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Abstract

We study whether the process of desertification in Spain has an impact on the volume of credit granted to Spanish non-financial corporations (NFCs). To this end, we use a panel data model at the municipal level from 1984 to 2019 for bank loans obtained from the Banco de España's central credit register, where the main explanatory variable is the aridity index. Given that aridity is a long-term climatic phenomenon, we also estimate the model with local projections (Jordà, 2005) to disentangle the impact of aridity on credit to NFCs over longer horizons. Consistent with the literature, we find that higher aridity leads to lower credit to firms, at both short and long-term horizons. We also show that the effect of aridity on credit is sector-specific and depends on the climate zone. Credit to the agricultural sector is most negatively affected by this climatic hazard, while this phenomenon leads to more credit to the tourism sector in the most humid regions.

Keywords: climate change, credit, aridity index, non-financial corporations, panel data model, local projections.

JEL classification: Q54, Q51, C33, E51.

Resumen

Este trabajo analiza en qué medida el gradual proceso de desertificación que sufre el territorio español afecta al volumen de crédito concedido a las sociedades no financieras (SNF) españolas. Para explicar los determinantes de los préstamos bancarios, obtenidos de la Central de Información de Riesgos (CIR) del Banco de España, se estima un modelo de datos de panel a escala municipal desde 1984 hasta 2019 cuya principal variable explicativa es un índice de aridez. Dado que la aridificación es un fenómeno climático con impacto a largo plazo, también se estima el modelo mediante proyecciones locales (Jordà, 2005). Ello permite cuantificar el impacto de la aridez en el crédito a las SNF a lo largo de horizontes temporales más amplios. En línea con la literatura existente, se concluye que una mayor aridez se asocia a un menor volumen de crédito a las empresas, tanto a corto como a largo plazo. Al mismo tiempo, el efecto de la aridez sobre el crédito varía por sectores y depende de la zona climática. El crédito al sector agrícola es el que se ve afectado de una manera más negativa por este riesgo climático, mientras que este fenómeno aumenta el crédito al sector turístico en las regiones más húmedas.

Palabras clave: cambio climático, crédito, índice de aridez, sociedades no financieras, modelo de datos de panel, proyecciones locales.

Códigos JEL: Q54, Q51, C33, E51.

1 Introduction

Although climate change poses a global threat to both the real economy and the financial system,[1] the analysis of its economic and financial implications remains an open field of research. This article focuses on the impact of desertification on lending to Spanish non-financial corporations (NFCs). Desertification is defined as the process of land degradation in arid, semiarid and dry subhumid areas, resulting from many factors, including human activities and climatic variations (United Nations, 1994).[2] Desertification is a phenomenon of growing importance, as evidenced by the fact that the extent and intensity of this process have increased in some drylands in recent decades (Intergovernmental Panel on Climate Change (IPCC), 2019). Like other physical hazards, desertification can have important economic and financial consequences. For example, it can lead to resource depletion and the relocation of households out of the affected area, among other socio-economic changes. In turn, these effects could have an indirect impact on banks by affecting economic growth and ultimately the creditworthiness of borrowers (BCBS, 2021).

Spain is one of the most vulnerable European countries to desertification, with almost three quarters of its territory classified as drylands prone to this phenomenon (Ministerio para la Transición Ecológica y el Reto Demográfico, 2022). Therefore, understanding the economic impact of this climate hazard can help formulate effective policies to address it. From an empirical point of view, Spain is an interesting country to analyze the economic impact of desertification for at least two reasons. First, aridity in Spain shows a remarkable variability over time. Desertification has worsened significantly over the last 50 years due to the growing influence of global warming, the intensification and transformation of agriculture and the imbalance between rural/urban and inland/coastal areas (Martínez-Valderrama et al. 2022),[3] although this evolution has been uneven across the territory. In this context, despite water scarcity, the country has experienced a rapid expansion of irrigated land and a shift towards more water-intensive crops (Pinilla, 2006).[4] Second,

[1] See Basel Committee on Banking Supervision (BCBS, 2021)

[2] In 1994, the United Nations created the United Nations Convention to Combat Desertification (UNCCD), which Spain incorporated into its legal system and ratified in 1996, through the Plan de Acción Nacional contra la Desertificación (PAND). This legally-binding text ensures that the Spanish government will prioritze combating the progressive desertification of the Spanish territory.

[3] According to Martínez-Valderrama et al. (2022), the modernization and intensification of agriculture through mechanization and the use of fertilizers place greater stress on cultivated land. This stress is mitigated by the increase in the stabling of livestock. However, the abandonment of these non-grazing lands subsequently heightens the risk of wildfires.

[4] According to Pinilla (2006), the area of irrigated land in Spain increased from almost 1.7 million hectares at the beginning of the 1950s to almost 3.2 million hectares in the early 1990s.

Spain is a country with great climatic heterogeneity, from wetlands to hyperarid regions. Thanks to this heterogeneity of climate zones, the Spanish data allow us to identify not only the costs of higher aridity, but also its potential benefits in humid regions. Spain thus fulfills to some extent the conditions for replicating a global study, but with the advantage of greater granularity.[5] Despite the importance of the desertification process in Spain, this paper is the first empirical study that quantifies its economic impact. Specifically, we analyze its impact on credit to NFCs using highly granular data.

Desertification is a chronic physical climate risk. Physical risks can be classified into acute and chronic risks. Acute physical risks are related to the increased severity and frequency of extreme climate phenomena, whereas chronic physical risks are associated with long-term shifts in climate patterns, such as rising sea levels or progressive soil desertification (United Nations Environment Programme (UNEP), 1992). Although there is a rich empirical literature on extreme events related to acute physical risks,[6] the analysis on chronic physical risks is more scarce. This lack of empirical studies on the economic and financial impacts of chronic physical risks is largely due to the complexity and limited availability of the data sources. However, this literature is expanding as climate data improve. For example, the regional studies by Dell et al. (2012); Dell et al. (2014); Burke et al. (2015), Kahn et al. (2021); Debandt et al. (2021); Newell et al. (2021), as well as the country-specific analyses by Deschênes and Greenstone (2007) and Olper et al. (2021), exemplify this line of research. Nevertheless, to date, these analyses of chronic physical risks have largely focused on the impact of higher temperatures and lower precipitation on output.[7] This paper contributes to this less explored branch of the literature that deals with the economic impact of chronic physical risks.

Desertification is a complex, difficult-to-quantify and multidimensional phenomenon that involves a variety of processes related to soil erosion, biodiversity loss, forest fires, forest cover, land use, type of agriculture, or groundwater degradation, among others. In this paper, we focus on the effects of aridity, which serves as a single indicator of desertification. Specifically, our main explanatory variable is a temperature-precipitation-based aridity index, defined as the total amount of precipitation divided by the soil's potential evapotranspiration (PET). The PET is a widely

[5]This is also the case for Italy as in Olper et al. (2021).

[6]See, for instance Faiella and Natoli (2018), Baldauf et al. (2020), Sloggy et al. (2021) and Schüwer et al. (2019), among others, for an empirical characterization of the relationship between different meteorological hazards on bank lending, real estate prices and climate change beliefs, respectively.

[7]This empirical literature suggests an overall negative impact of temperature on output, which is particularly pronounced in poorer countries or those heavily dependent on agriculture, although there is a significant degree of model uncertainty (Newell et al., 2021).

used measure of the atmosphere's capacity to remove water from the land surface by evaporation (Thornthwaite, 1948).

While temperature and precipitation are valuable variables for studying climate change, their combined use in a single measure simplifies the analysis of climate data. Moreover, the aridity index provides a quantitative measure of dryness, allowing for a more comprehensive understanding of a region's climate.[8] Additionally, the aridity index can capture non-linear relationships between temperatures and precipitation.[9] Despite its advantages, aridity has rarely been used in the literature on the economic and financial consequences of climate change. To the best of our knowledge, Malpede and Percoco (2023) and Malpede and Percoco (2024) are the only examples to date.

Our dependent variable is the credit to Spanish NFCs. While previous studies on the economic effects of chronic physical risks have predominantly analyzed their impact on output,[10] there is limited literature on the effects of physical risks, both acute and chronic, on bank lending. Schüwer et al (2019) and Faiella and Natoli (2018) are among the few studies examining the impact of physical risks on the financial sector.[11] Moreover, the available empirical evidence on the impact of climate change on NFCs is predominantly based on firm-level data.[12] We choose credit as a proxy for economic activity due to its high correlation with output (see, for instance, Cecchetti and Kharroubi, 2019 or Kelly et al., 2011). Additionally, credit is a simple measure that is available with a higher degree of geographical granularity than GDP and for longer time periods. The credit to NFCs dataset comes from the Central Credit Register (CCR) of the Banco de España with

[8]For instance, Gorczyński (1943) advocates for the use of aridity indices rather than precipitation and temperature separately, as aridity maps have direct application in the classification of world climates.

[9]As temperatures rise, the atmosphere 's capacity to hold water also increases (Hsiang and Kopp, 2018). While this should theoretically lead to an overall increase in precipitation, this is not always the case. Indeed, Dore (2005) shows that an increase in temperature in humid regions has been followed by an increase in precipitation over the twentieth century, whereas the opposite is true for dry regions. Hsiang and Kopp (2018) emphasise that changes in precipitation are complex to forecast due to a variety of interrelated factors beyond temperature itself, such as the movement of large air masses, wind and humidity.

[10]While global studies such as Dell et al. (2012), Burke et al. (2015), Malpede and Percoco (2024), Kahn et al. (2021) focus on the use of GDP growth as the dependent variable, country studies also take into account the impact of climate change on agriculture. For instance, Olper et al. (2021) analyse the agricultural GVA per worker and GDP per capita growth for Italy, and Deschênes and Greenstone (2007) study the impact of weather fluctuations on the agricultural output.

[11]Schüwer et al (2019) analyze how banks reacted to Hurricane Katrina, and Faiella and Natoli (2018) study the exposure of banks to Italian firms located in areas at risk of flooding.

[12]This literature suggests that firms located in or near disaster-prone regions tend to be less leveraged and hold more cash as a buffer to address climate change (Elnahas et al., 2018; Dessaint and Matray, 2017; Javadi and Al Masum, 2021; Ginglinger and Moreau, 2019; Huang et al., 2018).

information for each individual operation with national credit institutions. This granularity allows us to analyze the impact of aridification and to aggregate information by economic sector of the debtor at the municipal level.[13]

To analyze whether aridity impacts on lending, we fit a panel fixed effects model for the credit to Spanish NFCs at the municipal level between 1984 and 2019, with aridity as the main explanatory variable. In addition to estimating the baseline model, in which aridity has a contemporaneous effect on lending, we also estimate the model using local projections (Jordà, 2005). This approach allows us to disentangle the short-run and long-run effects of aridity on credit. To the best of our knowledge, this is the first empirical paper that analyzes the economic impact of chronic physical risks using local projections to provide a long-run perspective. We also extend our model to study the link between aridity and credit by economic sector and by climate zone. Finally, we perform some robustness exercises with alternative dependent variables.

The results indicate that aridity negatively impacts credit to NFCs in the medium to long term. Controlling for climate zones, we find a significant reduction in credit in dry and arid areas due to higher aridity, while humid areas remain unaffected. We also show that the impact of aridity on credit to NFCs is sector-specific, with the agricultural sector being the most negatively affected. However, when we interact sectoral credit with climate zones, higher aridity may actually benefit certain sectors, such as tourism in humid areas.

The rest of the paper is organized as follows. Section 2 describes our main explanatory variable, the aridity index. Section 3 provides a detailed description of our dataset. Section 4 outlines the empirical models used to analyze the relationship between credit to Spanish NFCs and aridity. Section 5 summarizes the main results. Finally, Section 6 presents our conclusions.

2 Aridity in Spain: Current conditions and trends

In this paper, the main explanatory variable is the aridity index in year t, that we denote as AI_t. The definition of the aridity index is not unique and, since the first proposal of an aridity index by de Martonne (1926), numerous alternative metrics have been developed to measure the degree of aridity in water-scarce regions based on different climatological variables.[14] To calculate this

[13] Rizzi (2022) and Goldsmith-Pinkham et al., (2023) represent alternative approaches to study the impact of physical risks at the municipal level. These works analyze the impact of the loss of wetlands and the sea-level rise, respectively, on US municipal bond prices. They implicitly assume that these physical risk hazards represent a depletion of natural capital.

[14] These different characteristics of the indices make their comparability difficult. At the empirical level, Andrade et al. (2021) provide a historical comparison of three alternative aridity indices for the Iberian Peninsula and conclude that they are complementary.

metric, we follow the definition of the United Nations Environment Programme (UNEP) (1992), which is one of the most widely used aridity indices due to its simplicity.[15] The annual aridity index by UNEP follows this expression,

$$AI_t = \frac{P_t}{PET_t} \tag{1}$$

where P_t stands for precipitations, calculated as the sum of the monthly averages over each year, and PET_t for the annual potential evapotranspiration. See Appendix A for further details on the computation of PET_t. Both variables are expressed in liters per square meter (l/m^2). Evapotranspiration represents the combined loss of water through the transpiration by the vegetation and the evaporation from the soil.[16] Thus, the aridity index characterizes the available water balance in a given area.

The lower the value of AI_t, the more arid the area is. Specifically, UNEP (1992) classifies lands into six categories according to the value of AI. A region is classified as humid if its AI is greater than or equal to 0.65. Drylands are defined as regions with an AI of less than 0.65 and can be further classified into four climate zones: hyperarid ($AI < 0.05$), arid ($0.05 \leq AI < 0.2$), semiarid ($0.2 \leq AI < 0.5$), and dry subhumid ($0.5 \leq AI < 0.65$).[17] In this exercise, we follow the classification of the aridity index by the Ministerio para la Transición Ecológica y el Reto Demográfico (MITECO) that coincides with the one of UNEP but splits non-drylands into humid and humid subhumid regions, with $AI \geq 1$ and $0.65 \leq AI < 1$, respectively.

We obtain daily data on temperature and precipitations from Cornes et al. (2018), available at the Copernicus Climate Data Store, the data access portal of the Copernicus Climate Change Service. This data repository developed by the European Commission is based on satellite Earth observation and in-situ data. This daily dataset is available in a gridded format with a resolution of 0.1° and provides data since January 1950.[18] To construct the historical aridity indices in (1) for Spain, we calculate the annual AI_t for each of the grid cells that cover the Spanish territory from 1970 to 2019 using daily data. Since the computation of AI_t in (1) requires the use of monthly data, we first calculate the monthly averages of the daily data on temperatures and precipitations.

[15] See Bannayan et al. (2010) or Zarei and Mahmoudi (2021) for some empirical applications of the UNEP aridity index.

[16] UNEP (1992) considers the potential evapotranspiration, PET, which does not depend on land use, instead of the effective evapotranspiration.

[17] The sixth category of UNEP (1992) classification corresponds to cold climates, with PET lower than 400 l/m^2, which is a subtype of non-drylands. This category is not relevant for our analysis as it does not occur in Spain.

[18] Cornes et al. (2018) obtain data from local stations and interpolate them to construct the gridded dataset. The authors pre- and post-process all the data. See https://www.copernicus.eu/en.

Second, we define the value of the aridity index in a municipality as the average of the values of the grid cells covering the municipality, weighted by the area inside the limits of the municipality.

Figure 1 shows the evolution of the aridity index in Spain from the 1970s to the 2010s, averaged by decade.[19] According to the latest decade aridity map, the northern regions of the Iberian Peninsula represent the vast majority of non-drylands. Nevertheless, the aridity index has worsened since the 1970s in almost all the Spanish territory as the country has become drier. This deterioration of the aridity index in Spain is also confirmed in aggregate terms. In this sense, Figure 2 illustrates that the distribution of the index has shifted over the last four decades towards drier climate zones for the entire Spanish territory. Indeed, the share of the semiarid areas has increased from 30% in the 1970s to 53% the 2010s. That is, almost 50% of the territory that was classified as dry subhumid in the 1970s is semiarid in the 2010s. Besides, although the hyperarid and arid areas remain small, they have expanded by approximately 30%. Regarding non drylands, the share of humid and humid subhumid regions has dropped by around 3 percentage points. The most recent aridity map in Figure 1 also shows that 25% of the South-Eastern province of Almería is arid, which represents 56% of the total arid area in Spain. The rest of the Spanish territory classified as arid is located in the Canary Islands (28%) and in some specific locations in the provinces of Murcia and Valencia (16%).

To further illustrate the aridification process of Spain throughout the last decades and its heterogeneity across time and regions, Figure 3 shows the percentage change in the average AI for the 1980s, 1990s, 2000s and 2010s compared to the 1970s. Most of the Spanish territory has experienced increased aridity, though to varying degrees. The humid regions of the North and some areas of central Spain exhibit a more pronounced deterioration in aridity than the rest of the country.[20] On the contrary, some specific areas around the western Pyrenees or the provinces of Castellón and Girona have lower aridity levels than in the 1970s.

3 Data and variables

To analyse the impact of desertification in Spain on the credit to NFCs, we use an annual panel data set of 7,894 municipalities across the 50 Spanish provinces from peninsular Spain, the Balearic

[19]Our aridity maps yield similar magnitudes to those reported by official sources (MITECO). However, the latter source only provides the average aridity indices from 1989 to 2000, which prevents its use for panel data analysis.

[20]The percentage change of the aridity index by municipality shows similar conclusions. Among the municipalities with more than 10,000 inhabitants, which is the criterion used by the INE to distinguish between rural and urban municipalities, those with the greatest increase in the aridity index since the 1970s are located in the south of the province of Madrid (Pinto, Getafe, Valdemoro, Parla, Humanes), in Galicia (Barbadás, Lalín, Ourense, O Carbaliño), and in the eastern Pyrenees (Seu d'Urgell).

Islands and the Canary Islands.[21] The sample period runs from 1984, the first year when data on credit to firms is available, until 2019.

The main explanatory variable is the aridity index AI_t defined in expression (1) but we use the natural logarithm of this indicator, to interpret the estimated coefficients as percentage changes in the dependent variable. Additionally, since a lower aridity index AI_t indicates higher the aridity of the municipality, we multiply this variable by (-1) to simplify the interpretation of the coefficient throughout estimates. Thus, the transformed variable, that we denote as *Aridity*, is,

$$Aridity_t = (-1) \times \ln(AI_t), \tag{2}$$

so that the higher *Aridity*, the dryer the municipality is.

3.1 The main dependent variable: Credit per capita to NFCs

Our main dependent variable is the credit per capita to NFCs from 1984 to 2019. We obtain data on the amount of drawn down loans to Spanish non-financial corporations (NFCs) from the Banco de España's Central Credit Register (CCR). This database is maintained by the Banco de España in its role as supervisor. It contains monthly information on all individual loans granted by commercial banks to their customers in Spain since 1984.[22] In our analysis, we use the outstanding stock of drawn financial credit at year-end. That is, we employ the amount drawn from the total available credit line, irrespective of its delinquency level, to non-financial corporations, regardless of the lender.

We compute credit data at the municipal level with alternative sources in a non-trivial way. First, we consider complementary datasets that link the unique tax identifier (NIF) of the firm to the postal code of the municipality where it is located. More specifically, we use the Central Balance Sheet Data Office (CBSO) of the Bank of Spain from 1995 to 2014, the Central Directory of Enterprises (DIRCE) from the National Statistics Institute (INE) between 1995 and 2020 which records the creation and destruction of companies in Spain, and, finally, the new version of the CCR for the years 2015-2022, which includes detailed geo-locational information. The coverage of NIFs in the old version of the CCR is extensive (from 55% in 1984 to 100% in 2019), with homogeneous

[21] We remove Ceuta and Melilla from the dataset because their inclusion would considerably shorten the sample period. Both autonomous cities obtained their status in 1995 and previously belonged to the autonomous community of Andalusia.

[22] Jiménez et al. (2004) provide a detailed description of the CCR.

sectoral and geographical representativity, which mitigates potential selection bias in the data.[23] We also carry out an additional adjustment of the overall volume of loans such that the sum of credit at the municipality level matches the actual value at the provincial level.[24] Second, once we have associated the postal code to the NIFs and the year, we match the postal code to the municipality and sum over that dimension.[25]

Since municipalities in Spain are heterogeneous in terms of population, we express credit on a per capita basis. We obtain population data at the municipal level from the National Statistical Institute (INE) from 1986 to 2021.[26] Additionally, credit per capita enters the regressions in natural logarithm to interpret the coefficient of aridity as an elasticity. We denote this transformed variable as $Credit\_pc$. This transformation prevents the use of those municipalities for which outstanding credit is not strictly positive for the whole sample. Consequently, the final sample consists of 7,894 municipalities.

Finally, to analyze the relationship between aridity and credit at the sectoral level, we classify the aggregated data on drawn down loans to NFCs into five economic sectors: agriculture and fisheries, industry (which includes extractive, light and heavy industries), real estate, tourism, and finally transport, commerce, and personal services.[27] Appendix B provides a detailed description of these five economic sectors according to their CCR classification. We denote the natural logarithm of the credit per capita to NFCs of those five sectors as $Credit\_pc_{AG}$, $Credit\_pc_{IN}$, $Credit\_pc_{RE}$, $Credit\_pc_{TO}$ and $Credit\_pc_{CO}$, respectively. Table 1 reports some descriptive statistics of $Credit\_pc$

[23] The total amount of drawn-down credit for which we could determine the precise location is very close to the actual value at the provincial level, ranging from a median of 92.1% in 1984 to a median of 98.5% in 2020 across the 50 provinces considered.

[24] The adjustment consists of multiplying the municipal values in a province such that the sum of the municipal values equals the value of the province as reported in the Bank of Spain's CCR.

[25] The aggregation by municipality rather than by postal code also takes into account the cases where the company moves its headquarters from one postal code to another but stays within the same municipality. Indeed, 12.4% of companies have changed postal code during the recording sample, whereas only 6.6% have changed municipalities and 1.6% the province. Moreover, 47% of the companies that changed postal code have not changed the municipality of their headquarters and 76% of companies which changed municipality remained in the same province. In any case, companies that change the location of their headquarters within the same municipality represent less than 0.5% of the overall credit volume on average per year.

[26] We obtain population data by merging the series of the de facto and the de jure population before and after 1996, respectively, given the absence of discontinuity in the series. To expand the sample further, we backcast the population from 1986 to 1984 using a univariate autoregressive process of order 4.

[27] As detailed in Appendix B, we exclude the following sectors: financial sector (deposit, credit, insurance, pension funds and other financial services), households as employers, public administration, activities of international organizations and sectors involved in the production or distribution of energy, water, or education, as the public sector has been or still is actively involved and may therefore not accurately reflect market mechanisms.

and the logarithm of the credit per capita by sector. Credit to the industrial sector has the highest average in the sample, followed by that to transport, commerce, and personal services.

3.2 Alternative dependent variables

In addition to our main results, we also explore the impact of aridity on alternative dependent variables. First, the estimates could be to some extent biased due to the fact that credit data is reported at the headquarters level and not where the business operation takes place. This could result in a mismatch between the reported location of credit and the location of the area affected by the aridity change, especially for larger firms. However, the data on the location where the business operation takes place is not available. To address this data limitation, we also perform the empirical analysis using the credit per capita to firms that employ less than ten employees as the dependent variable, which we denote as $Credit\_pc\_SMALL$. We use this variable as a proxy given that small firms are more likely to be registered in the same municipality as their business operation. In any case, the distribution of firms in Spain is highly skewed towards very small firms, so that this variable is relatively similar to $Credit\_pc$, as illustrated in Table 2.[28]

Second, one might alternatively interpret that the response of credit per capita may be driven by the number of inhabitants in the municipality, especially if there are population movements in response to the gradual aridification process. We address this issue by considering the population as an alternative dependent variable. Third, the economic impact of climate change can alternatively be proxied by employment indicators. We test this latter channel with three metrics in per capita terms: the number of new contracts in the municipality, the number of unemployed and finally the number of registered workers at year-end.[29] However, the time span of those series—2005 for the unemployment and new contracts series, and 2003 for the number of registered workers—is shorter than that of $Credit\_pc$.

4 Empirical strategy

4.1 Baseline specifications

The baseline panel data model to analyze the impact of aridity on the aggregate stock of credit is as follows:

[28]For instance, according to the Instituto Nacional de Estadística (INE), of the 3,430,663 firms registered in 2022, 1,942,319 did not have employees and 3,283,111 had less than 10 employees.

[29]The spatial attribution of these three variables could be different. While the number of new contracts represents the location of the place of work, the unemployment data characterizes the number of job seekers at the end of the period and refers to the residence of the registered person. Finally, workers registered at the Social Security Office are reported at the location of their employer, which may differ from their place of residence or the location of their actual work. For a discussion of the issue, see Fabra et al. (2023).

$$Credit\_pc_{it} = \beta_1 Aridity_{it} + \rho Credit\_pc_{it-1} + \alpha_p + \kappa_t + \nu_{pt} + \varepsilon_{it}, \tag{3}$$

where for all municipalities $i = 1, \ldots, N$ and year $t = 1, ..., T$, the dependent variable, $Credit\_pc$, represents the natural logarithm of the outstanding amount of granted credit per capita. We model $Credit\_pc_{it}$ as a function of $Aridity_{it}$, $Credit\_pc_{it-1}$, which captures the persistence of the stock of credit, and a set of fixed effects. Specifically, we include year, province, and province-year fixed effects. The key coefficient in Equation (3) is β_1, which can be interpreted as the percentage variation of the credit per capita after a 1% increase of the aridity index. Therefore, a negative estimate of β_1 would suggest that higher aridity leads to lower credit to NFCs.

We also examine whether the impact of aridity varies by climate zone. Once we distinguish a differential effect by climate zone, we could determine whether being a more or less arid region might harm or benefit certain economic activities as desertification advances. This effect could be offset by the fact that some of the most affected regions by aridification might have made investments to adapt or mitigate the effects of the aridification process. To this end, we interact $Aridity_{it}$ and $Credit\_pc_{it-1}$ with I_{ci}, which is a variable that is equal to one if the average AI in the municipality i in the decade of the 80's corresponds to climate zone c. For simplicity, climate zones are grouped into three categories on based on the UNEP aridity classification: (1) more humid areas, classified as "humid" and "humid subhumid" ($0.65 \leq AI$); (2) zones of intermediate aridity, classified as "dry subhumid" and "semiarid", with $0.2 \leq AI < 0.65$; and (3) dryer regions, classified as "arid" and "hyperarid", with $AI < 0.2$. We estimate the following expression:

$$Credit\_pc_{it} = \sum_{c=1}^{3} I_{ci} \times (\beta_{1c} Aridity_{it} + \rho_c Credit\_pc_{it-1}) + \alpha_p + \kappa_t + \nu_{pt} + \zeta_c + \varepsilon_{it}, \tag{4}$$

where the model also includes climate zone fixed effects and the coefficient of interest β_{1c} depends on the climate zone c.

Next, we analyze whether the impact of aridification on credit to NFCs depends on the economic sector. The sectoral model follows this expression:

$$Credit\_pc_{sit} = \beta_{1s} Aridity_{it} + \rho_s Credit\_pc_{sit-1} + \alpha_p + \kappa_t + \nu_{pt} + \gamma_s + \varepsilon_{sit}, \tag{5}$$

where $s = 1, \ldots, 5$ denotes the economic sector. Sector-year fixed effects are also included in the specification (5). This model allows for sectoral heterogeneity in the $Aridity$ coefficient β_{1s}.

Finally, we study whether aridity has a different sectoral impact on credit by climate zone. This type of analysis allows to assess, for instance, whether the response of credit to agricultural companies depends on the climate zone as desertification advances. Similarly, we can determine whether higher aridity affects the provision of credit to firms in the tourism sector differently in humid or in arid municipalities. To this end, we build on models (4) and (5) to fit this specification, where sector-climate zone fixed effects are also included:

$$Credit\_pc_{sit} = \sum_{c=1}^{3} I_c \times (\beta_{1sc} Aridity_{it} + \rho_{sc} Credit\_pc_{sit-1}) + \alpha_p + \kappa_t + \nu_{pt} + \gamma_s + \zeta_c + \varepsilon_{sit}. \quad (6)$$

Equations (3) to (6) are estimated via a panel multi-level fixed effect estimator, with standard errors clustered at the province level. This level of clustering is relevant because some decisions that could affect the volume of credit are taken at this administrative level.[30] The regression is weighted by the amount of credit in the municipality to reduce the influence of observations from municipalities that contribute less to the overall volume of credit in Spain on our estimates. Without this weighing scheme, municipalities with a small volume of credit would carry the same econometric weight as municipalities where credit is abundant, thus deviating from their economic weight.[31]

Regarding endogeneity issues, models (3) to (6) do not suffer from reverse causality as the aridity index is predetermined. Embedded in this specification is the assumption that economic growth, proxied by the volume of credit, does not contemporaneously affect *Aridity*. In line with Alessandri and Mumtaz (2022), economic growth may indeed influence various climate indicators, but the speed of this phenomenon makes it unlikely to affect climate-related indicators in an horizon shorter than one year. Finally, as in other autoregressive models with fixed effects, there could be potential biases, as described in Nickell (1981), due to the presence of a lag of the credit per capita, $Credit\_pc_{it-1}$, in our specifications. In our setting, the sample size T is sufficiently large for this bias to be negligible.

4.2 Local projections

Aridity, like any chronic physical risk, is related to long-term shifts in climate patterns. Consequently, changes in the aridity index will take several years before they fully impact on the volume of credit in a municipality. Therefore, specifications (3) to (6) cannot capture these long-term dynamics. To address this issue in our empirical analysis we propose to generalize equation (3) and estimate it dynamically in a local projections framework (Jordà, 2005). Thus, local projections allow to distinguish between short-term weather-related effects and long-term climate-related effects. We estimate Equation (3) for years $h = 0, \ldots, 20$ in the following way,

[30] Alternatively, we also estimated the equations using Newey-West standard errors (Newey and West, 1987). This alternative way of computing the standard errors does not alter our main conclusions.

[31] We implement this weighting scheme with the 'reghdfe' module in STATA, using the rounded amount of credit granted as frequency weight.

$$Credit\_pc_{it+h} = \beta_1^h Aridity_{it} + \sum_{j=1}^{h} \beta_2^h Aridity_{it+j} + \rho^h Credit\_pc_{it-1} + \alpha_p + \kappa_t + \nu_{pt} + \varepsilon_{it+h}. \quad (7)$$

Following Alloza et al. (2019) and Teulings and Zubanov (2014), we include in model (7) as many leads of $Aridity$ as horizons to forecast, with coefficients β_2^h. This method solves the compatibility problem between local projections with persistent shocks and theoretical non-serially correlated shocks. As a consequence, β_1^h, can be interpreted as the response of credit to an unexpected and serially-uncorrelated one-percent shock to aridity. Inference is performed in a similar way as in the baseline models from (3) to (6).

In an analogous way to the baseline models, we estimate the local projections model (4) by climate zone as follows,

$$Credit\_pc_{it+h} = \sum_{c=1}^{3} I_c \times \left(\beta_{1c}^h AI_{it} + \sum_{j=1}^{h} \beta_{2c}^h Aridity_{it+j} + \rho_c^h Credit\_pc_{it-1} \right) + \alpha_p + \kappa_t + \nu_{pt} + \zeta_c + \varepsilon_{it+h}, \quad (8)$$

as well as the sectoral model in (5), with the following expression,

$$Credit\_pc_{sit+h} = \beta_{1s}^h Aridity_{i,t} + \sum_{j=1}^{h} \beta_{2,s}^h Aridity_{it+j} + \rho_s^h Credit\_pc_{sit-1} + \alpha_p + \kappa_t + \nu_{pt} + \gamma_s + \varepsilon_{sit+h}. \quad (9)$$

Finally, we generalize model (6) to analyze simultaneously the impact by sector and climate zone with local projections as follows,

$$\begin{aligned} Credit\_pc_{sit+h} \quad &= \quad \sum_{c=1}^{3} I_c \times \left(\beta_{1sc}^h Aridity_{it} + \sum_{j=1}^{h} \beta_{2sc}^h Aridity_{it+j} + \rho_{sc}^h Credit\_pc_{sit-1} \right) + \\ & \quad\ \alpha_p + \kappa_t + \nu_{pt} + \gamma_s + \zeta_c + \varepsilon_{sit+h}. \end{aligned} \quad (10)$$

5 Results

5.1 Total credit to NFCs

Table 4 reports the estimates of the baseline model in (3) for different fixed effects specifications. First, we find that higher aridity contemporaneously leads to a slightly lower volume of credit to firms. This result holds irrespective of the fixed effects configuration. However, to disentangle the economic effect of chronic physical risks it is more appropriate to use econometric techniques that allow to analyze these dynamics at longer horizons, such as local projections.

Figure 4 shows the local projection estimates of the coefficients of $Aridity$, β_1^h, in model (7) over a twenty-year period. It illustrates the importance of considering a long term perspective of the relationship between aridity and credit to NFCs. Indeed, the increase in aridity negatively impacts on lending volumes across all horizons, but it takes a significant amount of time before the full effect is identified. Thus, unexpected variations in aridity in t lead to a negative but small response of credit to firms in the same period. This effect is rather subdued in the short to medium term but, as the time horizon extends, this negative impact increases and becomes significant around an eight-year horizon. The average estimated elasticity is around -0.22% from eight years onwards. In other words, a 1% increase in the aridity index is associated with a 22 basis points (bp) fall in the volume of lending to NFCs. Note that the average rate of growth of the aridity index, AI, between the 1980s and 2010s is 0.3% and ranges from -11% to 11% for the 5th and 95th percentiles. At these percentiles the variation in total credit would be between -242 and +242 bp, respectively.

This result, indicating a negative economic impact of aridity, is aligned with the literature that finds a detrimental effect of chronic physical risk hazards on economic activity (Malpede and Percoco, 2023; Olper et al. 2021). However, these works use different dependent and main explanatory variables. Our results are also in line with works that link temperature and rainfall shocks to economic activity (Dell et al., 2012; Dell et al., 2014; Burke et al., 2015; Kahn et al., 2021; Debandt et al., 2021; Newell et al., 2021). Additionally, this outcome aligns with those at a global level by Ginglinger and Moreau (2019), who report that firms exposed to greater climate risk are less leveraged.

Next, we extend these results by estimating the impact of aridity on lending by climate zone with model (4). Table 5 reports the coefficient estimates of changes in aridity interacted with climate zones categories for different fixed effects combinations. Although there is some variability in the coefficients across specifications, higher aridity in the most humid areas does not affect credit to NFCs contemporaneously, as illustrated by the lack of significance of the coefficient of the interaction of $Aridity$ with I_1. Conversely, in the most arid regions, higher aridity has a negative and significant contemporaneous impact on credit to firms, as evidenced by the negative estimate of β_{13} across specifications. Finally, intermediate climate zones, represented by the indicator variable I_2, tend to benefit from higher aridity contemporaneously, although this result is not consistent across specifications.

In a similar way to the estimates without interaction by climate zone, we extend the horizon of analysis by applying local projections. To this end, we report in Figure 5 the local projection estimates of $Aridity$ interacted with the climate zones I_1, I_2, and I_3. The "dry subhumid" and "semiarid" areas, I_2, and "arid" and "hyperarid" areas, I_3, experience a negative and significant decrease of credit as a result of higher aridity from an eight-year horizon. Specifically, the average elasticity is around -24% and -17% after 8 years, respectively. In contrast, credit to firms in the most humid areas are not affected by this phenomenon, which indicates its resilience to aridity variations. Taken together, we can conclude that this effect for the aggregate credit is dominated by the intermediate and most arid climate zones.

5.2 Sectoral credit

Next, we analyze whether there is a different impact of the aridification on the credit to NFCs by sector. Table 6 reports the estimates of the baseline specification in model (5) for different fixed effects specifications. According to these results, the impact of aridity on lending varies by sector in a contemporaneous manner. Three out of the five sectors that we analyze are negatively and significantly affected by an increase in aridity in period t: the agriculture sector, the industrial sector and the sector that comprises transport, commerce and sales. On the other hand, for some fixed effects specifications, the credit to the touristic sector is positively affected by the aridification process.

To interpret these results from a longer-term perspective, we estimate the sectoral model using local projections in specification (9). Figure 6 shows the estimates of β_{1s}^{h} in (9) for each of the five sectors s over a twenty-year horizon, h. Credit to all sectors except tourism is negatively affected by increased aridity, although there is a notable heterogeneity across sectors in terms of the magnitude of the effect of higher aridity and the time it takes for this phenomenon to materialize in credit. Agriculture is without doubt the hardest-hit sector, with lending to this sector falling by around 25 bp on average over the twenty-year period after a 1 pp increase in the aridity index. Indeed, credit to agriculture is persistently negatively affected by increased aridity after five years. The maximum impact in credit is reached nine years after a 1% increase in aridity (-0.53%). This result is consistent with other papers that conclude that there are important losses in agriculture as a result of the variation of weather variables (Olper et al., 2021; Jodha, 1981).[32]

Credit to firms in the real estate sector is also negatively affected by higher aridity, although to a lesser extent than in the case of the agricultural firms. As shown in Figure 6, β_1 estimates for real estate become significant in in the very short-term (up to two years), and around a twelve-year horizon, where each 1% aridity increase may decrease credit to that sector by up to 46 bp. One possible explanation of this result is that harsher climate may reduce productivity and the profitability in the construction sector, as projects would be lengthier and costlier (see, for example,

[32]Regarding the transmission mechanism, according to Jodha (1981), lower profitability reduces the capacity of agricultural firms to secure loans. In the long term, farmers may be forced to sell assets to cover losses, thereby reducing the value of collateral available to secure loans. Additionally, lending for sustenance rather than for investment is seen as particularly risky from the point of view of lenders' perspective, which may lead to stricter lending conditions.

Bendak et al., 2022, Li et al., 2016). This lower productivity may be the dominant effect that explains the negative impact on credit, as it discourages new projects. Although in our empirical exercise this negative effect dominates, there are also alternative arguments in the literature that justify a positive impact of higher aridification on credit to the real estate sector due to increased demand of construction materials to adapt to harsher climate conditions. For instance, rising heat creates new cooling needs for buildings, and water scarcity also leads to higher operating costs due to increased water prices (UNEP, 2023), as builders and officials have incentives to invest in water conservation efforts (World Bank, 2018). Additionally, building efficiency has become increasingly relevant in recent years, prompting households and construction firms to adapt to the new norms.

Finally, in aggregated terms, the Spanish tourism sector has proven relatively resilient to the effects of higher temperatures and less rainfall, as shown in Figure 6, which indicates that there is no significant effect on the credit volume of higher aridity. Similarly, credit to the industrial sector and to "Transport, commerce and services" are barely affected by the aridification process.[33]

However, the analysis of sectoral credit depends on characteristics of the region, such as the climate zone. To this end, we interact the economic sector and the climate zone indicator variables, I_1, I_2, and I_3, and these sectoral effects are shown in Figure 7. Indeed, in the case of the tourism sector, the fact of being a humid or a dry region does play a role. As shown in Figure 7, in humid regions higher aridity leads to more credit to the tourist sector firms over a long time horizon, up to twelve years. More specifically, a 1% increase in the aridity index is associated with up to a 110 basis points (bp) increase in the volume of lending to firms active in the tourism industry in humid regions. This result is in line with the literature that concludes that warmer temperatures and/or lower precipitations benefits the tourism sector in more humid and cold regions (see, for instance, Wilkins et al., 2018). These regions would need additional investment to accommodate a higher number of tourists as desertification advances. This is consistent with IMF (2022) which assess that higher temperatures or lower precipitations are positive for the tourism industry, at least in the Middle East and North Africa region but only up to a certain point. The report also stresses that tourism does not seem to benefit from temperature increases in already hot climate countries.[34]

[33]Following Somanathan et al. (2021), a harsher climate defined by higher temperatures is detrimental to labor productivity, which in turn may lead to lower access to financing opportunities through reduced expected profitability. Regarding the services sector, Cicarelli et al. (2024) refer to different direct price impacts on services due to temperature variations in warmer and colder months.

[34]It would be interesting to test whether the resilience of certain sectors, such as tourism, to increased aridity is prompting economic agents to shift their activities towards these sectors. However, the current lack of granular data on the productive use of the land at the municipal level hinders the ability to address this question.

Other sectors are also affected in a different manner depending on the climate zone. For instance, higher aridity lowers the volume of credit to agriculture firms in the most humid and arid regions, with a similar magnitude as in the case of total credit to the agriculture sector, around -52 bp and -24 bp on average after a 1% increase in the aridity index, respectively. Note that aridity generates a boom-bust dynamics in credit to agriculture in "dry subhumid" and "semiarid" areas, (I_2), with a peak to trough of 52 basis points. Regarding the real estate sector, the negative response of credit to aridity is particularly pronounced in the most humid and dryer areas, around -51 bp and -35 bp on average after a 1% shock in aridity, while arid regions only respond with a relatively long delay and a much lower magnitude (-9 bp).

5.3 Robustness exercises

Next, we present three robustness checks of our main results based on changing $Credit\_pc$ as dependent variable in the specification (7) with local projections. The estimates of the coefficients that quantify the impact of aridity on the alternative dependent variables are reported in Figure 8. First, we analyze $Credit\_pc\_SMALL$, which denotes the credit per capita to firms that employ less than ten employees. Loans in the CCR are reported at the headquarters of the firm, which may differ from the place of operations. Therefore, the analysis of credit to small firms, which are more likely to be registered in the same location as their business operation, allows us to assess possible measurement error of the data due to the location discrepancies. If this effect were important, there would be a mismatch between the location of the dependent variable and the location of the aridity variation. However, as Figure 8 illustrates, the response of $Credit\_pc\_SMALL$ is almost identical to that of $Credit\_pc$ in Figure 5, which suggests that loan concentration at headquarters is not a concern in our empirical exercise.

Second, the response of $Credit\_pc$ to higher aridity may be driven by the reaction of population to this phenomenon.[35] To address this issue we fit model (7) with local projections using the natural logarithm of population instead of the total credit per capita as dependent variable. The response of population is not significant for most horizons. However, after 12 to 16 years population significantly drops as a response of aridity variations, although very slightly (an average decrease of 7 bp after a 1% increase in the aridity index). Note that the estimates of the credit per capita as dependent variable are more than four times larger, according to the local projection estimates

[35] The direction and importance of the relationship between climate change and migration are not conclusive, given the methodological differences in the different analysis (Beine and Jeusette, 2021; Hoffmann et al., 2021). However, Moore and Wesselbaum (2023) also conduct a similar review and find that most papers in the literature present evidence that temperatures do increase migration, while evidence for precipitations is inconclusive.

in Figure 4, which implies that the negative estimate for $Credit\_pc$ is dominated by the drop in credit, while population movements slightly influence this result downwards.

Third, we use alternative dependent variables to credit to firms that can be considered as proxies for economic activity. Specifically, we estimate the link between aridity and three employment indicators: the number of new contracts, the number of unemployed and the number of registered workers in the municipality at year-end, all expressed on a per capita basis. As the sample size is smaller for these series than for the credit per capita, the time horizon of the local projection exercises in Figure 8 is shorter. Again, higher aridity indices are related to lower economic dynamism that is reflected in a lower number of new contracts, higher unemployment and fewer registered workers. Therefore, these estimates are in line with our main results. The number of unemployed per capita temporarily increases by up to 4 bp after a 1% aridity increase, although estimates are significant mostly in the short run. The number of new contracts and the amount of registered workers per capita follow the same negative trend. Specifically, the number of new contracts fall by around 76 bp after 12 years after a 1% increase in aridity, while the impact of aridity on the number of registered workers reaches its trough after 12 years (-27 bp).

6 Conclusions

In this article, we use geo-localized data of an aridity index over four decades to quantify the consequences of the progressive desertification of Spain on the volume of credit to NFCs as reported in the CCR. We use a local projections approach to link the annual aridity index to the stock of credit drawn at the municipal level. Local projections estimates capture the fact that the impact of aridity on credit is very gradual over several years. To the best of our knowledge, this is the first empirical analysis that examines the impact of chronic physical risks on economic variables through local projections. We also examine the impact of higher aridity on credit by economic sector, by climate zone, and the interaction of both dimensions.

According to our results, aridity has a negative impact on the credit to NFCs in the medium to long run, as shown by the local projections estimates. Moreover, the impact of aridity on credit varies across climate zones. We find that in most humid areas credit to firms is not affected by higher aridity, while in most arid areas, credit is negatively affected by the aridification process. The impact of the aridity index on credit to NFCs is also sector-specific. Indeed, credit to all sectors, except tourism, is negatively and significantly affected by higher aridity, although the magnitude of the impact varies across sectors. The agriculture sector is the most affected, as it is persistently negatively affected by the aridification process. Finally, once we simultaneously analyze economic sectors and climate zones, we can qualify some of the previous results. For instance, firms located in humid regions are still affected by aridity once the sectoral dimension is taken into account, but there are differences across sectors. In particular, while loans to the agricultural and the real estate sectors are mostly negatively affected, credit to the tourism sector is higher in the most humid regions. Taken together, the results suggest that the gradual process of desertification is relevant in explaining the behavior of credit to firms.

Our results contribute to the still scarce literature on the economic impact of chronic physical risks. Besides, a better understanding of the economic implications of desertification in Spain can help formulate effective policies to address it. There is a wide range of questions for further research. For instance, the study of the impact of aridity or alternative climate variables on default rates would allow us to calculate the value of credit that deteriorates as a result of climate change.

Appendix A: Computation of the potential evapotranspiration

The potential evapotranspiration, PET_t, in (1) follows the definition by Thornthwaite (1948), as proposed by UNEP (1992). According to Thornthwaite (1948), PET in year t is a function of the monthly average temperatures in year t, T_{tm}, and a correction coefficient, K_{Lat}, for the amount of solar radiation that depends on the latitude of the area, Lat. More specifically,

$$\begin{aligned} J_t &= \sum_{m=1}^{12} (T_{tm}/5)^{1.514} \\ PET_{tm}^{Lat} &= K_{Lat} \times 1.6(10T_{tm}/J_t)^{c_t} \\ PET_t &= \sum_{m=1}^{12} PET_{tm}^{Lat}, \end{aligned} \tag{11}$$

where T_{tm} is the mean monthly temperature in °C, PET_{tm}^{Lat} is the monthly evapotranspiration at a given latitude and J denotes the so-called heat index. The relation between J_t and the exponent c_t is given by,

$$c_t = 0.000000675J_t^3 - 0.0000771J_t^2 + 0.01792J_t + 0.49239. \tag{12}$$

Appendix B: Classification of economic sectors

	Sectors	CCR economic sectors
1	Agriculture and fisheries	Agriculture and forestry
		Fishing
2	Industry	Extractive industry
		Food and tobacco industry
		Textile, leather, wood and paper, and graphic arts industries
		Chemical industry
		Glass, ceramics and concrete industry
		Metallurgy and iron and steel industry
		Manufacture of engines, machines and industrial equipment
3	Real estate	Construction and development
		Real estate activities
4	Tourism	Tourism and accommodation
5	Transport, commerce, and personal services	Sales and commerce
		Services; computer, business management
		Passenger and freight transportation, telecommunications
	Not included	Financial sector; deposit
	Not included	Financial sector; credit
	Not included	Financial sector; insurance and pension funds
	Not included	Financial sector; other financial services
	Not included	Petroleum, coking and refining
	Not included	Energy supply
	Not included	Water supply and waste management; education and personal services
	Not included	Public administration
	Not included	Household as employers
	Not included	Activities of international organizations

Note: Classification of economic sectors based on that of he Spanish Central Credit Register (CCR).

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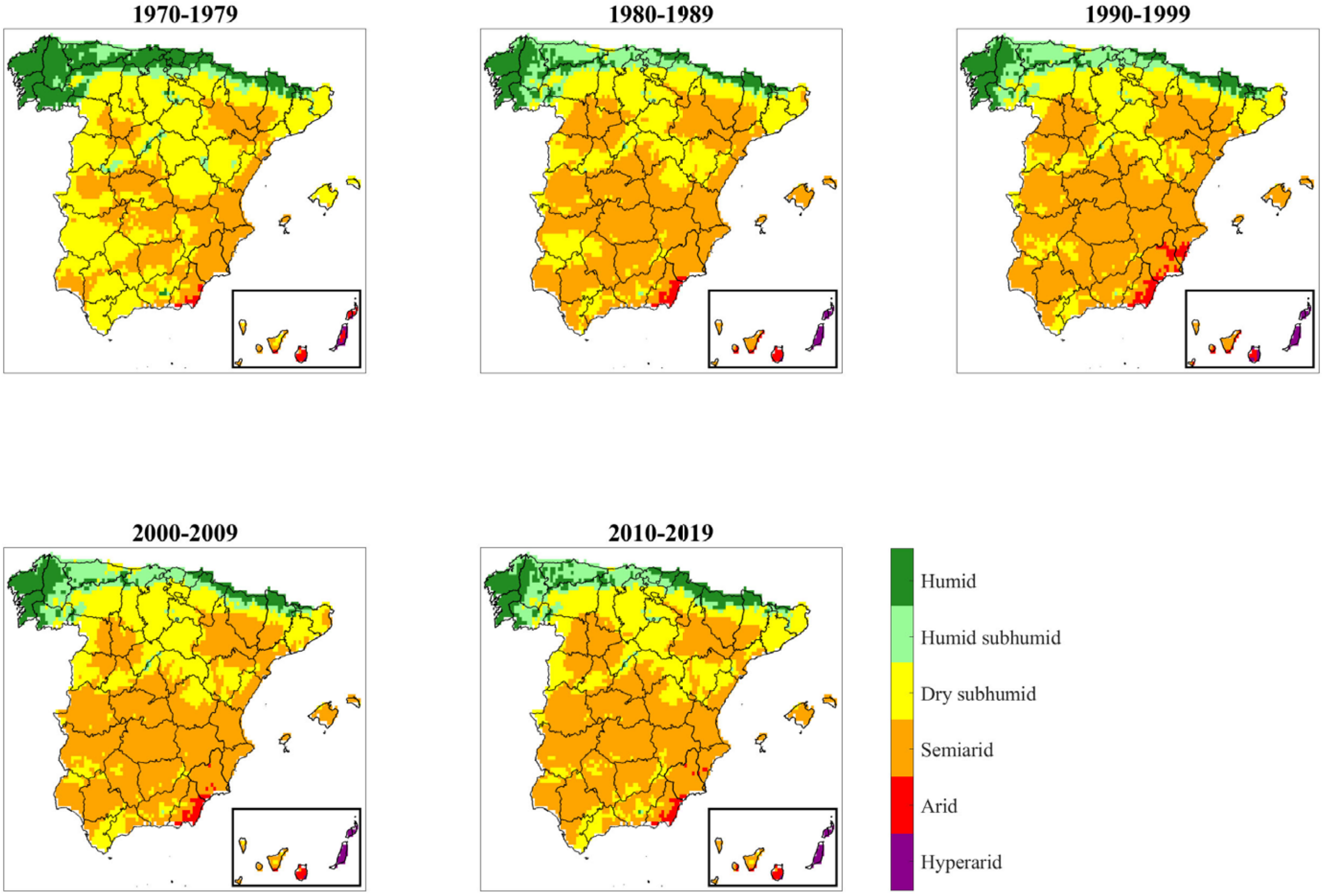
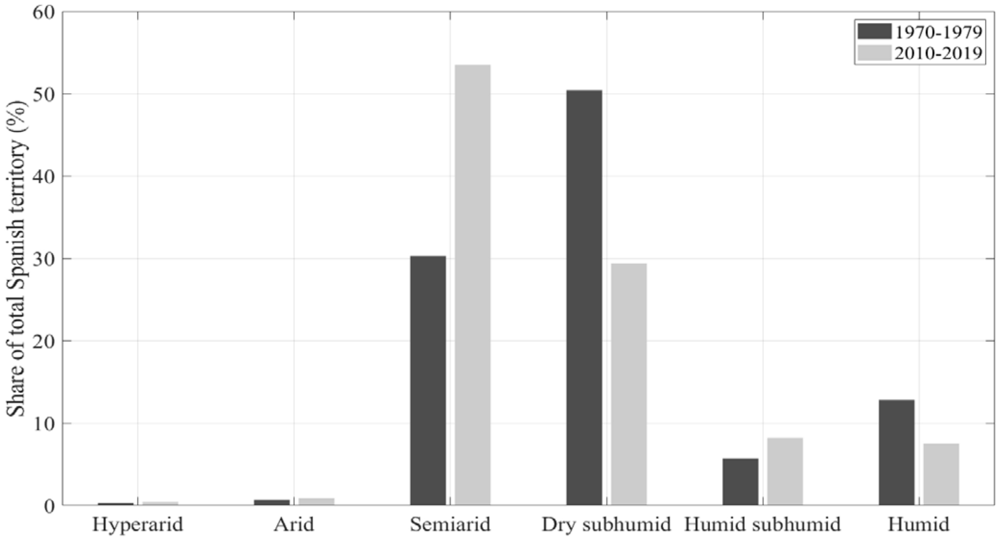
Figure 1: Average aridity index (AI) in Spain between 1970 and 2019



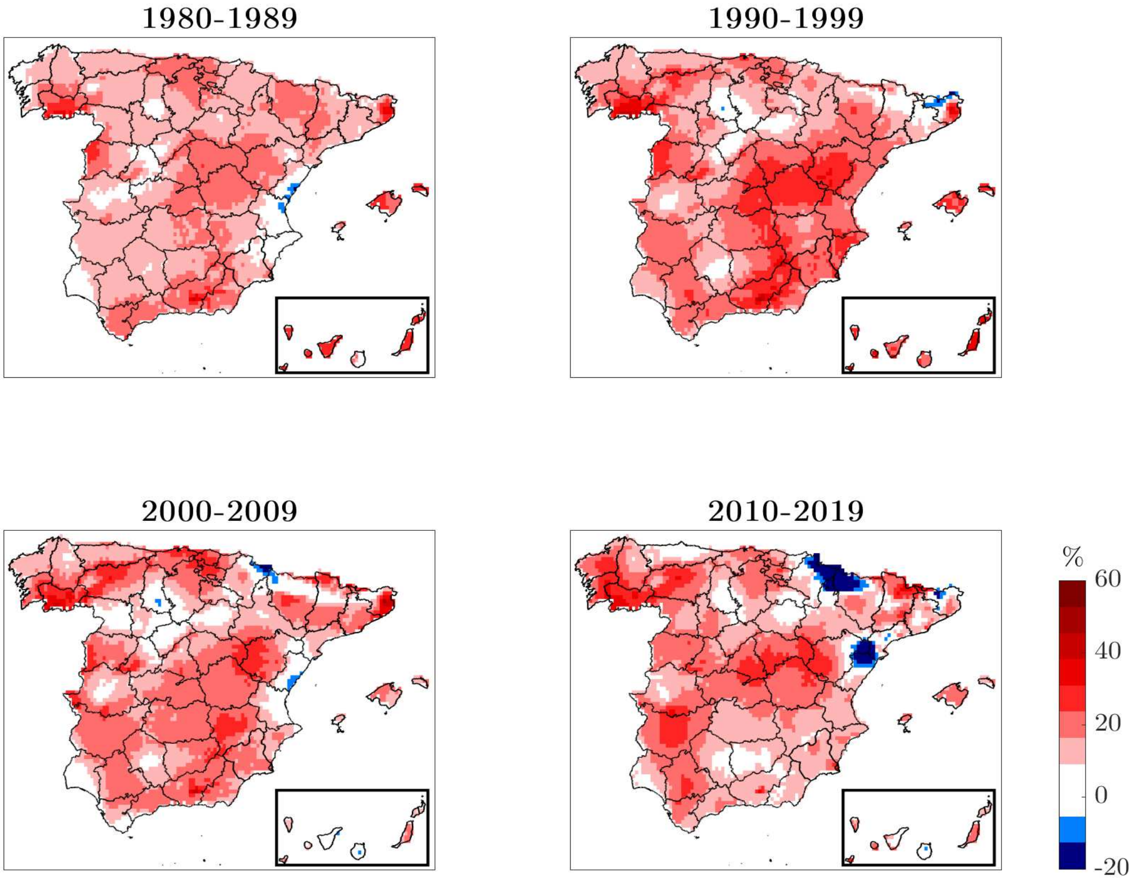
Note: Source: Cornes et al. (2018) available at the Copernicus Climate Change Service and own calculations. The AI is computed following the definition by UNEP (1992). The annual indices are averaged per decade. The six aridity categories are defined as follows: Hyperarid: $AI < 0.05$; Arid: $0.05 \leq AI < 0.2$; Semiarid: $0.2 \leq AI < 0.5$; Dry subhumid: $0.5 \leq AI < 0.65$; Humid subhumid; $0.65 \leq AI < 1$; Humid: $AI \geq 1$. The resolution of the grid is $0.1°$ (11km at the Equator, 8.5km at the latitude of continental Spain). Values of the grid cells outside of the displayed range have the same color as the bounds of the displayed range.

Figure 2: Distribution of the aridity index by climate zone in Spain



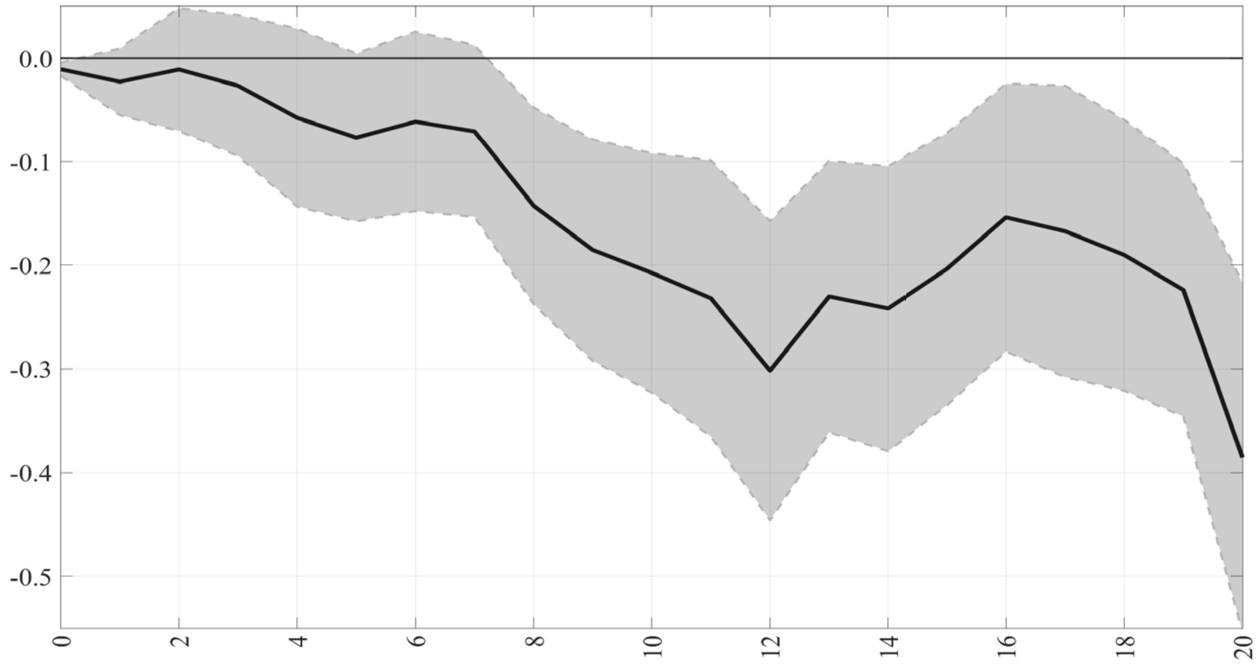
Note: Source: Cornes et al. (2018) available at the Copernicus Climate Change Service and own calculations. The bar chart illustrates the distribution of aridity in Spain according to the climate zones defined by UNEP (1992), where the annual index has been averaged per decade. The six aridity categories are defined as follows: Hyperarid: $AI < 0.05$; Arid: $0.05 \leq AI < 0.2$; Semi-arid: $0.2 \leq AI < 0.5$; Dry subhumid: $0.5 \leq AI < 0.65$; Humid subhumid; $0.65 \leq AI < 1$; Humid: $AI \geq 1$. The resolution of the grid is 0.1° (11km at the Equator, 8.5km at the latitude of continental Spain).

Figure 3: Percentage change of the Spanish aridity indices by decade with respect to the 1970s



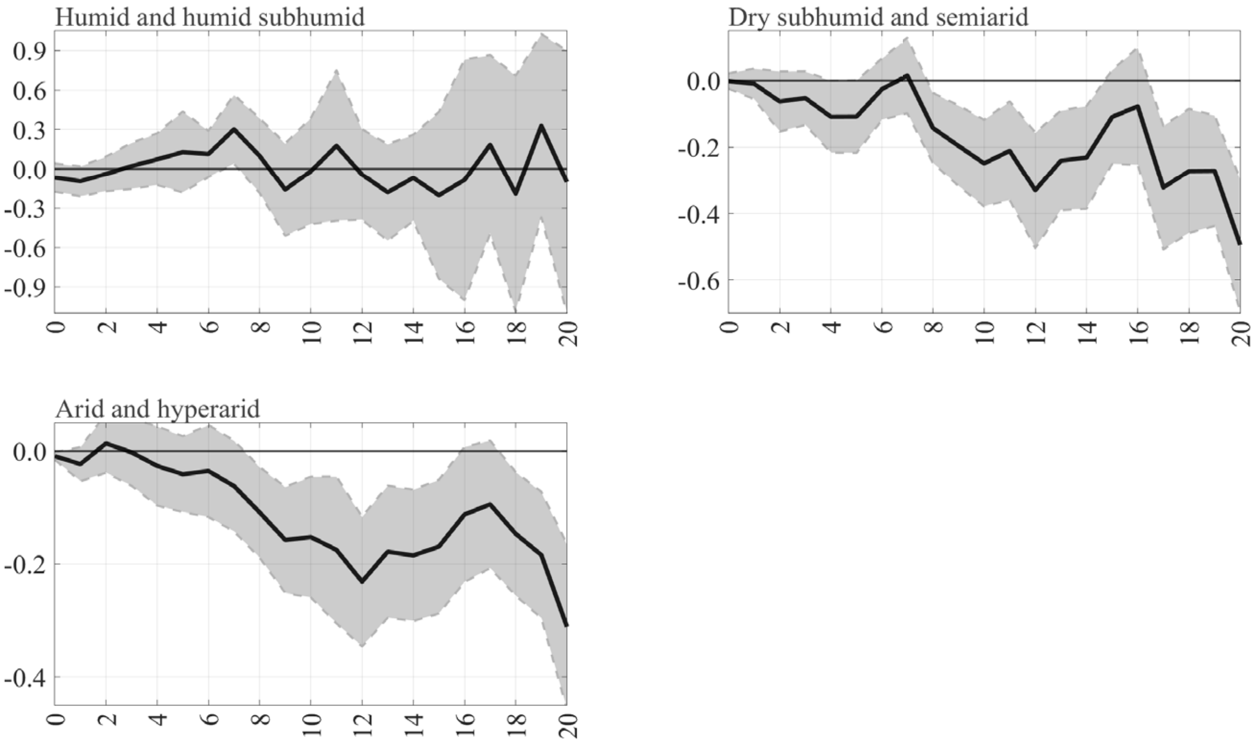
Note: Source: Cornes et al. (2018) available at the Copernicus Climate Change Service and own calculations. The AI is computed following the definition by UNEP (1992). The annual indices are averaged per decade. The maps represent the rate of change of these mean values of the AIs with respect to the average AI in the 1970s, so that the areas in red tones have increased their aridity and those in blue tones have decreased it with respect to that decade. The resolution of the grid is 0.1° (11km at the Equator, 8.5km at the latitude of continental Spain). Values of the grid cells outside of the displayed range have the same color as the bounds of the displayed range.

Figure 4: Local projection estimator of the impact of *Aridity* on the aggregate credit to NFCs for 20 years



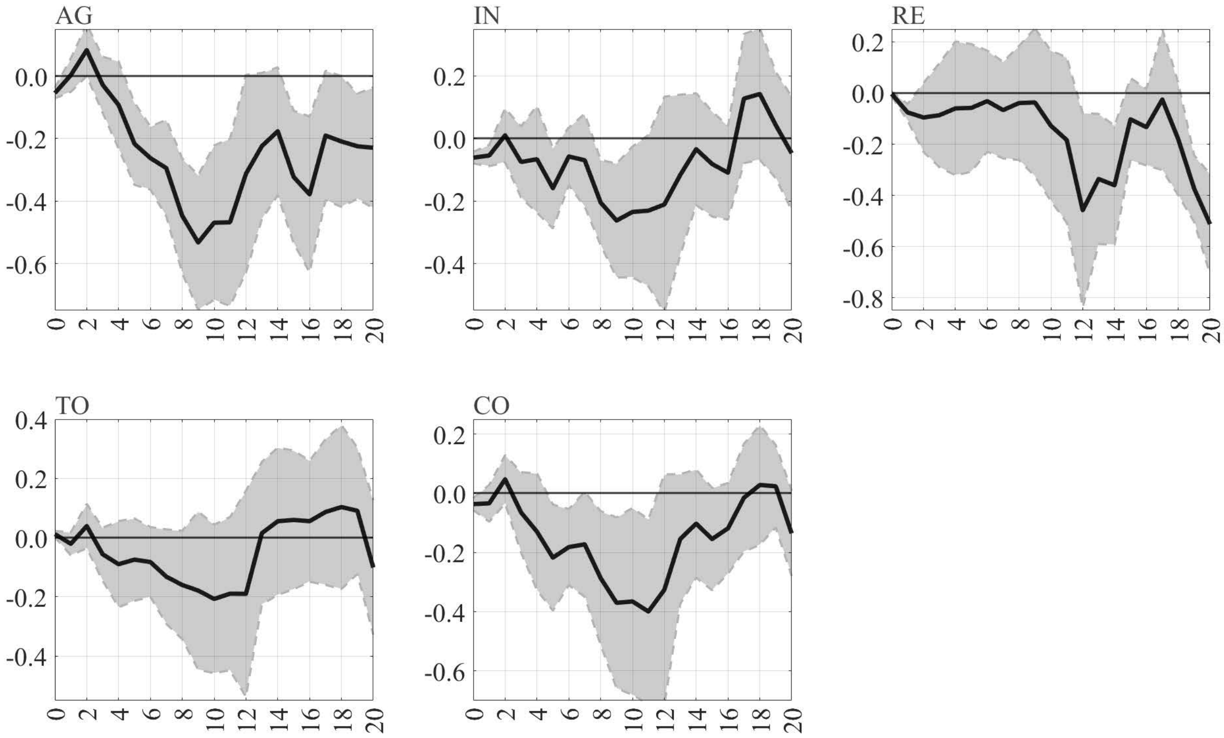
Note: The solid line represents the local projection estimators for the coefficients in model (7) of *Aridity*, β_1^h, for 20 years after a 1% increase in *Aridity* in the municipality. The grey area is the 90% confidence interval based on HAC-robust standard errors clustered at the province level. The x-axis represents the horizon h of the local projections exercise expressed in years. Y-axis in percentage points.

Figure 5: Local projection estimator of the impact of *Aridity* on the aggregate credit to NFCs for 20 years by climate zone



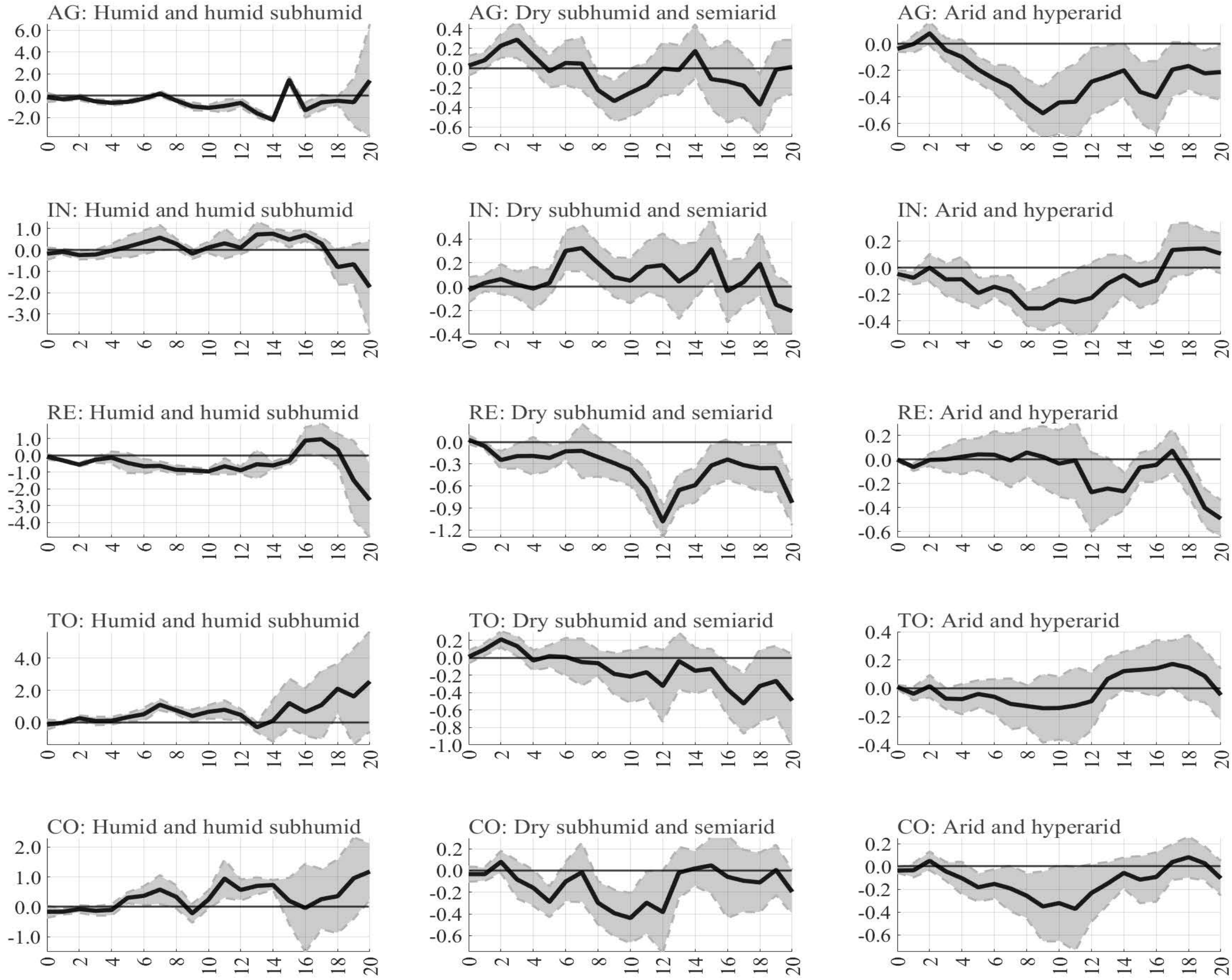
Note: The solid line represents the local projection estimators for the coefficients in model (8) of *Aridity*, β_{1c}^{h}, for 20 years after a 1% increase in *Aridity* in the municipality, where the subindex c denotes climate zone. Climate zones are grouped in three categories: humid and humid subhumid ($0.65 \leq AI$), dry subhumid and semiarid ($0.2 \leq AI < 0.65$) and arid and hyperarid ($AI < 0.2$). The grey area is the 90% confidence interval based on HAC-robust standard errors clustered at the province level. The x-axis represents the horizon h of the local projections exercise expressed in years. Y-axis in percentage points.

Figure 6: Local projection estimator of the impact of *Aridity* on sectoral credit for 20 years



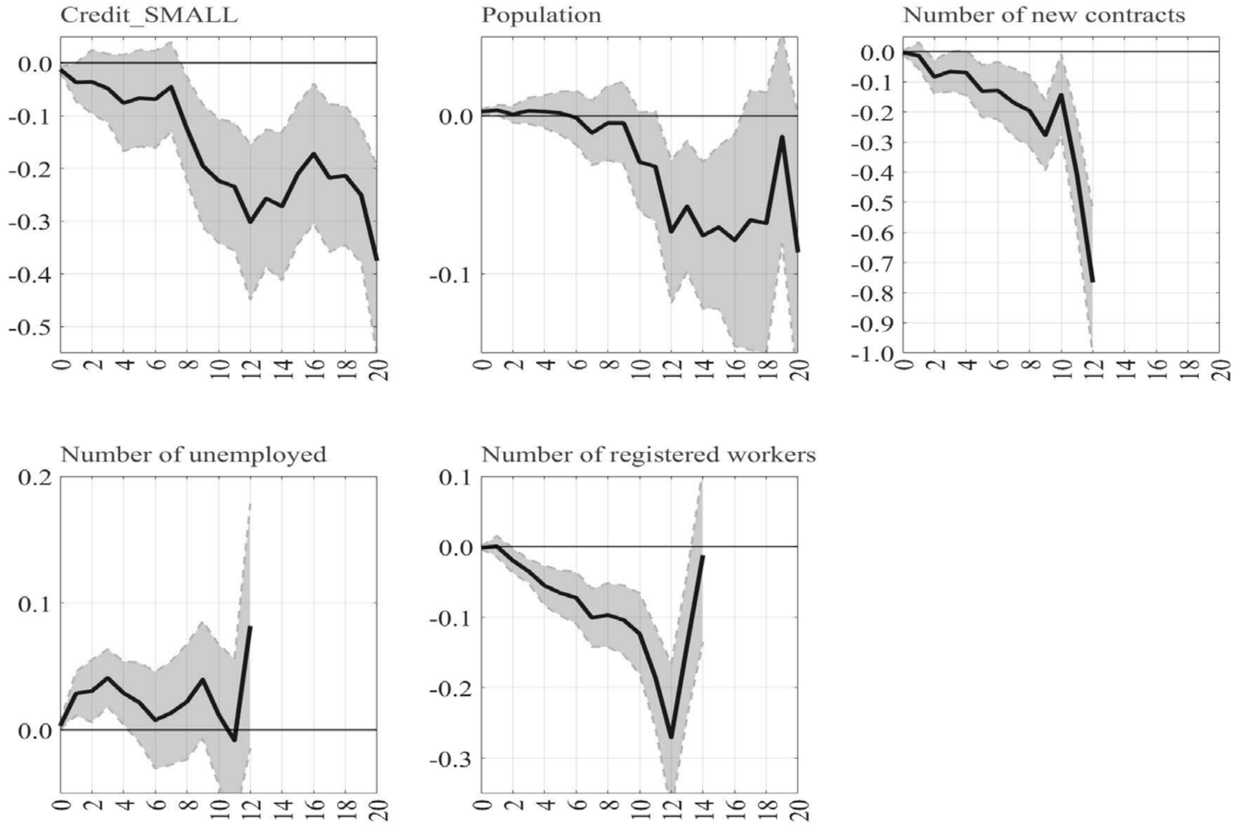
Note: The solid line represents the local projection estimators for the coefficients in model (9) of *Aridity* , β^h_{1s}, for 20 years after a 1% increase in *Aridity* in the municipality, where the subindex s denotes the economic sector. Economic sectors are defined according to their code in the CCR (see Appendix B). The abbreviations AG, IN, RE, TO and CO represent five economic sectors, namely (1) agriculture and fisheries, (2) industry, (3) real estate, (4) tourism, and (5) transport, commerce, and personal services, respectively. The grey area is the 90% confidence interval based on HAC-robust standard errors clustered at the province level. The x-axis represents the horizon h of the local projections exercise expressed in years. Y-axis in percentage points.

Figure 7: Local projection estimator of the impact of *Aridity* on sectoral credit for 20 years by climate zone



Note: The solid line represents the local projection estimators for the coefficients in model (10) of $Aridity$, β^h_{1cs}, for 20 years after a 1% increase in $Aridity$ in the municipality, where the subindex c denotes climate zone and s the economic sector. Each row corresponds to an economic sector and each column to a different climate zone. Sectors are defined according to their code in the CCR (see Appendix B). Climate zones grouped in three categories as follows: humid and humid subhumid ($0.65 \leq AI$), dry subhumid and semiarid ($0.2 \leq AI < 0.65$) and arid and hyperarid ($AI < 0.2$). The abbreviations AG, IN, RE, TO and CO represent five economic sectors, namely (1) agriculture and fisheries, (2) industry, (3) real estate, (4) tourism, and (5) transport, commerce, and personal services, respectively. The grey area is the 90% confidence interval based on HAC-robust standard errors clustered at the province level. The x-axis represents the horizon h of the local projections exercise expressed in years. Y-axis in percentage points.

Figure 8: Local projection estimator of the impact of *Aridity* on alternative dependent variables for different horizons



Note: The solid line represents the local projection estimators for the coefficients in model (7) of *Aridity*, β_1^h after a 1% increase in *Aridity* in the municipality for alternative dependent variables. All variables but *Population* are expressed in per capita terms. The variable *Credit_SMALL* stands for credit to Spanish NFCs with less than 10 employees. The grey area is the 90% confidence interval based on HAC-robust standard errors clustered at the province level. The x-axis represents the horizon h of the local projections exercise expressed in years. Y-axis expressed in percentage points.

Table 1: Descriptive statistics of the aridity index and the aggregated and sectoral credit per capita

Variable	Observations	Mean	SD	P1	P99	Min.	Max.
$Aridity$	286,416	1.57	0.54	0.31	2.96	−0.85	7.56
$Credit\_pc$	226,455	0.86	1.78	−3.74	8.65	−7.86	8.65
$Credit\_pc\_AG$	150,312	−0.67	1.99	−5.56	3.83	−9.29	7.53
$Credit\_pc\_IN$	158,688	−0.54	1.93	−5.1	4.11	−8.72	8.06
$Credit\_pc\_RE$	141,850	−0.71	1.92	−5.25	3.68	−9.07	8.53
$Credit\_pc\_TO$	95,192	−1.49	1.93	−5.98	3.07	−9.53	7.13
$Credit\_pc\_CO$	171,665	−0.3	1.76	−4.64	3.9	−7.98	8.06

Note: $Aridity$ is the natural logarithm of the aridity index, AI; $Credit\_pc$ stands for the natural logarithm of the stock of drawn down loans to Spanish non-financial corporations (NFCs); AG, IN, RE, TO and CO stand for the (1) agriculture and fisheries, (2) industry, (3) real estate, (4) tourism, and (5) transport, commerce, and personal services sectors, respectively; P1 and P99 denote the 1% and 99% percentiles, respectively.

Table 2: Descriptive statistics of alternative dependent variables

Variable	Observations	Mean	SD	P1	P99	Min.	Max.
$Credit\_pc\_SMALL$	211,460	0.65	1.82	−3.99	4.79	−7.86	8.61
$Population$	287,455	6.61	1.76	3.3	11.23	0	15
$New\_contracts\_pc$	91,927	−4.2	1.08	−6.54	−1.26	−8.27	1.79
$Unemployed\_pc$	113,783	−3.03	0.65	−4.88	−1.86	−6.64	−1.13
$Registered\_workers\_pc$	135,224	−1.45	0.51	−2.68	−0.02	−5.46	2.46

Note: $Credit\_pc\_SMALL$ denotes the logarithm of the credit per capita of firms that employ less than ten employees; the logarithm of the employment indicators (the number of new contracts, unemployment rate and the number of registered workers at year-end) are expressed in per capita terms and are denoted as $New\_contracts\_pc$, $Unemployed\_pc$, and $Registered\_workers\_pc$, respectively. P1 and P99denote the 1% and 99% percentiles, respectively.

Table 3: Data description and sources

	DESCRIPTION	SOURCE
Credit	Amount of drawn down loans granted by Spanish financial institutions (minimum 6,000 euros; at year-end; in euros)	Central Credit Register (Banco de España)
		Central Balance Sheet Data Office (CBSO)
		Central Directory of Enterprises (DIRCE)
Population	De facto population (1986-1995) and de jure population (1996-2019), at the municipal level (at year-end; units)	Instituto Nacional de Estadística (INE)
New contracts	Number of new contracts in the municipality, place of work (at year-end; units)	Instituto Nacional de Estadística (INE)
Unemployed	Number of people that ask for unemployment benefits, place of residence (at year-end; units)	Instituto Nacional de Estadística (INE)
Registered workers	Number of people registered at the Social Security Office, location of the employer (at year-end; units)	Instituto Nacional de Estadística (INE)
P_t	Annual precipitations: Sum of monthly averages (l/m^2)	Copernicus (Cornes et al., 2018)
T_{tm}	Monthly average temperature in year t (^oC)	Copernicus (Cornes et al., 2018)

Note: P_t and T_m are needed for the calculation of the aridity index, AI_t.

Table 4: Estimates of the baseline model

	(1)	(2)	(3)	(4)	(5)
$Aridity_{i,t}$	-0.010^{***}	-0.014^{**}	-0.013^{***}	-0.012	-0.009^{**}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
$Credit\_pc_{i,t-1}$	0.964^{***}	0.948^{***}	0.967^{***}	0.939^{***}	0.961^{***}
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
N	213,965	213,965	213,965	213,965	213,965
R^2_A	0.96	0.94	0.94	0.94	0.95
Year FE	Y	N	Y	N	Y
Province FE	Y	N	N	Y	Y
Year-Province FE	Y	N	N	N	N

Note: Dependent variable: Natural logarithm of the nominal credit to Spanish non-financial corporations per capita, $Credit\_pc$; $Aridity$: Natural logarithm of the aridity index, AI; Intercept is included but not reported; Year, province and year-province fixed effects are included in some specifications but not reported; R^2_A: Adjusted R^2; The sample runs from 1984 to 2019; Standard errors are shown in parenthesis; Standard errors are clustered at the provincial level and are HAC-robust; ***, **, * refer to significance at 1%, 5% and 10%, respectively.

Table 5: Estimates of the baseline model by climate zone

	(1)	(2)	(3)	(4)	(5)
$Aridity_{it} \times I_1$	-0.067	-0.029	-0.040	-0.040	-0.040
	(0.119)	(0.060)	(0.049)	(0.064)	(0.045)
$Aridity_{it} \times I_2$	-0.000	0.033^{***}	0.007	0.090^{***}	0.027^{**}
	(0.016)	(0.009)	(0.007)	(0.013)	(0.011)
$Aridity_{it} \times I_3$	-0.009^{**}	-0.029^{**}	-0.018^{***}	-0.022^{*}	-0.011^{**}
	(0.003)	(0.012)	(0.006)	(0.013)	(0.013)
$Credit\_pc_{it-1} \times I_1$	0.945^{***}	0.924^{***}	0.954^{***}	0.926^{***}	0.951^{***}
	(0.014)	(0.009)	(0.015)	(0.008)	(0.008)
$Credit\_pc_{it-1} \times I_2$	0.970^{***}	0.950^{***}	0.970^{***}	0.946^{***}	0.966^{***}
	(0.003)	(0.006)	(0.004)	(0.006)	(0.006)
$Credit\_pc_{it-1} \times I_3$	0.959^{***}	0.945^{***}	0.964^{***}	0.933^{***}	0.955^{***}
	(0.008)	(0.008)	(0.006)	(0.010)	(0.010)
N	213,965	213,965	213,965	213,965	213,965
R_A^2	0.96	0.94	0.95	0.94	0.95
Climate zone FE	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y
Province FE	Y	N	N	Y	Y
Year-Province FE	Y	N	N	N	N

Note: Dependent variable: Natural logarithm of the nominal credit to Spanish non-financial corporations per capita, $Credit\_pc$; $Aridity$: Natural logarithm of the aridity index, AI; I_1, I_2 and I_3 are the indicator variables that represent the climate zone. I_1 :“ Humid” and “humid subhumid” ($0.65 \leq AI$); I_2 :“dry subhumid” and “semiarid” ($0.2 \leq AI < 0.65$); (3) I_3 : “arid” and “hyperarid” ($AI < 0.2$). Intercept is included but not reported; Climate zone fixed effects are included in all specifications but not reported; Year, province and year-province fixed effects are included in some specifications but not reported; R_A^2: Adjusted R^2; The sample runs from 1984 to 2019; Standard errors are shown in parenthesis; Standard errors are clustered at the province level and are HAC-robust; The superscripts ***, **, * refer to significance at 1%, 5% and 10%, respectively.

Table 6: Estimates of the baseline model by sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\beta_{1,AG}$	-0.055^{***}	-0.036^{***}	-0.043^{***}	-0.036^{***}	-0.031^{***}	-0.038^{***}	-0.040^{***}	-0.030^{**}	-0.054^{***}	-0.037^{**}	-0.046^{**}
	(0.010)	(0.010)	(0.011)	(0.010)	(0.008)	(0.013)	(0.008)	(0.014)	(0.017)	(0.016)	(0.019)
$\beta_{1,IN}$	-0.061^{***}	-0.054^{***}	-0.056^{***}	-0.062^{***}	-0.051^{***}	-0.024^{*}	-0.054^{***}	-0.045^{***}	-0.038^{*}	-0.045^{***}	-0.047^{***}
	(0.011)	(0.013)	(0.013)	(0.016)	(0.015)	(0.014)	(0.013)	(0.013)	(0.02)	(0.017)	(0.014)
$\beta_{1,RE}$	-0.003	-0.010	-0.011^{*}	-0.014^{***}	-0.004	-0.001	-0.002	-0.008	-0.003	-0.010^{*}	-0.011^{*}
	(0.006)	(0.010)	(0.005)	(0.004)	(0.013)	(0.019)	(0.007)	(0.005)	(0.006)	(0.006)	(0.006)
$\beta_{1,TO}$	0.012^{*}	0.011	0.005	0.007	0.022^{**}	0.002	0.016^{*}	0.001	-0.003	-0.002	-0.003
	(0.006)	(0.009)	(0.007)	(0.007)	(0.010)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
$\beta_{1,CO}$	-0.037^{***}	-0.038^{***}	-0.041^{***}	-0.035^{***}	-0.029^{***}	-0.030^{***}	-0.032^{***}	-0.021^{*}	-0.037^{**}	-0.026^{*}	-0.021^{**}
	(0.012)	(0.007)	(0.008)	(0.007)	(0.008)	(0.011)	(0.010)	(0.012)	(0.012)	(0.013)	(0.010)
N	657,377	657,377	657,377	657,377	657,377	657,377	657,377	657,377	657,377	657,377	657,377
R^2_A	0.93	0.92	0.93	0.93	0.92	0.92	0.93	0.93	0.93	0.94	0.94
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	Y	N	N	Y	Y	Y	Y	Y
Sector-Year FE	N	N	N	Y	N	N	N	Y	N	Y	Y
Province FE	Y	N	N	N	Y	Y	Y	Y	Y	Y	Y
Sector-Province FE	N	N	N	N	N	Y	N	Y	Y	Y	Y
Year-Province FE	Y	N	N	N	N	N	N	N	Y	Y	Y
Sector-Year-Province FE	N	N	N	N	N	N	N	N	N	N	Y

Note: Dependent variable: Natural logarithm of the nominal credit to Spanish non-financial corporations per capita in sector s, $Credit\_pc$; $Aridity$: Natural logarithm of the aridity index; AI; AG, IN, RE, TO and CO stand for the (1) agriculture and fisheries, (2) industry, (3) real estate, (4) tourism, and (5) transport, commerce, and personal services sectors, respectively. Intercept and lagged of the dependent are included but not reported; Sector fixed effects are included in all specifications but not reported; Year, province, year-province, sector-province, and sector-year fixed effects are included in some specifications but not reported; R^2_A: Adjusted R^2; The sample runs from 1984 to 2019; Standard errors are shown in parenthesis; Standard errors are clustered at the province level and are HAC-robust; The superscripts ***, **, * refer to significance at 1%, 5% and 10%, respectively.

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