UNIVERSIDADE CATÓLICA PORTUGUESA

The impact of drought on firms' borrowing costs

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By,

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Resumo

Esta tese possui dois objetivos: (i) estudar a exposição da dívida de empresas portuguesas a risco de seca e (ii) medir o impacto do risco de seca no custo da dívida das empresas. Este tópico tem merecido a atenção da academia, reguladores e supervisores do setor financeiro, particularmente no sul da Europa, onde o risco de seca é considerado um dos principais riscos físicos. Esta tese procura contribuir para um ramo da literatura, que, até à data, se tem focado exclusivamente em empresas dos EUA. Para tal, aplicamos uma série de regressões a uma amostra de 12,512 empresas portuguesas que operam em indústrias intensivas em água, entre 2007 e 2019. O risco de seca é medido através do "Palmer Drought Severity Index" (PDSI). Os resultados sugerem que o montante de dívida anual exposta a risco de seca ascenda a cerca de 4.1 biliões de euros, nos anos mais intensos em risco de seca, em que os setores da agricultura e silvicultura são os mais intensamente expostos. Conclui-se ainda que o PDSI (risco de seca inverso) tem um impacto negativo no custo da dívida, com origem nas micro empresas e nas empresas do setor agrícola. Verifica-se também que o efeito de risco de seca no custo da dívida é particularmente intenso em empresas com uma situação financeira frágil. Os nossos resultados apresentam robustez a diversas alterações introduzidas na amostra.

Palavras-chave: Risco de seca, custo de dívida, PDSI, fragilidade financeira.

Abstract

This thesis has two main goals: (i) to study the debt exposure of Portuguese firms to drought risk, and (ii) to measure the impact of drought risk on the cost of debt. This topic has deserved the attention of academia, regulators, and supervisors of the financial sector, particularly in southern Europe countries, where drought risk is considered one of the main physical risks. This thesis attempts to contribute to a small body of literature that, so far, has focused exclusively on U.S. firms. To do so, we apply a set of firm-level panel regressions to a sample of 12,512 firms operating in water-intensive industries located in Portugal, between 2007 and 2019. To proxy for drought risk, we use the Palmer Drought Severity Index (PDSI). Our results suggest that approximately 4.1 billion euros of debt was exposed to drought annually in the years of more intense drought, particularly in the agriculture and forestry industries. Additionally, we find that PDSI (inverse drought risk) has a negative and statistically significant impact on the cost of debt, which is driven by micro firms and firms operating in the agricultural industry. Interestingly, we find that the effect of drought risk on cost of debt is particularly strong for fragile firms (i.e., operating in the lowest quartile of profitability and solvency). Our results are robust to changes in the sample related to the period of analysis, firm location, and dependent variable.

Keywords: Drought risk, cost of debt, PDSI, financial fragility.

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List of Abbreviations

BdP – Banco de Portugal

CAE – Classificação das Atividades Económicas

EBIT – Earnings before Interest and Taxes

GVA – Gross Value Added

IPCC – Intergovernmental Panel on Climate Change

IPMA – Instituto Português do Mar e da Atmosfera

PDSI – Palmer Drought Severity Index

SME – Small and Medium Enterprises

SPEI – Standard Precipitation Evapotranspiration Index

SPI – Standard Precipitation Index

Introduction

This thesis studies the relationship between drought risk and the cost of debt. There has been an increasing attention in the topic of climate risk in the financial sector (NGFS, 2019), given the expectation that climate change will increase the severity and frequency of extreme weather events, which can result in large financial losses to borrowers, and as a result to lenders (BCBS, 2021). Particularly, one of the key climate risks considered is the drought risk (IPCC, 2022) which has been historically high in southern Europe countries like Portugal and Spain (Forzieri *et al.*, 2015). As a case in point, according to estimates by Naumann *et al.* (2021) the annual drought losses in Europe are expected to reach more than 65 billion euros in 2100, wherein up to 60% in the Mediterranean region.

In this context, there is a small body of literature that has studied the effects of drought risk on the cost of debt of U.S. firms. Javadi & Masum (2021) analyze syndicated loans for U.S firms (1986-2017) and find evidence suggesting that climate risk is underpriced. The authors argue that this occurs due to the presence of information asymmetry. Similarly, Do *et al.* (2021) study a sample of US syndicated loans (1984-2016) and find that firms operating in food industries pay significantly higher loan spreads, when exposed to droughts. Finally, the Bank of Portugal (2023) has recently published the first report on the Portuguese banking sector's exposure to climate risk, where it is estimated that approximately 70% of the debt owed by Portuguese firms is exposed to water stress risk.

Considering the lack of European based studies focused on the nexus between drought risk and cost of debt, in this thesis we draw on a sample of 12,512 firms operating in water-intensive industries (Agriculture, Forestry, Electricity, Water Treatment, and Transportation by water), located in Portugal, which is one of the countries most affected by drought risk (Forzieri *et al.*, 2015), to (i) estimate firm debt exposure to drought risk per year, district, and industry; and (ii) run a set of regressions using the Palmer Drought Severity Index (PDSI) (Palmer, 1965) as the proxy for drought risk (Javadi & Masum, 2021; Huynh *et al.*, 2020) and the accounting based cost of debt (Cassar, 2011). Moreover, besides the baseline regression, we assess the impact of drought on the cost of debt by drilling down our initial sample using three dimensions: firm size, industry, and financial fragility. Finally, we perform a set of robustness tests related to the period of analysis, firm location, and dependent variable.

Our results can be summarized in the following way. First, we find that (i) in the period of analysis (2007-2019) Portugal recorded three years of more intense drought (2011, 2017, 2019); (ii) the exposure to drought risk is mainly focused in the southern region of Portugal, (iii) approximately 4.1 billion euros of firm debt was exposed to drought, annually in the years of more intense drought; the industries where debt is most exposed to drought are agriculture and forestry. Second, we find that drought risk (proxied by the inverse PDSI) has a negative and statistically significant impact on the cost of debt. However, the effect is economically low (one standard deviation of PDSI leads to 6.6 bps increase in the cost of debt). Third, we find significant heterogeneous effects of drought risk on cost of debt. Namely, the PDSI coefficient is only statistically significant for micro firms and firms operating in the agricultural industry. Fourth, we find that the effect of drought risk on cost of debt is particularly strong for fragile firms (i.e., operating in the lowest quartile of profitability and solvency). This is an interesting and novel result that has potential policy implications, as discussed in the **Conclusions**.

These findings contribute to the increasing literature on the financial effects of climate risk (Javadi & Masum, 2021; Do *et al.*, 2021). Namely, as previously mentioned, to the best of our knowledge, this is the first study analyzing the effects of drought risk on the cost of debt of European firms. Despite this, we are aware that this thesis suffers from a set of limitations related to the use of the firms' headquarters location as the location of all its operations, the lack of evidence on the mechanism via which drought risk affects cost of debt and the absence of loan level data to perform the analysis.

The remaining thesis is structured in the following way. In **Section 1** we present the literature review, including an overview of drought risk, theoretical framework and the expected loss model, and empirical literature. In **Section 2** we present an overview of the data and methodology used throughout the thesis. **Section 3** provides our empirical results. Robustness tests are performed in **Section 4**, and **Section 5** presents the limitations of the study. Conclusions and policy implications are presented in the last section of the thesis.

1. Literature review

1.1 Drought risk in the context of climate risk

Climate risk is related to the possibility that economic agents (households, non-financial corporations, financial firms, governments) may face losses caused by the environment and/or the transition to a low-carbon economy (NGFS, 2019), and can be divided into two categories: physical risk, which is the risk associated with physical damage due to extreme weather events/natural disasters or the long-term changes in climate patterns; and transition risk, related to the emerging changes of certain industries sensitive to the transition to low-carbon economies, e.g. oil and gas (BCBS, 2021). According to BCBS (2021), physical risks are sub-divided into acute (heat waves, floods, wildfires, and storms) and chronic risks (rising sea level, rising average global temperature and ocean acidification). Interestingly this taxonomy omits whether drought risk should be considered acute or chronic. According to the Intergovernmental Panel on Climate Change (IPCC), a drought can be defined as "an exceptional period of water shortage for existing ecosystems and the human population (due to low rainfall, high temperature, and/or wind)." (IPCC, 2022: p.2906). In this study we will explore droughts with a high level of severity, which according to the definitions above should be considered an acute risk.

This risk is historically higher in southern Europe countries like Portugal and Spain, according to Stahl *et al.* (2016), when looking at drought impacts on water supply, the southern regions of Europe are more severely affected. Another strand of literature also correlates this risk to economic or financial consequences, and most of them use the same indicators to measure drought risk. The most commonly used is the Palmer Drought Severity Index (Palmer, 1965), and it is an estimate for the relative soil moisture of a region based on precipitation and temperature data. The PDSI values range from +10 to –10 and a positive value indicates wet conditions whereas negative values indicate drought conditions, however the scale most used is from +4 to -4, while -2 is considered a moderate drought, -3 a severe drought and -4 an extreme drought. In corporate finance literature, Huynh *et al.* (2020) and Do *et al.* (2021) use this index to measure drought risk. Huynh *et al.* (2020) construct a yearly average value for each state from the monthly observations of the PDSI and Do *et al.* (2021) use a three-month average of the PDSI values prior to the loan start date. An alternative indicator for drought risk other is the Standardized Precipitation Evapotranspiration Index (SPEI), this index derives from the previously existing Standard Precipitation Index (SPI), but it includes the effect of temperature, considering evapotranspiration as a determinant on drought conditions (Vicente-Serrano et al., 2010). Using SPEI has some advantages compared to PDSI: SPEI is a better indicator for short-term droughts while PDSI is insensitive to short term droughts but is efficient for measuring medium- and long-term droughts (Zhao *et al.*, 2017). However, to ensure a greater comparability of our results we use the PDSI in this study.

1.2 Theoretical framework

The key concepts in the Finance literature that shed light on the determinants of cost of debt can be understood as a byproduct of the seminal work by Modigliani & Miller (1958) on the optimal capital structure. According to the authors the capital structure of a firm is irrelevant for its market value, only in the absence of taxes, bankruptcy costs, asymmetrical information, and agency costs. Each of these violations of the baseline scenario referred in the Modigliani & Miller model, can be seen as giving rise to potential determinants of the cost of debt, explored in the next sub-sections.

First, according to the theory proposed by De Angelo & Masulis (1980) the use of debt creates a tax shield via the interest payments which can be explored by firms to their advantage. However, such increase in debt has potential bankruptcy costs, that are particularly acute for small firms (Bradbury & Lloyd, 1994) and there is evidence that suggests that small firms have lower tax advantages than bigger firms, due to the combination of personal and business incomes by many small business owners (Day *et al.*, 1985).

Second, as suggested by Ross (1977) the capital structure can be used by firms to signal information about future cash flow risk, namely firms that are more confident about their future capacity to meet interest payments are more likely to increase debt. Alternatively, the Pecking Order Theory (Myers, 1984) indicates that firms have a hierarchy of preferred sources of financing, arising due to the presence of information asymmetry between insiders and outsiders of the firm.

Finally, the agency theory is based on the notion that, in an agency relationship, the principal (shareholder) and the agent (manager) may have different goals[1], and hence the principal faces agency costs due to the need to monitor the agent's actions. According to Jensen & Meckling (1976), debt has the capacity to reduce agency costs by pressuring firms' cash flows and hence the managers' performance. However, the monitoring by lenders, for instance via the enforcement of information disclosure by borrowers, can be costly (Leland & Pyle, 1977), particularly for smaller firms (Groves & Harrison, 1984).

In addition, another key theoretical concept to our study is economies of scale (Benston & Smith, 1976). This concept implies that firms can take advantage of their size, because the higher the production levels the more they can dilute the fixed costs. Size matters

[1] According to Jensen & Meckling (1976), an agency relationship can be defined as the contract where one or more individuals, who are defined as the principals, have authority over other individuals, who are defined as the agents, and these agents perform a service on the behalf of the principals, this contract implies that the principals delegate the decision-making process and the authority that comes with it to the agents. Then the problem arises: if we assume that both parties in the contract have the goal of maximizing their own utility, then the agent will have a moral hazard issue, because if he puts his own interest first, he might not always act on the principal's best interests.

when it comes to bargaining power when firms ask for bank loans, whether it is on the agreed interest rate or on the debt or in the commissions charged by the banks. Economies of scale can also be a determinant for a firm's debt structure, depending on whether a company can take advantage of it or not. As Krishnaswami *et al.* (1999) state in their article, larger firms can take advantage of scale economies reducing issuance costs of public debt and therefore will have less private debt.

1.3 Expected loss model

Another framework that may be useful to understand the potential impact of drought risk on the cost of debt is the expected loss model (Cohen, 2017). This model is commonly used in the banking industry to predict the expected loss on outstanding loans and influences the decision to grant loans and the respective pricing. The model includes three components: probability of default (PD), exposure at default (EAD) and loss given default (LGD).

Briefly, the PD is related to the expected probability of the borrower entering default in a given time window, which can be one year or the full maturity of the loan. The EAD is the amount of capital including all payments due by the borrower time window of analysis. The LGD is the percentage of the exposure that is expected to be lost in case of default and is highly related to the existence of collateral (Cohen, 2017)

Under this framework, Alogoskoufis *et al.* (2021) define two channels via which climate risk may affect the expected loss of a loan. First, the exposure to certain climate risks may decrease the value of the collateral of a firm, hence increasing its LGD. Second, a decrease in the firms' Gross Value Added (GVA), which would therefore imply an increase in the firms' PD. Both channels can potentially lead to higher loan spreads, which translates into a higher cost of debt. In our research design we hypothesize that drought risk will only impact the cost of debt via the GVA channel and only for water intensive industries (Rossi *et al*., 2023).

Importantly, the regulation and supervision of banks regarding climate risk is still at its early days (ECB, 2022). Namely the recent thematic review on climate related and environmental risks issued by ECB has shown that there are only a few banks that have a sound and comprehensive understanding of these risks (ECB, 2022). This context leads us to consider the possibility that drought risk may not yet be fully incorporated in bank risk management practices and hence not reflected in the pricing of loans.

1.4 Empirical evidence on the financial impact of drought

The number of studies tackling the relationship between drought risk and corporate financial performance is relatively scarce and can be organized according to the type of dependent variable: industry level losses, loan pricing, and stock returns / cost of equity.

Regarding industry level losses, based on simulations using climate change scenarios, Naumann *et al.* (2021) estimate that annual drought losses in Europe will arise to more than 65 billion euros in 2100, wherein "agriculture losses account for more than 50% of total drought losses in Europe, with the highest sector share in the Mediterranean (60%)" (p. 8).

With respect to literature on loan pricing, Javadi & Masum (2021) analyze syndicated loans for U.S firms, in the period between 1986 and 2017 and find evidence suggesting that climate risk is underpriced. The authors argue that this occurs due to the presence of information asymmetry that does not allow markets to properly understand and evaluate this specific risk. Additionally, Do *et al.* (2021) study a sample of US syndicated loans in the period between 1984 and 2016, and find that in specific water intensive industries such as food industries, firms affected by drought pay significantly higher loan spreads.

Concerning stock returns / cost of equity, Hong *et al.* (2019) study the returns of worldwide food stocks between 1927 and 2014 and find that there is a strong ability to forecast food industry profitability using drought risk, hence concluding that stock markets are inefficient when evaluating drought risk. On the other hand, Huynh *et al.* (2020) study the cost of equity for U.S. firms in the period between 1968 and 2015 and find that drought risk increases the firms' cost of equity.

In sum, to the best of our knowledge, our literature review indicates that there is currently no study relating drought risk to the cost of debt using a sample of European firms, which makes this thesis scientifically relevant.

2. Data and methodology

2.1 Drought risk measure

To measure drought, we use the Palmer Drought Severity Index (PDSI) (Palmer, 1965) for each municipality in Portugal per year, obtained from Instituto Português da Atmosfera e do Mar (IPMA). We use the period 2007-2019. This index is currently the standard to measure droughts and overall soil moisture (Huynh *et al*., 2020), and varies between -4 to +4, wherein drought is related to the negative values. **Table 1** shows the classification of drought risk, according to IPMA.

Table 1. PDSI classification

PDSI values	Classification
Higher or equal to 4.00	Extreme rain
Between 3.00 and 3.99	Severe rain
Between 2.00 and 2.99	Moderate rain
Between 1.00 and 1.99	Weak rain
Between -0.99 and 0.99	Normal
Between -1.99 and -1.00	Weak drought
Between -2.99 and -2.00	Moderate drought
Between -3.99 and -3.00	Severe drought
Lower or equal to -4.00	Extreme drought

Note: The content of this table was retrieved from IPMA (2023).

Following Javadi & Masum (2021) and Huynh *et al.* (2020) we construct our main independent variable, *PDSI*, as the 12-month average from June of year *t* until May from year *t+1* for the mean PDSI, at the municipality level.

2.2 Cost of debt

Our dependent variable is the cost of debt, proxied by the ratio between financing expenses and average finance related debt (short and long term):

$$Cost\ of\ Debt_{i,t} = \frac{Financing\ expenses_{i,t}}{Average\ Debt_{i,t}} = \frac{Financing\ expenses_{i,t}}{\left(\frac{Debt_{i,t} + Debt_{i,t}}{2}\right)}$$

This measure is considered a noisy proxy for the cost of debt by Cassar (2011). According to the author this proxy is unable to capture whether the loan is granted as a relationship loan or arms-length and is relatively stale, i.e. highly influenced by multi-year debt contracts, hence potentially unable to capture short-term effects. Regarding the first limitation, our setting mitigates this issue, given that our sample is mainly comprised of SMEs, which traditionally receive relationship loans (Hernández-Cánovas & Martínez-Solano, 2010). Regarding the second limitation we acknowledge that it would be preferable to have loan level data to capture the reaction of the cost of debt to changes in drought conditions, as done by several other articles which use syndicated loan data (Javadi & Masum, 2021) or bond and private placement transactions (Do *et al.*, 2021).

However, to study the landscape of Portuguese SMEs, which is our goal, such data is not available.

2.3 Impact of drought on the cost of debt

In order to estimate the impact of drought on the cost of debt we run the following model, using the OLS regression method, with size, industry, and year fixed effects, with White robust standard errors (1980):

$$COD_{i,t} = \beta_0 + \beta_1 PDSI_t + Firm\ Controls_{i,t} + Size\ FE_{i,t} + Industry\ FE_{i,t} + Year\ FE_{i,t} + \varepsilon_{i,t}$$

Our dependent variable is $COD_{i,t,s}$ which is the cost of debt for firm i, in year t. This means that we consider a firm to be located in one single municipality, namely, where its headquarters are located. For the majority of the firms in our sample (SMEs) this assumption can be considered reasonable, but less so for larger firms. This limitation is present in several studies in the literature (BdP, 2023).

The main coefficient of interest is β_1, which will show the impact of the PDSI 12-month average values on the firms' cost of debt. Given that drought corresponds to negative values of the PDSI, we predict that this coefficient should be negative and statistically significant.

Furthermore, we control for a set of firm-level financial variables that proxy for key dimensions that are bound to influence the cost of debt: firm size, solvency, liquidity, profitability, tangibility, and firm age (Chava, 2014; Javadi & Masum, 2021).

To control for firm size, we use the natural logarithm of the firms' total assets. As discussed in the literature review, firms are likely to enjoy economies of scale in the access to finance (Krishnaswami *et al.* ,1999).

Regarding solvency, we incorporate the solvency ratio which is the ratio between capital and total assets. The expected impact of solvency on the firms' cost of debt is relatively unclear: on one hand, a higher solvency ratio suggests a higher capital, which means less probability of default, which would translate into lower spreads and therefore lower cost of debt. On the other hand, excess capital might suggest difficulties in debt access or lack of growth opportunities (Ross, 1977), which would theoretically imply a higher cost of debt.

We measure firm liquidity using current ratio, which is the ratio of current assets to current liabilities. On one hand the level of liquid assets is often used as a predictor of corporate defaults (Altman, 1968); on the other hand, according to Acharya *et al.*, (2012) banks perceive cash holdings as a safety measure employed by firms that do not predict a strong financial position in the near future.

For profitability we employ EBIT to assets ratio. Jiang (2008) finds that firms with higher profitability levels reach lower loan spreads and therefore have a lower cost of debt.

We proxy for tangibility, using the ratio of fixed assets to total assets. According to the literature, firms with higher tangibility ratio are more likely to have lower cost of debt, having the ability to use tangible assets as collateral for loans (Keasey *et al*., 2015).

Finally, to control for firm age, we use the natural logarithm of the firm's age. The expectation is that the firms' age is negatively correlated with the firms' cost of debt (Sakai *et al*., 2010), in line with reputation theory (Diamond, 1989).

Moreover, we include three types of fixed effects: size, industry, and year. The size fixed effects are related to the definition of micro, small, medium, and large firms (EU, 2023) The industry fixed effects control for the two-digit "Classification of Economic Activities" (CAE rev. 3). The year fixed effects comprise the period between 2007 and 2019, and aim to capture variations in the cost of debt that are related to key events that occurred in Europe / Portugal in this period: the 2007-2009 crisis, the sovereign debt crisis (2012-2014) and the low interest rates environment (2014-2019). We also considered the possibility of including region fixed effects in order to control for potential region-specific dynamics in the demand and supply for debt which may influence the cost of debt, however, given that the PDSI is a region-specific variable, including such fixed effect would capture the effects of drought risk. Alternatively, one could consider a different research design, such as using matching techniques. Due to this limitation, one should take the interpretation of β_1 with care, given that it may capture regional effects that go beyond the drought risk.

2.4 Sample

Our sample is comprised of 12,512 firms operating in five water-intensive industries in Portugal, in the period between 2007 and 2019. The total number of observations (unbalanced) is 68,420 (average of 5.5 years per firm). The financial data was collected from SABI database and the PDSI was accessed via IPMA. Importantly, the number of firms is quite stable over the sample period (min: 4,154; max: 6,756), indicating that there is no particular period bias in the sample. Moreover, the majority of firms operate in the agricultural sector. According to Rossi *et al.* (2023) the water intensive industries are those most impacted by drought risk, namely:

- Agriculture (CAE: 01);
- Forestry (CAE: 02);
- Electricity, gas, steam, hot and cold water and air conditioning (CAE: 35);
- Water abstraction, treatment and distribution (CAE: 36);
- Transportation by water (CAE: 50).

Untabulated results show that the large majority of the firms in our sample operate in the agricultural industry (81.7%), followed by forestry (13.0%), electricity (4.1%), water treatment (1.0%), and transportation by water (0.2%). Regarding firm size, as expected, the large majority of firms are either micro (83.9%) or small (12.2%), although all four categories of size are represented in the sample. Such concentration of the sample in micro and small firms is not common in the literature we reviewed, which impairs the possibility to compare results. However, the corporate landscape in Portugal is heavily populated by micro and small firms, hence, we opted to maintain these firms in the sample. The fact that our sample has this focus on micro and small firms and agricultural firms draws us to inspect, later in this dissertation, the potential role of financial fragility in the nexus between drought risk and cost of debt. Finally, given the potential lower quality of financial reporting by micro and small firms we opted to winsorize data at the 5^{th} and 95^{th} percentiles (Vander Bauwhede, 2015) and drop all observations with missing values for at least one of the control variables or inexistent bank debt.

2.5 Descriptive statistics

In **Table 2** we present the descriptive statistics. First, regarding our dependent variable, the mean value of cost of debt is approximately 4.63%. As expected, during the sample period the mean cost of debt steadily declined from a maximum of 6.92% in 2008 to a minimum of 3.13% in 2019. Moreover, the coefficient of variation, given by the ratio between standard deviation and mean is close to 1, which reveals a significant heterogeneity in our sample. Regarding our independent variable, PDSI, the average value is -0.63, which shows that on average Portugal experiences weak drought. Importantly, the minimum value is close to -4., which represents periods of extreme drought – as will be discussed in more detail in the next section.

Table 2. Descriptive statistics

Variable	Obs.	Mean	SD	Min.	Median	Max.
Cost of debt	68,420	0.0463071	0.0439290	0.0003003	0.0351516	0.1695926
PDSI	68,420	-0.6281688	1.1037860	-4.1013150	-0.5968101	2.470163
Total Assets	68,420	13.1666200	1.3894580	10.8739900	13.02823	16.05945
Solvency ratio	68,420	0.0863614	0.1228881	0.0022818	0.0309284	0.4617357
Current ratio	68,420	3.2474270	4.5917500	0.1830510	1.37488	18.46505
EBIT to assets	68,420	0.0232841	0.0994377	-0.2138009	0.0254229	0.2207823
Tangibility ratio	68,420	0.4453266	0.2743337	0.0103670	0.4406599	0.9028484
Age	68,420	2.1886690	0.8356069	0.6931472	2.302585	3.433987

Regarding the other variables, they allow us to understand that the average firm in our sample is small (mean total assets of approximately 519.2 thousand euros) with low capitalization (solvency ratio of 8.6%), high liquidity (current ratio of 3.2), and low profitability (EBIT to assets of 2.3%). Moreover, the average firm age is 8.92 years. One striking feature is the high level of heterogeneity in almost all variables.

In **Table 3** we present the correlation matrix among the independent variables. The goal is to understand whether there is potential multicollinearity in our regression analysis (Farrar & Glauber, 1967). Overall, the results in **Table** 3 show that the correlation coefficients are generally low, which mitigates concerns regarding this potential issue.

Table 3. Correlation matrix

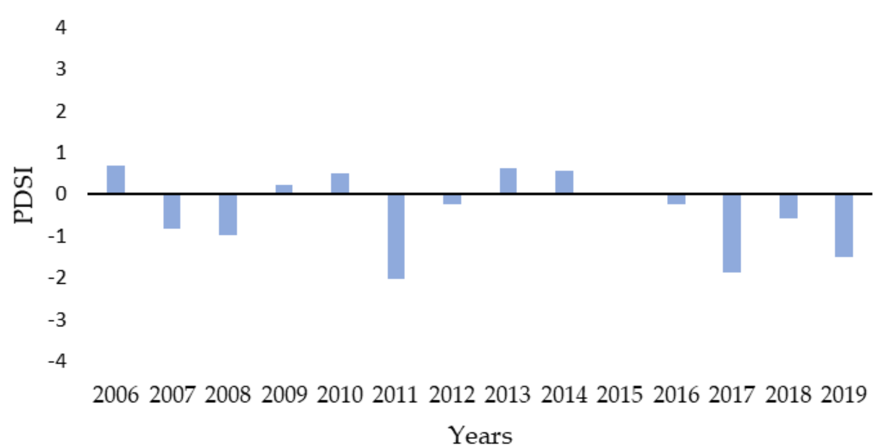
	PDSI	Total assets	Solvency ratio	Current ratio	EBIT to assets	Tang. ratio	Age
Total assets	-0.0460	1.0000					
Solvency ratio	0.0416	-0.0893	1.0000				
Current ratio	-0.0538	-0.0828	0.0035	1.0000			
EBIT to assets	-0.0245	0.1032	-0.1631	0.0705	1.0000		
Tangibility ratio	0.0091	0.1551	-0.0346	-0.1597	-0.1100	1.0000	
Age	-0.0179	0.3009	0.1185	0.0237	0.0266	-0.0973	1.0000

3. Results

3.1 Firms' exposure to drought risk

Figure 2 shows the average PDSI values for Portugal during the 2006-2019 period. During this period the years with lowest PDSI were 2011 (-2,0), 2017 (-1,9), and 2019 (-1,5). Based on this result, the next analysis will focus particularly on these three years.

Figure 1. Average PDSI in Portugal (2006-2019)



According to **Table 4**, during the years with the lowest PDSI values, the maximum number of municipalities experiencing moderate, severe, or extreme drought was recorded in 2011 (124), mainly driven by moderate droughts (106). On the contrary, 2019 recorded the lowest number of municipalities experiencing drought (97) of which 42 experienced severe or extreme drought – the highest number recorded in the sample period. Effectively, the previous result is confirmed by **Table 5**, which shows that the top 10 municipality-year observations with the lowest PDSI were all recorded in 2019.

Table 4. Number of municipalities per drought classification per year

Years	Moderate drought	Severe drought	Extreme drought	Total
2011	106	18		124
2017	108			108
2019	55	36	6	97

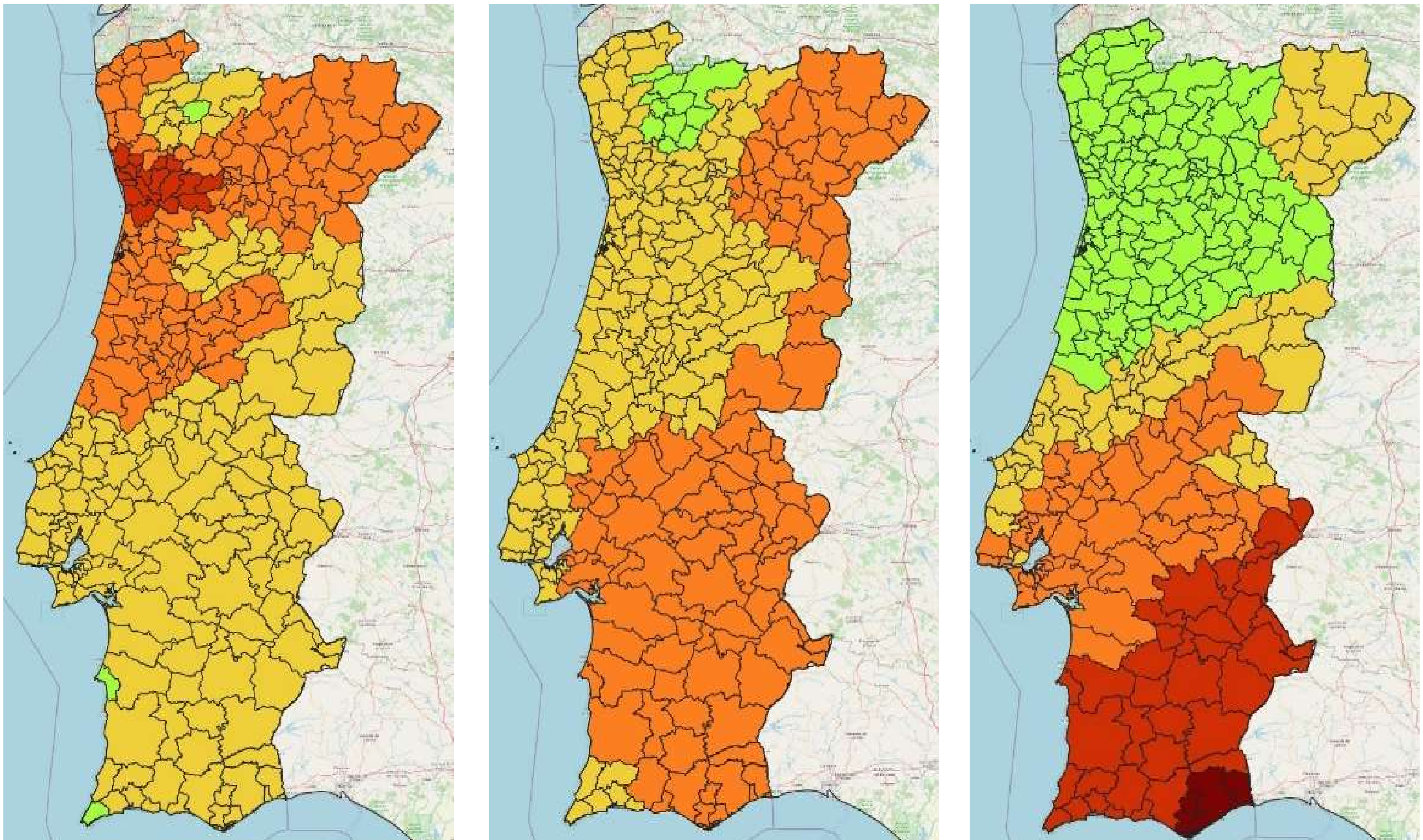
Moreover, **Table 5** seems to suggest that drought is regionally concentrated in the southern area of Portugal. Namely, all top 10 municipality-year observations in terms of lowest PDSI occur in the same district, Faro, located in the southern region of Portugal. However, when observing **Figure 3** one notices that the drought of 2011 was concentrated in the northern part of Portugal, and the 2017 drought affected both the north and south of Portugal, mainly in the interior. In sum, our results suggest that the exposure to drought risk is not exclusive to firms located in any given municipality, although the southern region is typically exposed to more intense droughts.

Table 5. Top 10 droughts in municipalities

Rank	Municipality	Firms	Total debt	District	Year	PDSI
1	Faro	109	€ 221,754,893	Faro	2019	-4.10
2	Olhão	41	€ 22,658,738	Faro	2019	-4.09
3	Vila Real de Santo António	23	€ 3,256,947	Faro	2019	-4.08
4	Castro Marim	17	€ 3,313,135	Faro	2019	-4.03
5	São Brás de Alportel	6	€ 3,216,696	Faro	2019	-4.03
6	Tavira	108	€ 37,940,845	Faro	2019	-4.03
7	Loulé	62	€ 16,666,142	Faro	2019	-3.94
8	Alcoutim	22	€ 56,031,788	Faro	2019	-3.93
9	Albufeira	38	€ 9,200,663	Faro	2019	-3.92
10	Lagoa	26	€ 8,742,469	Faro	2019	-3.85

Figure 2. PDSI average values for Portugal per municipality for key drought years (2011, 2017, 2019)

2011	2017	2019



Legend: dark red: severe drought (PDSI: <-4) | red: severe drought (PDSI: -4,-3) | orange: moderate drought (PDSI:-3,-2) | yellow: weak drought (PDSI: -2,-1), green: normal (PDSI: -1,1).

Next, we analyze the debt exposure to drought in 2011, 2017 and 2019. Namely, **Table 6** shows that the highest total amount of debt exposed to drought was recorded in 2011 (4.5 billion euros), representing 28.5 % of total debt in the sample. However, the year with the highest share of debt exposed to drought was 2019 (32.3%). While this exposure seems to be quite high, they are lower than the estimates produced by BdP (2023) that 71% of total bank debt to firms is exposed to high or severe water stress risk.

Table 6. Debt exposure to drought risk per year

Year	Debt exposed to drought	Total debt of sample	% of debt exposed to drought
2011	4,492,560,284	15,778,704,789	28.47%
2017	3,877,820,606	17,032,266,086	22.77%
2019	3,895,020,385	12,071,726,325	32.27%
Mean 2011/17/19	**€ 4,088,467,092**	**€ 14,960,899,067**	**27.33%**

Table 7 presents the distribution of debt exposed to drought per district. We observe five districts with more than 50% of total debt exposed to drought, namely Beja (69.1%), Bragança (67.8%), Évora (64.6%), Faro (64.8%), Portalegre (64.5%), and Setúbal (72.1%). As reported previously, there is a significant exposure to drought risk in different parts of the country. Importantly, the district with the largest total debt (Lisboa) has the lowest drought risk exposure (3.7%).

Table 7. Debt exposure to drought risk per district, mean 2011/17/19

District	Debt exposed to drought	Total debt	% of debt exposed to drought
Aveiro	66,181,512	217,988,282	30.36%
Beja	990,378,365	1,432,931,895	69.12%
Braga	30,027,293	253,638,075	11.84%
Bragança	71,785,063	105,826,171	67.83%
Castelo Branco	176,221,405	440,566,212	40.00%
Coimbra	208,903,836	429,575,287	48.63%
Évora	151,923,436	235,093,387	64.62%
Faro	242,401,891	374,007,049	64.81%
Guarda	57,905,112	501,829,414	11.54%
Leiria	23,009,230	238,401,491	9.65%
Lisboa	194,877,652	5,210,585,469	3.74%
Portalegre	89,509,754	164,135,570	54.53%
Porto	597,199,103	2,257,972,054	26.45%
Santarém	385,761,776	1,110,320,354	34.74%
Setúbal	197,803,467	274,177,439	72.14%
Viana do Castelo	126,859,168	300,692,989	42.19%
Vila Real	147,959,904	393,073,922	37.64%
Viseu	329,759,126	724,794,425	45.50%
Total	**€ 4,088,467,092**	**€ 14,960,899,067**	**27.33%**

Finally, the results presented in **Table 8**, show that agriculture is the industry where debt is most exposed to drought (50.0%), followed by forestry (43.2%). Unfortunately, we are not able to compare such results with alternative studies given that BdP study on climate risk (2023) does not provide detail on water-stress risk for the subset of industries in our sample.

Table 8. Debt exposure to drought risk per industry

Industry	**Debt exposed to drought**	**Total debt**	**% of debt exposed to drought**
Agriculture	1,385,689,565	2,769,947,197	50.03%
Forestry	89,765,158	208,004,395	43.16%
Electricity	1,673,736,848	9,258,988,220	18.08%
Water treatment	934,009,657	2,601,319,083	35.91%
Transport by water	5,265,863	122,640,171	4.29%
Total	**€ 4,088,467,092**	**€ 14,960,899,067**	**27.33%**

3.2 Impact of drought on the cost of debt

3.2.1 Baseline regressions

Table 9 presents the results of our baseline regressions for the impact of PDSI on the cost of debt. In both tested models (model 1: year and industry fixed effects, model 2: year, industry, and size fixed effects), we find that the coefficient of PDSI is negative and statistically significant. However, the size of the effect is economically low: considering a one standard deviation reduction of PDSI (-1.104), the estimated impact on the cost of debt is +6.6 bps (-0.00060 x -1.104), which represents an increase of 1.43% of the mean cost of debt (6.6 / 463.1 bps).

This effect follows the expected sign (negative) and suggests that the cost of debt is higher for firms located in drought affected municipalities. Such results are in line with previous literature. For instance, using a sample of firms located in the U.S., Javadi & Masum (2021) find a statistically significant relationship between the inverse PDSI and loan spreads.

Table 9. Impact of drought on firms' cost of debt.

	Model 1	Model 2
PDSI	**-0.00057****	**-0.00060****
	(0.01900)	(0.01300)
Total assets	**-0.00202*****	**-0.00243*****
	(0.00000)	(0.00000)
Solvency ratio	0.00177	0.00140
	(0.21300)	(0.32700)
Current ratio	**-0.00116*****	**-0.00116*****
	(0.00000)	(0.00000)
EBIT to assets	**0.04557*****	**0.04575*****
	(0.00000)	(0.00000)
Tangibility ratio	**-0.01640*****	**-0.01634*****
	(0.00000)	(0.00000)
Age	0.00023	0.00030
	(0.26400)	(0.15200)
Adjusted R^2	0.11030	0.11050
Observations	68,420	68,420
Year Fixed Effect	Yes	Yes
Industry Fixed Effect	Yes	Yes
Size Fixed Effect	No	Yes

Notes: Values presented are the coefficient estimates of OLS regressions with firm-level controls and fixed effects for year, industry, and size category using White-robust standard errors. In parenthesis we present the detailed p-value. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Next, we analyze how the control variables affect the cost of debt in our model. Regarding firm size, we find that total assets are negatively correlated with cost of debt, in both models. This suggests that a higher value of total assets negatively affects the cost of debt, which is in line with a perspective that larger firms enjoy economies of scale in the access to finance, for instance by having a higher bargaining power with banks (Krishnaswami *et al.* ,1999). With respect to solvency, we find that the solvency ratio coefficients for both models are not statistically significant, reflecting the two effects reviewed in the literature, lower probability of default vs agency costs (Jensen & Meckling, 1976). Moreover, we find that liquidity (current ratio) is negatively correlated with cost of debt and statistically significant at the 1% level on both models, in line with the notion that firms with higher cash holdings tend to have lower default probability (Altman, 1968). Surprisingly we find that the firms' profitability increases the cost of debt. One explanation for this result might lie in the composition of our sample, with the majority of the firms belonging to the agricultural industry, which has relatively low profitability. However, more research is needed to understand the underlying rationale for this result. As expected, tangibility ratio is negatively correlated with cost of debt, in line with the notion that a higher tangibility ratio implies a greater availability of collateral, that may be used as a guarantee in case of default, hence lowering the loan spreads (Keasey *et al*., 2015). Finally, regarding firm age, we do not find statistical significance.

3.2.2 Regressions per firm size

Next, we are interested in exploring whether our baseline results change for different firm sizes. **Table 10** presents the regression results for firm size sub-samples: micro, small, medium, and large. Overall, we find that the impact of drought on the firms' cost of debt is negative and statistically significant at the 5% level only for the micro firms, while for other categories the coefficient is negative but not statistically significant. Moreover, that effect has a low economic impact, considering a one standard deviation reduction of PDSI (-1.089) the estimated impact on the cost of debt is +7.2 bps (-0.00066 x -1.089), which represents an increase of 1.53% of the mean cost of debt (7.2 / 470.3 bps).

This result suggests that lenders are relatively more concerned about drought related effects for smaller firms which may have more difficulty in geographically diversifying their business (Huynh *et al*., 2020). Alternatively, this result may be linked to industry factors, given that most micro firms in our sample operate in the agricultural industry. Namely, 83.8% of the agricultural firms are micro while for the remaining industries that weight is reduced to 66.3% - this point will be further explored in the next sub-section.

Table 10. Impact of drought on firms' cost of debt per size category

	Micro	Small	Medium	Large
PDSI	**-0.00066****	-0.00079	-0.00092	-0.00109
	(0.01600)	(0.19700)	(0.40500)	(0.48200)
Adjusted R^2	0.10770	0.14940	0.15680	0.12670
Observations	56,298	8,867	2,246	1,009
Firm-level Controls	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes

Notes: Values presented are the coefficient estimates of OLS regressions with firm-level controls and fixed effects for year, industry, and size category using White-robust standard errors. In parenthesis we present the detailed p-value. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

3.2.3 Regressions per industry

Table 11 presents the results for the regressions using industry specific sub-samples. Overall, the results suggest that the impact of PDSI on the cost of debt is negative and statistically significant only for firms operating in the agricultural industry.The coefficient of the impact of PDSI on agricultural firms' cost of debt is economically low (-0.00050), considering a one standard deviation reduction of PDSI (-1.096) the estimated impact on the cost of debt is +5.5 bps (-0.00050 x -1.096), which represents an increase of 1.23% of the mean cost of debt (5.5 / 448.6).

Table 11. Impact of drought on firms' cost of debt per industry

	Agriculture	Forestry	Electricity	Water treatment	Transportation by water
PDSI	**-0.00050***	-0.00077	-0.00065	0.00071	0.00406
	(0.06700)	(0.30700)	(0.46000)	(0.70400)	(0.48400)
Adjusted R^2	0.10660	0.14300	0.07820	0.16500	0.30370
Observations	55,207	8,557	3,445	1,052	159
Firm-level Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Size Fixed Effect	Yes	Yes	Yes	Yes	Yes

Notes: Values presented are the coefficient estimates of OLS regressions with firm-level controls and fixed effects for year, industry, and size category, using White-robust standard errors. In parenthesis we present the detailed p-value. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

According to Rossi *et al.* (2023), a key aspect of the impact of drought in the different industries depends on vulnerability factors such as soil conditions, irrigation mechanisms, agro-management practices, forestry management practices, or the composition of the shipping fleet (transportation by water). While the study of these mechanisms falls outside of the scope of this thesis, under this perspective our results indicate that the agricultural industry seems to be relatively more vulnerable to drought.

3.2.4 Financial fragility

In this sub-section we study whether the previous results are driven by the firms that are financially fragile. To measure financial fragility we use two indicators, EBIT to assets ratio and solvency ratio, and consider fragile firms to be the ones on the first quartile of EBIT to assets ratio and on the first quartile of solvency ratio. According to Mechler *et al.* (2010), country-level financial vulnerability is an important determinant of the losses incurred due to climate related natural hazards, given that national governments that are more financially vulnerable may not be able to raise sufficient and timely recovery capital. Likewise, we hypothesize that such nexus may happen at the firm level.

Regarding the results for the total sample, our findings suggest that the effect of PDSI on the cost of debt is stronger for fragile firms. Namely, the joint coefficient of PDSI plus PDSI x Fragile firms is -0.00176, which is 2.9 times greater than the baseline coefficient. More specifically, a one standard deviation reduction of PDSI (-1.181) leads to an estimated impact of +20.8 bps (-0.00176 x -1.181), which represents an increase of 5.87%

of the mean cost of debt (20.8 / 354.5). Interestingly, the sub-sample regressions for micro and agricultural firms suggest that this effect is originated only in the agricultural firms.

Table 12. Impact of drought on fragile firms' cost of debt

	Total sample	Micro firms	Agriculture
PDSI	**-0.00055****	**-0.00061****	-0.00044
	(0.02700)	(0.03000)	(0.11200)
Fragile firms	-0.00051	0.00005	-0.00018
	(0.57500)	(0.95900)	(0.85700)
PDSI x Fragile firms	**-0.00121****	-0.00103	**-0.00112***
	(0.04900)	(0.13600)	(0.09400)
Adjusted R^2	0.11060	0.10780	0.10670
Observations	68,420	56,298	55,207
Firm-level Controls	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	No
Size Fixed Effect	Yes	No	Yes

Notes: Values presented are the coefficient estimates of OLS regressions for fragile firms with firm-level controls and fixed effects for year, industry, and size category, using White-robust standard errors. In parenthesis we present the detailed p-value. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The first column applies to the total sample, second column to the micro firms and third column to firms belonging to the agricultural sector.

Such results suggest that financial fragility matters for lenders' credit assessment of the effects of drought risk in corporate lending, particularly to the agriculture industry. In other words, following the perspective laid out by Mechler *et al.* (2010), agricultural firms are not only the most vulnerable to drought risk (**Section 3.2.3**) but also the only firms where lenders have significant concerns about their ability to raise capital necessary to recover from the exposure to drought – although the economic magnitude of the effect is generally low.

4. Robustness tests

Our approach may raise some concerns regarding specific research design choices. First, although we have a 12-year period of analysis there are 3 years where drought is much more intense than in the other years, 2011, 2017 and 2019. Second, we are aware that drought is normally more frequent for the southern regions of Portugal, the top 10 more intense droughts all belong to municipalities in the same southern district which is Faro (see **Table 5**), this raises doubts regarding the dependence of the results on specific regions or districts. Third, our results relie on one single proxy for the dependent variable (cost of debt). Given these concerns we perform several robustness tests which are reported in **Table 13**.

In the first robustness test, we remove observations belonging to the main drought years one at the time and then all at once and run our regressions on each of these sub-samples. Overall, the results remain unchanged as the impact of drought remains negative and statistically significant for all tested sub-samples.

In the second robustness test, we remove all observations belonging to Faro district, the most affected by droughts in our sample period. The results show that, without the observations of firms located in Faro, the impact of drought on the firms' cost of debt remains negative and statistically significant at the 1% level.

Table 13. Robustness tests

	2011	2017	2019	All years	Faro	FE growth
PDSI	**-0.00067*** **	**-0.00065*** **	**-0.00052***	**-0.00064** **	**-0.00066*** **	**-0.02155** **
	(0.00800)	(0.01000)	(0.07200)	(0.04000)	(0.00900)	(0.03200)
Assets	**-0.00242*** **	**-0.00227*** **	**-0.00219*** **	**-0.00193*** **	**-0.00249*** **	**0.03926*** **
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Solvency ratio	0.00154	0.00197	0.00225	**0.00333***	0.00197	**-0.21345*** **
	(0.29900)	(0.19100)	(0.14100)	(0.05200)	(0.17600)	(0.00000)
Current Ratio	**-0.00117*** **	**-0.00121*** **	**-0.00122*** **	**-0.00132*** **	**-0.00115*** **	**0.00979*** **
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
EBIT to assets ratio	**0.04612*** **	**0.04769*** **	**0.04723*** **	**0.05028*** **	**0.04544*** **	**-0.21217*** **
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00400)
Tangibility ratio	**-0.01645*** **	**-0.01681*** **	**-0.01682*** **	**-0.01766*** **	**-0.01620*** **	0.00775
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.75400)
Age	0.00032	0.00020	0.00005	-0.00010	0.00029	**-0.26758*** **
	(0.14400)	(0.38600)	(0.81900)	(0.70100)	(0.17500)	(0.00000)
Adjusted R^2	0.11480	0.11020	0.10190	0.10320	0.10960	0.02750
Observations	64,266	62,283	61,664	51,373	66,099	52,183
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
CAE Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Size Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Values presented are the coefficient estimates of OLS regressions for firms with firm-level controls and fixed effects for year, CAE, and size category, using White-robust standard errors, for altered samples without crucial drought years and crucial districts affected by drought for the purpose of robustness tests. In parenthesis we present the detailed p-value. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The first column applies to the sample without observations of year 2017, second column applies to the sample without observations of year 2019, third column applies to the sample without observations of years 2011, 2017 and 2019, fourth column applies to the sample without observations belonging to the district of Faro, and the fifth column applies to the change of the dependent variable to FE (financing expenses) growth.

In the third robustness test, we replace the dependent variable, cost of debt, for a proxy variable, growth of financing expenses, calculated as the ratio of financing expenses of year *t* over financing expenses of year *t-1.* The results are very similar to the baseline regressions, suggesting that the baseline findings are not driven by the choice of proxy for the dependent variable.

5. Limitations

The first limitation of our study is related to the firms' location. In this thesis we follow Huynh *et al.* (2020) who argue that a firm's headquarters location is a relatively good proxy for the location of all its operations. Moreover, in the same line Chaney *et al.* (2012) argue that normally a firm's major production site is located within the same state as the firm's headquarters. This is likely to be particularly true for smaller firms, which comprise the majority of our sample. However, for larger firms it is less plausible that the headquarters are in the same location as all its operations. For instance, the headquarters of the largest Portuguese power company, EDP, are located in Lisbon, whereas the majority of its power generation facilities are spread throughout the country. This limitation is present in other reports such as BdP (2023).

A second limitation of this study is related to the lack of evidence on the mechanisms that explain the nexus between exposure to drought and higher cost of debt. Indeed, several tests were performed using the impact of drought on the GVA as a potential mechanism (BCBS, 2021) that would explain the higher cost of debt faced by drought exposed firms. However, more time would be needed to calibrate the models for this step.

The third limitation concerns the choice of dependent variable. According to Cassar (2011) our proxy for the cost of debt (ratio of financing expenses to average debt) is unable to capture whether the loan is granted as a relationship loan or arms-length and is relatively stale, i.e. highly influenced by multi-year debt contracts, hence potentially unable to capture short-term effects. Effectively, it would be preferable to have loan level data to capture the reaction of the cost of debt to changes in drought conditions, as done by several other articles which use syndicated loan data (Javadi & Masum, 2021) or bond and private placement transactions (Do *et al.*, 2021).

Fourth and final limitation is related to firm-level data availability. Although we had access to PDSI data for the period of 2002-2019, we didn't have sufficient firm specific data on the period 2002-2006 in the SABI Database, so we opt to drop that period so we could have an analysis period with data consistency, which results in a period of 2007-2019 (12 years). Ideally, we would want a larger period of analysis, that would fit in with the remaining literature on the impact of drought on firms' financial conditions, Javadi & Masum (2021) analysis period for their observations is 1986-2017 (31 years), Huynh *et al.* (2020) analysis period was 1968-2015 (47 years).

Conclusions

In this thesis we have analyzed the "drought risk – cost of debt" nexus for a sample of firms operating in water-intensive industries located in Portugal. Effectively, this topic has deserved the attention of academia, regulators, and supervisors of the financial sector (NGFS, 2019), particularly in southern Europe countries, where drought risk is considered one of the main physical risks (IPCC, 2022; Forzieri *et al.*, 2015; Naumann *et al.*, 2021). This thesis attempts to contribute to a small body of literature that, so far, has focused exclusively on U.S. firms to study the effects of drought risk on the cost of debt (Javadi & Masum, 2021; Do *et al.*, 2021).

This thesis has tackled two separate research questions: how exposed is the debt of Portuguese firms to drought risk? What is the impact of drought risk on the cost of debt? Regarding the first question, our results suggest that approximately 4.1 billion euros of debt was exposed to drought annually in the years of more intense drought, particularly in the agriculture and forestry industries.

Concerning the second question, we find that PDSI (inverse drought risk) has a negative and statistically significant impact on the cost of debt (although economically low). Moreover, the PDSI coefficient is only statistically significant for micro firms and firms operating in the agricultural industry, which can be seen as evidence of the heterogeneous effects of drought risk on the cost of debt. Interestingly, we find that the effect of drought risk on cost of debt is particularly strong for fragile firms (i.e., operating in the lowest quartile of profitability and solvency).

We believe that these findings have potentially relevant policy implications. First, the fact that 50% of the debt of agricultural firms is exposed to drought risk in the years of most intense drought may be considered as a warning signal for banks and supervisors to consider drought risk as a material risk, particularly in a future scenario where the severity and frequency of drought events is expected to increase (NGFS, 2019). Second, the low economic significance of the relationship between drought risk and cost of debt suggests that there is a long road in considering this risk in the loan pricing. Additionally, the lack of significance in the coefficients for non-micro and non-agricultural firms adds to the previous concern. Third, our results regarding the higher sensitivity of fragile firms' cost of debt to drought risk suggests that policy tools may be useful to reduce the effect of drought exposure for firms in fragile conditions, e.g. public guaranteed loans.

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