing loans by sector	aggregate irregular credit by sector, monthly	BCRA

Annex II. Descriptive statistics. For baseline model (without firm and bank controls, sample 1) and models with bank and firm controls (sample 2).

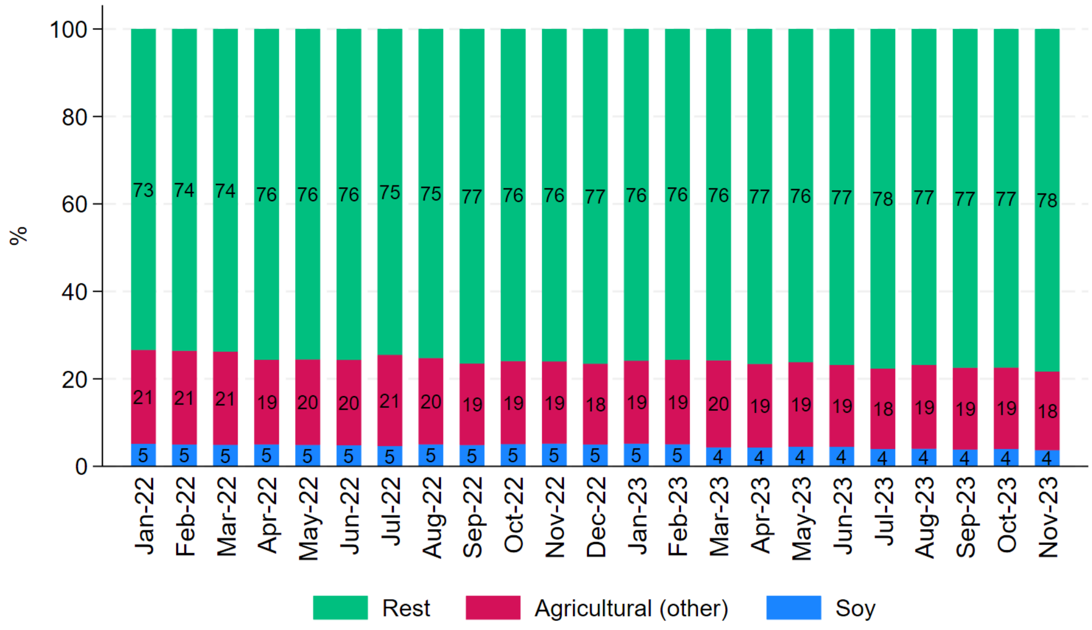
Sample 1: excludes the top 10% of YoY % change in credit

Variable	Obs	Mean	Std. dev.	Min	Max
YoY % change in credit	5.769.804	-6,21	88,8	-100,0	378,2
Credit situation	5.769.804	1,14	0,7	1	5
ROE	5.769.804	12,02	9,4	-237,1	70,8
Liquidity	5.769.804	74,62	437,2	0	14.089,1

Sample 2: excludes the top 10% of YoY % change in credit,
as well as the 1st and 99th percentiles of roe and liquidity.

Variable	Obs	Mean	Std. dev.	Min	Max
YoY % change in credit	5.599.509	-5,38	89,0	-100,0	378,2
Credit situation	5.599.509	1,14	0,7	1	5
ROE	5.599.509	12,57	6,9	-30,2	29,0
Liquidity	5.599.509	54,55	12,0	13,9	98,0

Annex III. Sectoral shares in total outstanding credit



Annex IV. Identification source of firms for the firm-level model

	Source	Criterion	# Firms
Treated	Credit Registry (BCRA)	Main activity: agriculture and livestock	43.537
	Tax collection agency (AFIP)	Exporters of soybean, wheat and corn	308
	FX market registry - BCRA	Exporters of cereals or oilseeds selling proceeds in local FX market (MULC)	5.756
Non-treated			223.592
Total number of firms (non financial private sector)			**273.193**

Annex V. Summary of studies on the impact of weather shocks on credit and banking

Authors	Country	Methodology	Variable	Evidence	Coefficients
Reinder et al. (2021)	**Colombia**	DiD	Bank loan provisions	The 2010-2011 La Niña event in Colombia led to increased bank provisions due to a deterioration in asset quality.	Each percentage point of GDP lost due to flood damages causes an increase of 0.12 percentage points in loan provisions.
Azañedo et al. (2024)	**Peru**	DiD	Bank loan provisions	Climate risks such as droughts and floods increase bank loan provisions and tighten credit conditions due to heightened risk perception.	The results indicate that there is an increase in the late payment of agro-exporting companies (average effect of approximately 1.3 percentage points)
Rodríguez Novoa (2022)	**Colombia**	Fixed effect panel regression	Bank loan provisions	Lower-than-average rainfall increases bank loan provisions in Colombia due to higher credit risk in affected regions.	Each additional day of heavy rain in the current quarter increases loan provisions in the agricultural sector by 0.054 pp.
Oliveira (2022)	**Brazil**	Fixed effect panel regression	Bank loan provisions and credit supply	Extreme deviations in rainfall (both excess and shortage) in Brazil lead to higher loan provisions and reduced credit supply.	A 1-standard deviation change in rainfall leads to a 0.8% increase in default rate.
Aguilar-Gómez et al. (2022)	**Mexico**	Fixed effect panel regression	Delinquency rate	Extreme temperatures in Mexico raise delinquency rates, particularly in heat-sensitive sectors.	One unusual day of extreme temperature per quarter increases the delinquency rate of SMEs by 0.012 percentage points.
Alvarez-Roman et al. (2024)	**Spain**	Fixed effect panel regression	Bank loan provisions and credit supply	They find that wildfires lead to a reduction in credit supply, particularly by outsider banks, while local banks reduce lending less due to better access to soft information.	After wildfires, local banks reduce credit less than outsider banks (0.324). The increase in lending does not raise non-performing loans.
Brown et al. (2021)	**United States**	Two Stage Least Square	Credit supply and interest rate	Severe winter weather in the U.S. leads firms to increase credit line withdrawals, while banks adjust credit limits and interest rates.	Firms affected increase credit line drawdowns by 50 cents per $1 lost (-0.524). Banks respond by raising credit limits (-0.526) and charging higher interest rates. These effects are strongest for firms with less than $100 million in assets

Annex VI. Robustness checks.

Table A1.
Credit growth following the impact of the drought in 2023

	Dependent variable: credit growth (YoY %)				
	Firm - Bank			**Firm**	
	(1)	(2)	(3)	(4)	(5)
ATET	-5.653***	-5.468***	-5.662***	-8.091***	-7.839***
	[0.3571]	[0.3578]	[0.3649]	[0.4577]	[0.4579]
Individual fixed effects	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES
Banks and firms controls	NO	YES	YES	NO	YES
Observations	5.769.804	5.769.804	5.599.509	4.018.709	4.018.709

Standard errors in brackets. Residuals clustered by bank-firms (1-3) and firms (4-5)
* p<0.10, ** p<0.05, *** p<0.01

Table A2

NPLs' growth following the impact of the drought in 2023

	Dependent variable: NPL credit growth (YoY %)				
	Firm - Bank			**Firm**	
	(6)	(7)	(8)	(9)	(10)
ATET	5.8125***	5.3315***	6.2367***	6.8465*	6.8234*
	[1.9518]	[1.9582]	[2.1055]	[3.7363]	[3.7323]
Individual fixed effect	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES
Banks and firms controls	NO	YES	YES	NO	YES
Observations	112.057	112.057	108.668	106.881	106.881

Standard errors in brackets. Residuals clustered by bank-firms (6-8) and firms (9-10)
* p<0.10, ** p<0.05, *** p<0.01

Table A3.

Credit supply growth following the impact of the drought in 2023 (firms with multiple banks)

	Dependent variable: credit growth (YoY %)			
	DiD Panel		**HDFE**	
	(11)	(12)	(13)	(14)
ATET	-1.6031***	-1.6607***	-2.1771***	-1.9244***
	[0.4681]	[0.4691]	[0.4510]	[0.4517]
Bank-firm fixed effect	YES	YES	NO	NO
Time controls	YES	YES	YES	YES
Banks and firms controls	NO	YES	NO	YES
Firm FE	NO	NO	YES	YES
Observations	3.207.743	3.207.743	3.197.819	3.197.819

Standard errors in brackets. Residuals clustered by bank-firms

* p<0.10, ** p<0.05, *** p<0.01

Table A4

Banks' credit, liquidity and NPLs following the impact of the drought, 2022-23

	Dependent variable: credit growth (%)		**Dependent variable: liquidity**		**Dependent variable: NPL credit growth**	
	Bank		**Bank**		**Bank**	
	(12)	(13)	(14)	(15)	(16)	(17)
ATET	-17.4805*	-17.1165*	11.7791*	10.0833	-23.0458	-10.5287
	[9.5570]	[9.1717]	[6.8085]	[6.2376]	[29.1289]	[25.6407]
Individual fixed effect	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES
Aditional Controls	NO	YES	NO	YES	NO	YES
Observations	649	649	1381	1381	555	555

Standard errors in brackets * p<0.10, ** p<0.05, ***p<0.01

Table A5
Banks' credit, liquidity and NPLs following the impact of the drought, 2022-23, weighted by banks outstanding credit

	Dependent variable: credit growth (%)		**Dependent variable: liquidity**		**Dependent variable: NPL credit growth**	
	Bank		**Bank**		**Bank**	
	(18)	(19)	(20)	(21)	(22)	(23)
ATET	-4.8285	-4.3039	4.0816*	3.8757*	-12.5306	-9.3622
	[4.7835]	[5.0569]	[2.2228]	[2.2511]	[21.8296]	[24.6698]
Individual fixed effect	YES	YES	YES	YES	YES	YES
Time controls	YES	YES	YES	YES	YES	YES
Aditional Controls	NO	YES	NO	YES	NO	YES
Observations	649	649	1381	1381	555	555

Standard errors in brackets * p<0.10, ** p<0.05, ***p<0.01