Is drought risk priced in private debt contracts?

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ABSTRACT

We investigate whether banks price drought risk – measured by Palmer Drought Severity Index – in the interest rates charged to corporate borrowers. The results show that banks do charge drought-affected borrowers higher loan spreads. The price increase is most pronounced among food industry borrowers. Lenders more experienced in lending to drought-affected borrowers charge a lower drought risk premium compared to less experienced lenders. Borrowers' credit ratings can act as a mitigating factor on drought risk effects. Drought-affected borrowers experience a smaller hike in loan spreads if they are investment-grade firms.

Keywords: Drought risk, loan spreads, food industry, lending experience

JEL: G21, G32

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I. INTRODUCTION

One of the most challenging issues facing humanity in the twenty-first century is climate risk. Climate risk has affected many aspects of human life, in which economics and finance are no exception. Surprisingly, work on how climate risk is perceived and priced in the financial market is very limited. Bansal, Kiku, and Ochoa (2014) use temperature as a proxy for climate risk from global warming, and find global warming has a significant negative effect on stock price. While also examining the impact of climate risk, Hong, Li and Xu (2019) use a different proxy – Palmer Drought Severity Index (PDSI) – to investigate the effect of prolonged drought periods on market efficiency and show that the equity market has not fully accounted for such risk.

In this paper, we explore how climate risk affects the pricing of loan contracts. Following Hong *et al.* (2019), we focus on drought risk as drought is considered to have one of the most damaging impacts on global economy. Lesk, Rowhani, and Ramankutty (2016) document that heat wave and drought could reduce crop production by 9%-10% while food and cold spells had little impact. Trenberth, Dai, van der Schrier, Jones, Barichivich, Briffa, and Sheffield (2014) conclude that drought could cause significant damage on a firm's profit. This result is particularly strong for firms in the food sector where revenue is heavily dependent on water supply (Blackhurst, Hendrickson, and Vidal, 2010).

Different from previous studies, this paper focuses on the private debt market rather than the equity market. We investigate whether banks take into account previous drought levels when setting loan price by adding another layer of risk – drought risk – to the existing well-established loan pricing model in the literature.[1] Our results indicate that banks charge higher interest rates to borrowers located in drought-affected areas, and this higher premium is more pronounced for food industry borrowers. A one standard deviation increase in our drought

[1] See, for example, Berger and Udell (1990), Dennis, Nandy, and Sharpe (2000), and Bharath, Dahiya, Saunders, and Srinivasan (2011).

measure would lead to an 8.92-basis-point increase in loan spreads for a food industry borrower. Certain factors can mitigate the effect of drought risk on loan spreads. From the bank's perspective, we find that not all banks price drought risk equally; lenders more experienced in lending to drought-affected borrowers charge a lower premium for drought risk compared to less experienced lenders. From the borrower's perspective, we find that investment-grade borrowers experience a smaller loan price hike associated with drought conditions compared to non-investment grade firms and unrated firms. This finding might be explained by the fact that borrowers' credit ratings can signal the quality of their risk management strategies where more credit-worthy firms often adopt more sophisticated diversification and hedging strategies.

The remainder of the paper is structured as follows. Section II discusses data sources and variables. Sections III and IV present the results for drought risk effects on loan spreads, and mitigating factors on these effects. Section V concludes the study.

II. DATA AND SAMPLE

A. Drought measures

We use the Palmer Drought Severity Index (PDSI) to construct our drought measures. Even though several drought indices have been used to quantify drought, PDSI is the most widely used measure in the U.S. (Dai *et al.*, 2016). The index was first developed in 1965 by Palmer to evaluate the severity and frequency of abnormally dry periods. Different from most of the other drought indices, PDSI uses precipitation as well as temperature of surface air as inputs, thus takes into account the impact of global warming (Dai *et al.*, 2016). The index is standardized and ranging from about -10 to +10 and the lower the value, the more severe dry it indicates. A normal condition is indicated by a PDSI of -0.5 to 0. A PDSI of 0 and above suggests different wet conditions whereas a PDSI below -0.5 suggests different drought conditions.

We obtain PDSI data from the website of the National Centers for Environmental Information (NCEI) which belong to the National Oceanic and Atmospheric Administration (NOAA). Monthly data for PDSI are available from January 1895 for all contiguous U.S. states (PDSI data for Hawaii and Alaska are not available). Based on the PDSI of the state where the borrower's headquarter is located prior to the loan start date, we construct two (2) drought measures. Our first drought measure is *Drought (-1)* which is simply the PDSI of the borrower's state in the month leading to the loan contract. The second measure is *Drought (-3)* obtained by taking the average PDSI over 3 months prior to the loan start date. We multiply the PDSI by -1 when constructing drought measures to make the interpretation more intuitive, *i.e.* high values of *Drought (-1)* and *Drought (-3)* indicate more severe drought conditions.

B. Loan and borrower characteristics

Description of loan and borrower characteristics variables is shown in Table 1, where data for loan and borrower characteristics are obtained from the LPC database and the Merged CRSP Compustat database respectively. Each loan facility is matched with the most recently available borrower characteristics. That is, given a loan being originated in year *t*, we match it with the Compustat financial information for the same fiscal year if the loan active date is six months or more after its firm's Compustat fiscal year ending month. If the loan active date is less than six months after the fiscal year ending month, we match it with the Compustat financial information for the previous fiscal year. This process is similar to that described in Bharath *et al.* (2011).[2] Compustat also provides borrowers' primary SIC code. We exclude all loans obtained by financial services borrowers (SIC codes between 6000 and 6999). Our final sample consists of 34,392 loan facilities spanning from 1984 to 2016.[3]

{INSERT TABLE 1}

C. Descriptive statistics

Table 2 reports the summary statistics of variables of loan characteristics, borrower characteristics, and drought measures, for the entire sample. The data are winsorized at the 1% and 99% levels to remove extreme outliers.

{INSERT TABLE 2}

[2] The matching process is aided by the Dealscan-Compustat link file that identifies the GVKEY of borrowers in the LPC database. We thank Professor Michael R. Roberts for sharing this link file. Details of this link file are described in Chava and Roberts (2008).

[3] Our food industry classification follows Fama and French (1997)'s approach. Details can be found on Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The average AISD is 184 basis points (bps), the average maturity and facility size are 49 months and US$357 million respectively. About 52% of our sample loans are secured loans, 34% carry three or more types of covenants, and 59% are revolving loans. The mean book value of assets for our sample borrowers is US$14.4 billion. Both facility size and borrower size are highly skewed, indicating strong heteroscedasticity in our sample. The two drought measures exhibit a similar range between -9 and +8 with a mean value around -0.1, which suggests that our sample loans are relatively evenly spread across dry and wet weather conditions.

III. DROUGHT RISK AND LOAN SPREAD

A. Univariate tests

We first investigate the effect of drought on loan spreads using simple univariate tests and report the result in Table 3.

{INSERT TABLE 3}

In Panel A, the sample is segregated into loans made to borrowers experiencing severe drought or worse (*i.e.* when *Drought (-3)* is at least 3) and loans made to borrowers with non-severe drought conditions at the time of loan.[4] In panel B, the segregation is between loans made to borrowers headquartered in the top 5 (most affected) drought states and those made to borrowers headquartered in the bottom 5 (least affected) drought states at time of loan. We conduct *t*-test for the differences in mean and Wilcoxon test for the differences in median between these two groups, for the entire loan sample and for food industry loans. We define food industry using Fama and French (1997) 17-industry classification. The univariate test results show that across the full sample as well as the food industry sub-sample, the differences in loan spreads (both mean and median) between (severe) drought-affected and non (severe) drought-affected loans are positive and statistically significant at 1%. However, the magnitude of the loan spread difference is larger among loans made to food industry borrowers. For example, in panel A, the mean AISD difference for the entire sample is 27.26 bps and for food loans is 55.2 bps. In panel B, the mean difference for the entire sample is 37.41 and for food

[4] A PDSI with value below -3 represents severe drought conditions (Dai *et al.*, 2016).

loans is 64.65 bps. While we cannot draw a meaningful conclusion from these tests, this is the first evidence suggesting that banks price past drought conditions into loan spreads where borrowers more prone to severe drought conditions appear to pay more on their loans. Naturally, the effect of drought is much more pronounced among food borrowers given the direct link of their revenue with weather conditions.

B. Multivariate regressions

Next, we adopt the following regression to test whether drought risk has any effect on loan spreads:

$$AISD = \beta_0 + \beta_1(Drought) + \Sigma\beta_i(Loan_i) + \Sigma\beta_j\left(Borrower_j\right) + \Sigma\beta_k(Controls_k) \qquad (1)$$

Where *AISD* is the loan spread above LIBOR, *Drought* is the drought measure, which is proxied by *Drought (-1)* or *Drought (-3)*. *Loan* and *Borrower* are vectors of variables that include loan characteristics and borrower characteristics (*for details, refer to Table 1*). *Controls* refer to other control variables including dummies for borrower credit ratings (AAA, AA, A, BBB and other ratings), loan purpose dummies, loan year dummies, and borrower's industry dummies (based on one-digit primary SEC codes) where applicable. We estimate equation (1) using pooled OLS regression. The result is presented in Table 4. The standard errors are adjusted for heteroscedasticity and clustered at the firm level (see Saunders and Steffen, 2011).[5]

{INSERT TABLE 4}

The results in columns 1-4 of Table 4 confirm our univariate observation. Drought-affected borrowers pay higher loan spreads. The coefficients on *Drought (-1)* and *Drought (-3)* are statistically significant in both the entire loan sample (columns 1-2) and food loan subsample (columns 3-4). Among food loans, drought conditions in the month immediately before the loan month appear to have a stronger influence on loan price than the 3-month average drought measure (the latter is of smaller magnitude and statistically significant at 10%). The impact of drought on price is much more pronounced for food loans compared to the entire sample, given the larger coefficient magnitude (3.656 against 1.056). This result is not surprising given the natural direct linkage between drought and agricultural business. Given

[5] Our results are also robust when clustering at the loan deal level.

the standard deviation of *Drought (-1)* for food loans is 2.44, the estimated coefficient of *Drought (-1)* among food loans of 3.656 indicates that an increase in *Drought (-1)* by one standard deviation is associated with an increase of 8.92 (=3.656×2.44) basis points in *AISD* per annum. The economic magnitude of the drought risk premium is material. Given the average size of food loans of US$402 million, an 8.92-basis-point premium translates into an extra interest payment of approximately US$358,584 per annum. Our early evidence provides support for the view that lenders perceive historical drought conditions affecting borrowers, especially food industry firms, as an additional layer of risk hence, attach an interest premium to this new factor.

Results for loan characteristics, borrower characteristics and other control variables are consistent with the prior literature. Larger, unsecured, and revolving loans are associated with a lower loan spread. Loan spreads are also found to increase with loan maturity and covenant strictness.[6] The literature has documented similar findings regularly and often explained this as the trade-off among loan terms (Berger and Udell, 1990; Dennis *et al.*, 2000; and Bharath *et al.*, 2011). As expected, we find larger borrowers and those with lower leverage, higher interest coverage, higher market-to-book, and better profitability pay a lower loan spread on average.

We also seek to confirm the stronger effect of drought on food loans by running the multivariate regression with an interaction between drought risk and the food industry dummy on the entire loan sample. We estimate the following model:

$$AISD = \beta_0 + \beta_1(Drought) + \beta_2(Food) + \beta_3(Food \times Drought) + \Sigma\beta_i(Loan_i) + \Sigma\beta_j\left(Borrower_j\right) + \Sigma\beta_k(Controls_k) \qquad (2)$$

Food is a food industry dummy that is constructed following Fama and French (1997) 17-industry classification. It is coded one for any loan made to a borrower operating in one of these food/farming-related industries, and zero otherwise. The estimation output is presented in columns (5) and (6) of Table 4. Three important results are drawn from these two columns. First, the coefficients of both drought measures remain strongly significant at the 1% level. The magnitude of both coefficients is very similar to that reported in columns (1) and (2) of Table 4. Second, the coefficient for the stand-alone *Food* is statistically insignificant in both columns.

[6] Detailed results are available from the authors on requests.

It indicates that after controlling for all other factors, food industry borrowers do not pay more for their loans when compared to other industries. Third and most importantly, the coefficient of the interaction term is positive and significant at the 5% (column 5) and 10% (column 6) levels. This means that the marginal effect of drought on loan spreads is significantly stronger for food industry borrowers. Based on *Drought (-1)* (column 5), it can be calculated that if PDSI increases by one standard deviation, the average loan price will increase by about 2.21 (=0.895×2.47) basis points for non-food borrowers and 11.24 (=(0.895+3.657)×2.47) basis points for food borrowers. Drought appears to have a more economically significant impact on borrowing costs for food industry borrowers compared to other borrowers.

IV. MITIGATING THE IMPACT OF DROUGHT RISK ON LOAN SPREADS

The multivariate analysis in the previous section has established a significant role played by drought risk in lenders' loan pricing decisions. Given this represents an additional layer of risk to be priced, we further explore the various channels via which the effect of drought on loan price can be mitigated. We consider mitigating factors attributed by both lenders and borrowers. Specially, we examine whether lenders more experienced in lending to drought-affected borrowers charge a loan rate premium different from that of less experienced lenders. We conjecture that drought risk is a relatively new type of risk, hence lenders are still learning to price it appropriately. More experienced lenders may understand, thus probably manage this risk better and therefore price it more accurately. Less experienced lenders, in trying to protect their exposure, may have a tendency to overprice it. We investigate the role of borrowers' credit ratings in offsetting the effect of drought risk. Lenders may be willing to charge a lower drought risk premium when lending to observably better quality borrowers since these borrowers often adopt more effective diversification strategies in their business model.

We test our hypotheses using the following model:

$$AISD = \beta_0 + \beta_1(Drought) + \beta_2(Mitigating\ Factor) + \beta_3(Mitigating\ Factor \times Drought) + \Sigma\beta_i(Loan_i) + \Sigma\beta_j\left(Borrower_j\right) + \Sigma\beta_k(Controls_k) \quad (3)$$

The two mitigating factors are *Lender Experience* (in lending to drought-affected borrowers) and *Investment Grade*. The interaction term captures the marginal effect of these mitigating factors on drought risk premium. We estimate equation (3) on food loans given the much stronger effect of drought on pricing those loans found in the previous section. The output is presented in Table 5.

{INSERT TABLE 5}

Columns 1-2 of Table 5 examine the mitigating effect of *Lender Experience,* which is calculated in a similar manner to Bharath *et al.* (2011)'s relationship variable. For a loan made on date X by lead bank A, we obtain the number of loans originated by lead bank A to all borrowers in our database up until date X. We then look into each of these loans to check if its borrower experienced a severe drought in the 3 months prior to the loan commencement. We count the number of these drought-affected loans and divide it to the total number of loans originated by lead bank A. We use this ratio as a proxy for lead bank A's experience in lending to drought-affected borrowers.

Not surprisingly, lender experience to drought-affected borrowers does not seem to help food borrowers get cheaper loans, which is evidenced by the insignificant coefficients in both columns 1-2. Nevertheless, lender experience effectively helps offset the increased borrowing costs brought about by more severe drought conditions. The coefficient of the interaction term *Drought*×*Lender Experience* is statistically negative at the 5% level. This result lends support to our hypothesis that lenders more experienced in lending to drought-affected borrowers charge a lower premium for drought risk.

Columns 3-4 present the output of equation (3) using *Investment Grade* as the mitigating factor, where *Investment Grade* dummy takes the value of 1 if borrower credit ratings are BBB or higher. As expected, investment grade borrowers receive lower loan spreads due to their higher credit quality, as seen in the statistically negative coefficient of the *Investment Grade* dummy in both columns 3-4. Beyond this effect, investment grade borrowers who are more prone to severe drought conditions are also charged a lower risk premium associated with drought risk. The interaction term *Drought* × *Investment Grade* exhibits a negative and significant coefficient at 5%. This finding is anticipated given that more credit-worthy firms often have a well-defined risk management plan in their business model, for example, hedging strategies against various weather conditions. So lenders, in making loans to these firms, are likely to accept a lower risk premium.

V. CONCLUSION

This study investigates the impact of drought risk on the pricing of private loan contracts. We focus on drought risk which, as shown in Hong *et al.* (2019), has one of the most damaging impacts on global economy. Given prolonged drought risk can severely affect agricultural firms' revenues hence their repayment capability, we highlight the importance of drought risk to borrowing costs of food industry firms.

First, we show that food industry borrowers exposed to higher levels of drought risk pay significantly higher loan spreads. Second, we provide evidence that the impact of drought risk on loan price can be mitigated by various factors. Lenders who are more experienced in lending to drought-affected borrowers charge a lower premium on drought risk when compared to less experienced lenders. Furthermore, credit ratings can help signal the quality of borrowers' risk management strategies against drought risk, hence reduce the risk premium that lenders require for lending in severe drought periods.

Our work contributes to the under-explored climate finance literature by studying drought risk from credit providers' perspectives. We provide evidence suggesting that this new layer of risk is viewed by banks as systematic risk and hence incorporated in loan spreads. Our findings have important implications for policymakers, borrowers and other market participants. They reflect increasing awareness of extreme weather risk in particular from the lenders' viewpoint. More importantly, our paper sheds some light on the various channels via which the impact of drought risk can be mitigated, which may provide input to lenders and borrowers in their future lending and borrowing decisions.

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Table 1 Description of loan and borrower characteristics variables

Variable	Description
Loan characteristics	
AISD	All-In-Spread-Drawn, which represents the interest rate margin over LIBOR on drawn loan amount plus annual fees
LNLOANSIZE	Natural logarithm of loan facility amount adjusted for inflation in year 1983 dollars
LNMAT	Natural logarithm of loan maturity in number of months
SECURED	A binary variable taking the value of 1 for secured loans and zero for unsecured loans
REVOLVER	A binary variable taking the value of 1 if the loan facility is a revolving facility and zero otherwise
STRICT	A binary variable taking the value of 1 if the loan facility carries three or more types of covenant restrictions and zero otherwise
Borrower characteristics	
LNASSETS	Natural logarithm of borrower's book value of total assets adjusted for inflation in year 1983 dollars
LEV	Borrower's leverage ratio calculated as book value of total debts divided by book value of total assets
CURRENT	Borrower's current ratio calculated as current assets divided by current liabilities
LNCOVERAGE	Natural logarithm of (1 + EBITDA/Interest expenses)
PROFIT	Borrower's ratio of EBITDA over sales
MTB	Borrower's market to book ratio calculated as ratio of (book value of assets – book value of equity + market value of equity) to book value of assets
PPE	Borrower's ratio of property, plant and equipment over total assets

Table 2 Descriptive statistics for loan and borrower characteristics, and drought measures

Variable	Obs.	Mean	Std. Dev.	Min	Max
Loan characteristics					
AISD (bps)	34,392	184	118	18	600
MAT (months)	33,422	49	24	6	107
LOANSIZE ($ millions)	34,621	357	598	2.6	3,800
SECURED	34,623	0.519	0.5	0	1
STRICT	34,623	0.337	0.473	0	1
REVOLVER	34,623	0.585	0.493	0	1
Borrower characteristics					
ASSETS ($ millions)	34,623	14,431	36,296	47	262,493
LEV	34,623	0.344	0.210	0.000	0.897
CURRENT	33,205	1.877	1.073	0.407	6.656
COVERAGE	33,267	16.502	41.529	0.483	319.026
PROFIT	34,310	0.162	0.115	0.01	0.601
MTB	30,708	1.698	0.913	0.726	6.066
PPE	34,623	0.465	0.273	0.024	0.985
Drought Measures					
Drought (-1)	31,695	-0.102	2.471	-9.16	8.05
Drought (-3)	31,695	-0.109	2.346	-9.19	8.65

This table presents the descriptive statistics for various loan characteristics and borrower characteristics. AISD, All in Spread Drawn, is the interest rate margin over LIBOR on the drawn loan amount plus annual fees. Maturity is length in number of months between the loan's activation date and its maturity date. Facility amount is the dollar amount of loan facility in million. Secured dummy is a binary variable taking the value of 1 if a loan has collateral and zero otherwise. Strict is a binary variable taking the value of 1 if the loan facility carries three or more types of covenant restrictions and zero otherwise. Revolver dummy is a binary variable taking the value of 1 if the loan facility is a revolving facility and zero otherwise. Total assets is the borrower's book value of total assets in million, adjusted for inflation. Leverage is calculated as long term debt plus current liabilities, divided by book value of total assets. Current ratio is the ratio of current assets to current liabilities. Interest coverage is the ratio of EBITDA to interest expenses. Profitability is the ratio of EBITDA over sales. Market-to-book ratio is calculated as the ratio of (book value of assets – book value of equity + market value of equity) to book value of assets. PPE ratio is the ratio of property, plant and equipment to total assets. *Drought (-1)* is the PDSI of the borrower's state in the month leading to the loan contract. *Drought (-3)* is the average PDSI over 3 months prior to the loan start date. We multiply the PDSI by -1 when constructing *Drought(-1)* and *Drought(-3)* to make the interpretation more intuitive, *i.e.* high values of *Drought (-1)* and *Drought (-3)* indicate more severe drought conditions. All the values are winsorised at 1% and 99% levels.

Table 3 Univariate tests for loan spreads between drought-affected loans and other loans

Panel A	**Severe drought or worse (X)**		**Non-severe drought (Y)**		**Difference (X-Y)**	
	Mean	Median	Mean	Median	Mean	Median
Entire loan sample						
AISD (bps)	212.07	200	184.81	175	27.26***	25***
N	1,347	1,347	30,124	30,124		
Food industry loans						
AISD (bps)	227.09	225	171.89	150	55.2***	75***
N	52	52	1458	1458		

Panel B	**Top 5 (most affected) drought states (X)**		**Bottom 5 (least affected) drought states (Y)**		**Difference (X-Y)**	
	Mean	Median	Mean	Median	Mean	Median
Entire loan sample						
AISD (bps)	216.58	200	179.17	175	37.41***	25***
N	2,401	2,401	2,683	2,683		
Food industry loans						
AISD (bps)	216.54	200	151.89	175	64.65***	25***
N	55	55	150	150		

This table presents mean and median of AISD, All in Spread Drawn, which is the interest rate margin over LIBOR on the drawn loan amount plus annual fees. In panel A, the first two columns show the mean and median for firms which are affected by moderate drought or worse at the time of the loan. The next two columns show mean and median AISD for loans originated during normal drought conditions. The last two columns present the t-statistic for mean tests and z-statistic for Wilcoxon median tests. In panel B, the first two columns show the mean and median for firms which are located in the top 5 (i.e. most affected) drought states at the time of the loan. The next two columns show mean and median AISD for loans of firms being located in the bottom 5 (i.e. least affected) drought states. The last two columns present the t-statistic for mean tests and z-statistic for Wilcoxon median tests. ***, **, * represent significance at the 1%, 5%, and 10% level, respectively.

Table 4 The effect of drought on loan spreads

Dep. Var. = AISD						
	Entire sample		Food borrowers		Entire sample	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Drought (-1)	1.056***		3.656***		0.895***	
	(0.302)		(1.382)		(0.306)	
Drought (-3)		1.215***		2.854*		1.091***
		(0.326)		(1.458)		(0.331)
Food					-3.298	-3.420
					(4.411)	(4.451)
Drought (-1) Food*					3.657**	
					(1.539)	
Drought (-3) Food*						2.939*
						(1.621)
Constant	Y	Y	Y	Y	Y	Y
Loan characteristics	Y	Y	Y	Y	Y	Y
Borrower characteristics	Y	Y	Y	Y	Y	Y
Credit ratings, loan purpose, and loan year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	N	N	Y	Y
Observations	24,887	24,887	1,194	1,194	24,887	24,887
Adj R-squared	0.553	0.553	0.647	0.645	0.553	0.553

This table presents the OLS regression output for All-in-Spread Drawn (AISD) on drought measures. *Drought (-1)* is the PDSI of the borrower's state in the month leading to the loan contract. *Drought (-3)* is the average PDSI over 3 months prior to the loan start date. We multiply the PDSI by -1 when constructing *Drought(-1)* and *Drought(-3)* to make the interpretation more intuitive, *i.e.* high values of *Drought (-1)* and *Drought (-3)* indicate more severe drought conditions. All regressions include loan characteristics, borrower characteristics, borrower industry, loan purpose, and year dummies. The numbers in parentheses are standard errors corrected for clustering at the firm level and heteroscedasticity. ***, **, * represent significance at the 1%, 5%, and 10% level, respectively.

Table 5 Mitigating the effect of drought on food-industry loan spreads

Dep. Var. = AISD				
	Mitigating factor: Lender experience		*Mitigating factor:* Borrower investment grade	
Variable	(1)	(2)	(3)	(4)
Drought (-1)	7.132***		5.390***	
	(2.336)		(1.838)	
Drought (-3)		6.528***		4.741**
		(2.439)		(1.904)
Lender Experience	2.476	5.181		
	(22.080)	(20.644)		
Investment Grade			-35.372**	-35.061**
			(14.082)	(14.279)
Drought (-1) × *Lender Experience*	-23.403**			
	(10.257)			
Drought (-3) × *Lender Experience*		-24.843**		
		(10.689)		
Drought (-1) × *Investment Grade*			-5.657**	
			(2.365)	
Drought (-3) × *Investment Grade*				-5.758**
				(2.457)
Constant	Y	Y	Y	Y
Loan characteristics	Y	Y	Y	Y
Borrower characteristics	Y	Y	Y	Y
Credit ratings, loan purpose, and loan year dummies	Y	Y	Y	Y
Observations	1,190	1,190	1,194	1,194
Adj R-squared	0.649	0.647	0.661	0.659

This table presents the OLS regression output for All-in-Spread Drawn (AISD) on drought risk and different mitigating factors to drought effected borrowers. Columns 1-2 examine the mitigating effect of Lender Experience, which is calculated in a similar manner to Bharath et al. (2011)'s relationship variable. For a loan made on date X by lead bank A, the number of loans originated by lead bank A to all borrowers in our database up until date X are obtained. We then look into each of these loans to check if its borrower experienced a severe drought in the 3 months prior to the loan commencement. We count the number of these drought-affected loans and divide it to the total number of loans originated by lead bank A. This ratio is used as a proxy for lead bank A's experience in lending to drought-affected borrowers. Columns 3-4 use Investment Grade as the mitigating factor, where Investment Grade dummy takes the value of 1 if borrower credit ratings are BBB or higher. All regressions include loan characteristics, borrower characteristics, borrower industry, loan purpose, and year dummies. The numbers in parentheses are standard errors corrected for clustering at the firm level and heteroscedasticity. ***, **, * represent significance at the 1%, 5%, and 10% level, respectively.