Drought risk in private debt contracts

Viet Do

Department of Banking and Finance, Monash University
Clayton, Victoria 3800, Australia
Minh.Do@monash.edu

Hannah Nguyen

Department of Banking and Finance, Monash University
Caulfield East, Victoria 3145, Australia
Hannah.Nguyen@monash.edu

Cameron Truong

Department of Accounting, Monash University
Caulfield East, Victoria 3145, Australia
Cameron.Truong@monash.edu

Tram Vu

Department of Banking and Finance, Monash University
Caulfield East, Victoria 3145, Australia
Tram.Vu@monash.edu

Drought risk in private debt contracts

Abstract

This study investigates the effect of climate change risk – proxied by Palmer Drought Severity Index (PDSI) – on private debt contracts. We raise a very simple yet important question: Do banks include drought risk in their pricing model of business loan contracts? The result indicates that banks indeed do take into account drought risk in their pricing model. Intuitively, the effect is most pronounced among food industry borrowers where drought has a direct impact. We also report that the bank's prior experience in lending to drought-affected borrowers appears to be important in setting loan spreads. Lenders with strong experience in lending to drought-affected borrowers charge a lower premium on drought risk when compared to less experienced lenders. These results point towards drought risk being viewed as a systematic risk by credit providers. It adds a new dimension to credit risk evaluation and attracts a price premium whose magnitude is stronger for food industry borrowers.

Keywords: Drought risk, climate change, loan spreads and loan covenants

JEL: G21, G32

1. Introduction

One of the most challenging issues facing humanity in the twenty-first century is climate change. Climate change has affected many aspects of human life. Economics and finance is no exception. Among the financial sector, the insurance industry exhibits the most obvious example of such effect. The head of the Bank of England in a recent speech identified three types of risks that climate change poses to financial stability: physical risk, liability risk, and transition risk. He highlighted that: "*insurers stand exposed to each of the three types of risk climate change poses to finance; and while the sector is well-placed to respond in the near-term you should not assume your ability to manage risks today means the future is secure. Longer term risks could have severe impacts on you and your policyholders.*"

This paper focuses on one key aspect of climate change, the risk from prolonged drought periods – or drought risk. According to Hong, Li and Xu (2017), drought is considered to have one of the most damaging impacts on global economy. Lesk, Rowhani, and Ramankutty (2016) documented 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) concluded 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).

We explore drought risk from the perspective of banks as credit providers and study how they perceive and price such risk in their loan contracts. Similar to the insurance industry, the banking sector is sensitive to effects from climate change, especially when borrowers' revenues are highly exposed to drought risk. A standard loan pricing model takes into account borrower characteristics (*e.g.,* credit rating, asset size, leverage, profitability, etc.), loan characteristics (*e.g.*, maturity, loan size, collateral, and covenant requirements), and conventional macro-economic conditions.[1] Utilizing a well-established loan pricing model, we add another layer of risk, drought risk, to investigate whether banks take into account previous drought levels when setting loan price. In other words, do borrowers have to pay a higher loan price following a period of prolonged drought?

Work on how climate change risk is perceived and priced in the financial market is very limited with two notable exceptions. Bansal, Kiku, and Ochoa (2014) use temperature as a proxy for climate change risk from global warming. They investigate the elasticity of global equity price on temperature and find global warming has a significant negative effect on stock price. More importantly, their result suggests that the magnitude of the elasticity is exacerbated over time indicating that the impact of global warming is increasing. Overall, this means the global equity market has taken climate change risk into account in asset pricing. Hong, Li and Xu (2017) report the opposite finding, where they use a different proxy for climate change risk – Palmer Drought Severity Index (PDSI). Their paper investigates the effect of prolonged drought periods on market efficiency and shows that the equity market has not fully accounted for such risk. Their long-short food industry portfolio based on the drought index generates a significant return of 9.2% per annum. Their results indicate that many global markets underreact to drought risk.

We utilize PDSI as a proxy for drought risk and focus on the private debt market rather than the equity market. We test if banks consider drought risk in determining loan contract terms made to corporate borrowers. Our results indicate that banks do take into account drought risk in loan pricing. A one standard deviation increase in

[1] See, for example, Berger and Udell (1990), Dennis *et al*. (2000), and Bharath *et al*. (2011).

PDSI would lead to a 9 basis point increase in loan spreads for a food industry borrower. Not only that, there appears to be a drought risk premium for non-food borrowers as well, even though the economic significance of drought risk drops to about 2.35 basis points. This result remains statistically significant. Our findings also suggest that not all banks price drought risk equally. Banks with more experience in lending to drought-affected borrowers charge a lower risk premium for drought risk than less experienced ones.

This study provides a number of important contributions to the very limited literature on finance and climate change. Both key papers focus on whether climate change risk is priced in the equity market. To the best of our knowledge, this work is the first to document the importance of drought risk in the design of a private loan contract. Our results are relatively intuitive given that revenues of food industry borrowers are highly correlated with drought severity. Our findings also suggest spillover effects of drought risk to non-food industry borrowers who may not be directly affected by drought. This is strong evidence for the inter-link between industries and indicates that drought risk or climate change risk is a systematic risk. The results also suggest that when lenders do not understand drought risk well (i.e., less experienced lenders), they tend to overprice such risk via a higher premium.

The remainder of the paper is structured as follows. Section 2 discusses data sources and variable construction. Sections 3 to 5 present the results for the effects of drought risk on loan spreads. Finally, section 6 concludes the study.

2. Data and sample selection

The data in this paper come from three main data sources. The loan characteristics are from the Loan Pricing Corporation (LPC) DealScan database. The borrower characteristics are from Merged CRSP Compustat database, and the drought risk proxy PDSI is from the National Centers for Environmental Information (NCEI) of the US National Oceanic and Atmospheric Administration (NOAA).

2.1 Drought risk measures

We use the Palmer Drought Severity Index (PDSI) to construct our drought measures. Even though there have been several drought indices that have been used to quantify drought, PDSI is the most widely used measure in the US (Dai and Eds, 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 and Eds, 2016). The index is standardized and ranging from about -10 to +10 and the lower the value, the more severe dry it indicates. More specifically, different categories are defined based on the values of PDSI. If the PDSI is -4 and below, it indicates an extreme drought condition. If it is between -4 and -3, it is a severe drought. If the PDSI is between -3 and -2, it suggests a moderate drought. A PDSI of -2 to -1 indicates a mild drought condition whereas that of -1 to -0.5 suggests an incipient drought. A normal condition is indicated by a PDSI of -0.5 to 0. A PDSI of 0 and above suggests different wet conditions.

We obtain the 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 is available from

January 1895 to August 2016 for all contiguous US states (PDSI data for Hawaii and Alaska is 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 *PDSI* which is simply the PDSI of the borrower in the month leading to the loan contract. The second measure is *PDSI_ma3* obtained by taking the average PDSI over 3 months prior to the loan start date.

2.2 Loans and borrowers characteristics

Loan characteristics, such as loan price (All-in-Spread Drawn), maturity, collateral, covenant, and loan purpose, are obtained from the LPC database. Borrower characteristics such as asset size, leverage, profitability, and interst coverage are obtained from the Merged CRSP Compustat database. Each loan facility is matched with the most recently available borrower characteristics. That is, given a loan is 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).

Insert table 1 here

The distribution of the sample loan facilities across year, loan purpose, borrower industry, and borrower credit rating is presented in table 1. Panel A shows the calendar

[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).

year distribution of the loans during our sampling period. In relation to the number of loans originated, the 2000s saw strong growth which however reduced to about half after the global financial crisis. Since 2010, the market started to recover in the number of loans extended to borrowers. Panel B shows the main purposes for which these loans are used, with the most common being working capital and debt repayment, followed by acquisition and takeover. Panel C lists the one-digit primary SIC code of the borrowers in our sample. The main concentration is among borrowers in the manufacturing sector (SIC code between 2000 and 3999) and transportation, communication, electric, gas and sanitary services (SIC code between 4000 and 4999). Panel D lists the borrower's publicly available credit rating at time of loan origination.

Table 2 reports summary statistics of the key loan characteristics, borrower characteristics, and drought risk proxies. The data are winsorized at the 1% and 99% levels to remove extreme outliers. The average loan spread (also known as All-in-Spread Drawn or AISD) is 184 bps, mean maturity 49 months and mean facility size US$357 million. The mean book value of assets for our borrowers is US$14 billion. PPBoth facility size and borrower size are highly skewed, indicating strong heteroscedasticity in our sample.

Insert table 2 here

3. Drought risk and loan price

We first investigate the effect of drought on loan spreads using simple univariate tests (mean test and Wilcoxon rank-sum test) on loan spreads. Table 3 reports results from the univariate tests.

Insert table 3 here

The sample is segregated into loans to borrowers experiencing moderate drought or worse (X) and loans to borrowers with normal condition (Y). We conduct *t*-test for the differences in mean and Wilcoxon test for the differences in median between these two groups for food industry borrowers and non-food borrowers. The univariate test results show evidence that borrowers who are experiencing drought have to pay a significantly higher loan price. The average AISD on loans to food borrowers with moderate drought or worse is 227 bps while that on loans to food borrowers not affected by drought is 171 bps. The difference of about 56 bps is significant at the 1% level. This difference for non-food borrowers is 26 bps (26=211-185). The Wilcoxon tests for the differences in median are also statistically significant for both groups of food and non-food borrowers. While we cannot draw a meaningful conclusion from these tests, this is the first evidence banks do take into account the drought conditions of borrowers when setting loan price. Naturally, the effect of drought is much more pronounced among food borrowers given their revenue is directly linked with climate conditions.

Next, we adopt the following regression to test whether drought risk has any effect on loan spreads, controlling for firm characteristics, loan characteristics and macroeconomic conditions:

$$AISD_i = \beta_0 + \beta_1(Drought) + \sum\beta_i\,(Loan_i) + \sum\beta_j\,(Borrower_j) + \sum\beta_k\,(Controls) \qquad (1)$$

The variables are defined as follows:

- $AISD_i$: The dependent variable is "All-in-spread-drawn" (*AISD*) which represents the interest rate margin over LIBOR on drawn loan amount plus annual fees. This variable is expressed in basis points.
- *Drought*: This is the key variable of interest for our research question. We use two different proxies for this measure (*PDSI* and *PDSI_ma3*). The original PDSI

measure is between 10 and -10. The lower value indicate more severe drought. We multiply this by -1 to make interpretation of the result more intuitive. Detailed description of these variables is in section 2.1.

❖ *Loan*$_i$: A vector of loan characteristics including the following variables,

- *LNMAT*: Natural logarithm of loan maturity in number of months.
- *LNLOANSIZE*: Natural logarithm of loan facility amount adjusted for inflation in year 1983 dollars.
- *SECURED*: A binary variable taking the value of 1 for secured loans and zero for unsecured loans.[3]
- *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*$_j$: A vector of borrower characteristics including the following variables,

- *LNASSETS*: Natural logarithm of borrower's book value of total assets adjusted for inflation in year 1983 dollars.
- *LEVERAGE*: Borrower's leverage ratio calculated as book value of total debts divided by book value of total assets.

[3] Dennis, Nandy, and Sharpe (2000) documented that the secured status as recorded on Dealscan is subject to missing information in several instances. To treat missing information as an unsecured loan creates bias, while straight exclusion of that observation significantly reduces the sample size. Following Dennis *et al.* (2000), we overcome this issue by creating a fitted value of the *SECURED* variable for facilities with missing collateral information via a two-step estimation. First, the binary variable *SECURED* is regressed on all borrower characteristics among facilities with available information on secured status using a Probit model. The estimated coefficients are then used to calculate a fitted value of *SECURED* for facilities with missing collateral information. If the fitted value is greater than 0.5, *SECURED* is taken to be 1 for that loan facility; if the fitted value is less than 0.5, *SECURED* is taken to be zero.

- *CURRENT*: Borrower's current ratio calculated as current assets divided by current liabilities.
- *LNCOVERAGE*: Natural logarithm of (1 + EBITDA/Interest expenses).
- *PROFITABILITY*: 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.

❖ *Controls*: A vector of control variables including dummies for borrower credit ratings (AAA, AA, A, BBB and other ratings), loan purpose dummies, loan year dummies, and borrower 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).[4]

Insert table 4 here

The results show evidence that drought risk is taken into consideration by banks when setting loan price for food industry borrowers. The coefficients of both drought measures (*PDSI* and *PDSI_ma3*) are positive and significant at the 5% and 10% level respectively. Given the observed coefficient of *PDSI* is 3.6 and standard deviation of PDSI for food industry is 2.49, we interpret this as follows: if PDSI in the month prior to the loan start date increases by one standard deviation, the loan price will increase by about 9 (3.6* 2.49= 8.96) basis points. This is not only statistically significant but also economically significant. Given the average loan size for a food industry borrower

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

is US$423 million, the interest premium is US$380,700 per annum. The second proxy *PDSI_ma3* captures the drought level at the location of the borrower over 3 months leading up to the loan. The coefficient is 2.85 and significant at the 10% level. Although this is not as strongly significant as PDSI, this result is consistent and provides further supporting evidence to our conjecture that banks do view drought risk as an additional risk factor and hence attach a risk premium into this new risk.

The results for other loan characteristics, borrower characteristics and controls are consistent with the prior literature. Larger, unsecured, and revolving loans are associated with a lower loan spread. 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 higher interest coverage, better profitability pay a lower loan spread on average. At the same time borrowers with higher leverage ratio and those who require collateral pay higher loan spreads.

4. Drought risk spillover

In this section, we re-estimate model (1) for all borrowers. While non-food industries may not be directly affected by drought, the inter-link between industries within the economy means that such risk may be transmitted. For example, the transportation industry could be affected if the agriculture sector suffers a loss of crop due to drought. Bansal *et al*. (2014) model the effect of climate change risk on equity price through the consumption channel. They argue a market wide impact of climate change risk on dynamic consumption and show that temperature increases lower the wealth to consumption ratio therefore reduce equity price. They hence conclude that rising temperature poses significant costs.

A similar argument could be made for our study, albeit with the use of a different proxy for climate change risk. As drought risk increases, local as well as national consumption may decrease. This in turn affects revenues of firms in every industry, food or non-food. Hence drought risk at the state level may be viewed as local systematic risk which could then result in higher borrowing costs for all firms from that state. Table 5 presents the results for non-food borrowers and the entire sample.

Insert table 5 here

Column (1) and (2) in table 5 show the result from re-estimating equation (1) on non-food borrowers. It shows that drought risk continues to be priced even for non-food borrowers. Both coefficients are strongly significant at the 1% level. When compared to that of food borrowers, the stronger significance level is likely due to the much larger sample size. Importantly, the coefficient magnitude for both proxies is about less than half of that observed for food industry borrowers. The coefficient of PDSI (column 1) is 0.95 which means that a one standard deviation increase in *PDSI* would lead to loan prices for a non-food borrower increasing by about 2.35 (2.35=0.95*2.48) basis points. The marginal effect on loan spreads of non-food borrowers is less than one-third of the food industry borrowers.

We also seek to confirm our finding by running the multi-variate regression using the entire sample. We estimate the following model:

$$AISD = \beta_0 + \beta_1\,(Drought) + \beta_2\,(Food\_dummy) + \beta_3\,(Drought)*(Food\_dummy) + \sum\beta_i\,(Loan_i) + \sum\beta_j\,(Borrower_j) + \sum\beta_k\,(Controls) \quad (2)$$

The result is presented in columns (3) and (4) of table 5. Three important results can be drawn from these two columns. First, the coefficients of both drought proxies remain strongly significant at 1% level. The magnitude of both coefficients is very similar to that reported in column (1) and (2) of table 4. Second, both coefficients for *Food_dummy* are statistically insignificant. This is an important result. 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 coefficients of the interaction terms (β_3) are also positive and significant at 1% level. This means that the marginal effect of drought is significantly stronger for food industry borrowers. From column (4) of the table 5, we can see that if PDSI increases by one standard deviation, the average loan price will increase by about 2.23 (2.23=0.909*2.48) basis points for non-food borrowers and 11 (11= (0.909+3.541)*2.48) basis points for food borrowers. Overall, this result suggests that there is a spillover effect of drought risk for non-food borrowers who are found to pay a premium for drought risk albeit at less than a third of that for food-industry borrowers.

5. Drought experience and drought risk premium

In this section, we investigate the effect of lender experience in lending to drought-affected borrowers on their drought risk premiums. Specifically, we test if lenders who are more experienced in lending to drought-affected borrowers charge a lower loan rate premium when compared to less experienced lenders. We conjecture that drought risk or climate change risk is a relatively new type of risk, hence lenders are still learning to price it appropriately. More experienced lenders may understand 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 test our hypothesis using the following model:

$$AISD = \beta_0 + \beta_1 (Drought) + \beta_2 (Drought\ Experience) + \beta_3 (Drought)*(Drought\ Experience) + \sum\beta_i (Loan_i) + \sum\beta_j (Borrower_j) + \sum\beta_k (Controls) \quad (3)$$

Drought Experience 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 and pricing drought risk. The interaction term captures the marginal effect of such experience on drought risk premium. We estimate model (3) on borrower from food industry. The result is presented in table 6.

Insert table 6 here

We can observe that the coefficients of both *PDSI* and *PDSI_ma3* remain strongly positive and significant at the 1%. The main variable of interest is the interaction term between *Drought* and *Drought Experience* (β_3). Both coefficients are negative and significant at the 1% level. This indicates that lenders with drought lending experience on average charge a lower drought premium when compared with less experienced lenders. The results lend support to our hypothesis. In un-reported results, we also estimate equation (3) for non-food borrowers. The result shows that the interaction terms are not statistically significant. It shows that this experience works best for food-industry borrowers where the effect of drought risk is most pronounced.

6. Conclusion

This study investigates the impact of climate change risk on the design of private loan contracts including price and non-price terms. We focus on the risk of prolonged drought which has been shown to have the strongest impact on crop production (Lesk *et al*., 2016). Given prolonged drought risk can severely affect agricultural borrowers' revenues hence their repayment capability, we highlight the importance of drought risk to food industry borrowers and even find evidence of spillover effects to non-food industry firms.

We document a significant impact of drought risk on loan price setting. First, we show that food industry borrowers exposed to higher levels of drought risk pay significantly higher loan spreads. In particular, a one standard deviation increase of drought risk in the month leading loan origination is associated with an additional 9 basis points in borrowing costs for food industry borrowers. Second, we provide evidence that the impact of drought risk is not limited to food industry borrowers. We observe a spillover of such risk to non-food industry borrowers even though the magnitude is lower at about 2.3 basis points. Third, we show that lenders who are more experienced in lending to drought-affected borrowers charge a lower premium on drought risk when compared to less experienced lenders. It shows that when banks have better understanding of this risk they may be able to charge a more accurate premium. At the same time, when lender have less or no experience on the new risk, they tend to impose higher premiums to cover their exposure.

Climate change is considered one of the major issues in the twenty first century. Yet, the volume of research on the impact of climate change in financial markets remains negligible. The two notable exceptions are Bansal, Kiku, and Ochoa (2014) and Hong, Li and Xu (2017). Both of these papers focus on the equity market. Our work contributes to this very limited literature and studies climate change risk from credit providers' perspectives. We provide evidence to suggest that this new layer of risk is viewed by banks as systematic risk and hence incorporated in loan spreads; the extent to which this risk is priced appropriately varies with lender experience. Our findings have important implications for policymakers, borrowers and other market participants. They reflect increasing awareness of climate change risk in particular from bank lenders' viewpoint. It raises a question whether equity holders and even credit rating agencies have adequately considered climate change risk in their asset pricing and risk measurement models.

References

Bansal, R., Kiku, D., and Ochoa, M. (2014). Climate change and growth risks. Working Paper, Duke University.

Berger, A. and Udell, G. (1990). Collateral, loan quality and bank risk. *Journal of Monetary Economics*, 25(1), 21-42.

Bharath, S. T., Dahiya, S., Saunders, A., and Srinivasan, A. (2011). Lending relationships and loan contract terms. *Review of Financial Studies*, 24(4), 1141-1203.

Blackhurst, B. M., Hendrickson, C., and Vidal, J. S. I. (2010). Direct and indirect water withdrawals for US industrial sectors. *Environmental Science & Technology*, 44(6), 2126-2130.

Chava, S., and Roberts, M. (2008). How does financing impact investment? The role of debt covenants. *Journal of Finance*, 63(5), 2085-2121.

Dai, A., and National Center for Atmospheric Research Staff (Eds) (2016). *The climate data guide: Palmer Drought Severity Index (PDSI)*. Retrieved from http://climatedataguide.ucar.edu/climate-data/palmer-drought-severity-index-pdsi.

Dennis, S., Nandy, D., and Sharpe, I. G. (2000). The determinants of contract terms in bank revolving credit agreements. *Journal of Financial and Quantitative Analysis*, 35(1), 87-110.

Hong, H. G., Li, F. W., and Xu, J. (Forthcoming). Climate risks and market efficiency. *Journal of Econometric*.

Lesk, C., Rowhani, P., and Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84-87.

Saunders, A., and Steffen, S. (2011). The costs of being private: Evidence from the loan market. *Review of Financial Studies*, 24(12), 4091-4122.

Trenberth, K. E., Dai, A., van der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., and Sheffield, J. (2014). Global warming and changes in drought. *Nature Climate Change*, 4(1), 17-22.

Appendix 1: Food industry identification based on Fama-French 17-industry classification

SIC code	Industry description	SIC code	Industry description
0100-0199	Agricultural production - crops	2082-2082	Malt beverages
0200-0299	Agricultural production - livestock	2083-2083	Malt
0700-0799	Agricultural services	2084-2084	Wine
0900-0999	Fishing, hunting & trapping	2085-2085	Distilled and blended liquors
2000-2009	Food and kindred products	2086-2086	Bottled-canned soft drinks
2010-2019	Meat products	2087-2087	Flavoring syrup
2020-2029	Dairy products	2090-2092	Misc food preps
2030-2039	Canned-preserved fruits-vegs	2095-2095	Roasted coffee
2040-2046	Flour and other grain mill products	2096-2096	Potato chips
2047-2047	Dog and cat food	2097-2097	Manufactured ice
2048-2048	Prepared feeds for animals	2098-2099	Misc food preparations
2050-2059	Bakery products	5140-5149	Wholesale - groceries & related prods
2060-2063	Sugar and confectionery products	5150-5159	Wholesale - farm products
2064-2068	Candy and other confectionery	5180-5182	Wholesale - beer, wine
2070-2079	Fats and oils	5191-5191	Wholesale - farm supplies
2080-2080	Beverages		

Table 1
Distribution of loan facilities
This table presents the distribution of loan facilities over the period 1984-2016. Option is a binary variable taking the value of 1 if the borrower has listed options available for trading in the year before the loan year, and zero otherwise. Panel A presents loan distribution (number of facilities) by year. Panel B summarizes loan purposes. Panel C reports borrower SIC code. Panel D reports borrower bond ratings.

Panel A: Number of facilities by year		**Panel B: Number of facilities by primary loan purpose**	
1984	3		
1985	6	Acquisition Line	1765
1986	37	Debt Repayment	5671
1987	299	Commercial Paper Backup	1837
1988	586	Takeover	4639
1989	515	LBO, MBO	1042
1990	534	General Corporate Purposes	11809
1991	447	Working Capital	5236
1992	607	Other	1765
1993	912	**Total**	**34623**
1994	1295		
1995	1292	**Panel C: Number of facilities by borrower's industry**	
1996	1788		
1997	2160	SIC=0	166
1998	1921	SIC=1	1834
1999	1899	SIC=2	6483
2000	1787	SIC=3	9711
2001	1674	SIC=4	4963
2002	1553	SIC=5	5188
2003	1539	SIC=7	4123
2004	1757	SIC=8	1946
2005	1746	SIC=9	209
2006	1517	**Total**	**34623**
2007	1518		
2008	780	**Panel D: Number of facilities by borrower's rating**	
2009	491		
2010	816		
2011	1178	AAA	111
2012	997	AA	414
2013	1064	A	2713
2014	929	BBB	4571
2015	765	Other Rated	9884
2016	211	Not Rated	16930
Total	**34623**	**Total**	**34623**

Table 2
Descriptive statistics for key loan terms and borrower characteristics
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. All the values are winsorised at 1% and 99% levels.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Loan characteristics					
AISD (bps)	34392	184	118	18	600
MAT (months)	33422	49	24	6	107
LOANSIZE ($ millions)	34621	357	598	2.6	3,800
SECURED	34623	0.5188	0.4997	0	1
STRICT	34623	0.3372	0.4728	0	1
REVOLVER	34623	0.5853	0.4927	0	1
Drought Proxies					
PDSI_ma3	31695	0.1086	2.3463	-8.65	9.19
PDSI	31695	0.1044	2.4858	-9.01	8.83
Other borrower characteristics					
ASSETS ($ millions)	34623	14431	36296	47	262493
LEV	34623	0.3438	0.2102	0.0000	0.8973
CURRENT	33205	1.8773	1.0730	0.4067	6.6558
COVERAGE	33267	16.5019	41.5290	0.4826	319.0256
PROFIT	34310	0.1618	0.1146	0.0099	0.6007
MTB	30708	1.6977	0.9133	0.7261	6.0662
PPE	34623	0.4646	0.2729	0.0238	0.9850

Table 3
Differences in loan spread between drought and normal conditions
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. 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. ***, **, * represent significance at the 1%, 5%, and 10% level, respectively.

	Moderate drought or worse (X)		Normal conditions (Y)			
Variable	Mean	Median	Mean	Median	Mean t-test (X-Y)	Median Wilcoxon test (X-Y)
Panel A: Food industry						
AISD (bps)	227.09	225	171.89	150	3.21***	2.78***
Panel B: Non-food industry						
AISD (bps)	211.46	200	185.47	175	7.86***	6.98***

Table 4
Drought risk and loan yield spreads of food-industry borrowers
This table presents the OLS regression output for All-in-Spread Drawn (AISD) on option listing dummy. All regressions include 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.

	(1)	(2)
PDSI	3.599**	-----
	(1.486)	-----
PDSI_ma3	-----	2.854*
	-----	(1.458)
LNASSETS	4.822	4.741
	(4.794)	(4.855)
LEVERAGE	69.881**	68.451**
	(34.123)	(34.477)
CURRENT	-3.158	-3.381
	(4.437)	(4.398)
LNCOVERAGE	-0.321**	-0.336**
	(0.136)	(0.135)
PROFITABILITY	-105.979*	-109.062*
	(63.677)	(62.963)
MTB	-7.331	-7.392
	(5.215)	(5.224)
PPE	-26.373	-26.571
	(20.479)	(20.798)
LNLOANSIZE	-20.014***	-20.111***
	(4.028)	(4.072)
LNMAT	3.718	3.833
	(5.007)	(5.047)
SECURED	51.420***	51.759***
	(13.015)	(13.096)
STRICT	8.335	7.510
	(8.023)	(8.010)
REVOLVER	-25.085***	-25.280***
	(5.171)	(5.226)
Constant	396.786***	399.671***
	(103.243)	(101.032)
Year dummies	Yes	Yes
Loan purpose dummies	Yes	Yes
Rating dummies	Yes	Yes
Industry dummies	NO	NO
Observations	1,194	1,194
Adj R-squared	0.647	0.645

Table 5
Drought risk and loan yield spreads of all borrowers
This table presents the OLS regression output for All-in-Spread Drawn (AISD) on non-food borrowers and the entire sample. All regressions include 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.

Dep. Var. = All-in-Spread Drawn (*AISD*)				
	Non-Food industries		Entire sample	
	(1)	(2)	(3)	(4)
PDSI	0.947***	-----	-----	0.909***
	(0.301)	-----	-----	(0.300)
PDSI_ma3	-----	1.145***	1.091***	-----
	-----	(0.332)	(0.331)	-----
*PDSI*Food_dummy*	-----	-----	-----	3.541**
	-----	-----	-----	(1.630)
*PDSI_ma3 *Food_dummy*	-----	-----	2.939*	-----
	-----	-----	(1.621)	-----
Food_dummy	-----	-----	-3.420	-3.164
	-----	-----	(4.451)	(4.453)
LNASSETS	-8.560***	-8.561***	-8.179***	-8.185***
	(1.248)	(1.247)	(1.214)	(1.213)
LEVERAGE	101.395***	101.296***	100.056***	100.162***
	(5.821)	(5.812)	(5.734)	(5.739)
CURRENT	0.921	0.922	0.667	0.664
	(0.952)	(0.951)	(0.934)	(0.935)
LNCOVERAGE	-0.051**	-0.051**	-0.053**	-0.053**
	(0.022)	(0.022)	(0.022)	(0.022)
PROFITABILITY	-28.518**	-28.646**	-31.356***	-31.178***
	(11.143)	(11.137)	(10.932)	(10.939)
MTB	-9.882***	-9.887***	-9.831***	-9.822***
	(1.056)	(1.055)	(1.028)	(1.029)
PPE	-7.170*	-7.171*	-7.604*	-7.594*
	(3.956)	(3.956)	(3.897)	(3.895)
LNLOANSIZE	-12.346***	-12.350***	-12.641***	-12.627***
	(0.951)	(0.952)	(0.932)	(0.930)
LNMAT	5.260***	5.244***	5.105***	5.094***
	(1.268)	(1.267)	(1.236)	(1.236)
SECURED	52.061***	52.088***	52.104***	52.057***
	(2.066)	(2.065)	(2.057)	(2.056)
STRICT	11.652***	11.637***	11.325***	11.387***
	(2.094)	(2.094)	(2.047)	(2.047)
REVOLVER	-29.724***	-29.714***	-29.492***	-29.492***
	(1.347)	(1.347)	(1.308)	(1.308)
Constant	367.807***	367.767***	370.587***	370.626***
	(23.415)	(23.406)	(23.133)	(23.128)
Year dummies	Yes	Yes	Yes	Yes
Loan purpose dummies	Yes	Yes	Yes	Yes
Rating dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	23,693	23,693	24,887	24,887
Adj R-squared	0.548	0.548	0.553	0.553

Table 6
Drought risk premium and lender experience
This table presents the OLS regression output for All-in-Spread Drawn (AISD) on drought risk and lender experience lending to drought effected borrowers. All regressions include 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.

	(1)	(2)
PDSI	6.971***	-----
	(2.405)	-----
PDSI_ma3	-----	6.528***
	-----	(2.439)
PDSI Drought Experience*	-23.754**	-----
	(10.340)	-----
*PDSI_ma3 * Drought Experience*	-----	-24.843**
	-----	(10.689)
Drought Experience	-1.309	5.181
	(23.085)	(20.644)
LNASSETS	4.739	4.936
	(4.752)	(4.787)
LEVERAGE	69.152**	67.731*
	(34.239)	(34.396)
CURRENT	-3.038	-3.006
	(4.461)	(4.376)
LNCOVERAGE	-0.326**	-0.348**
	(0.137)	(0.137)
PROFITABILITY	-107.966*	-115.752*
	(64.162)	(62.610)
MTB	-7.165	-6.958
	(5.210)	(5.189)
PPE	-25.442	-23.573
	(20.678)	(21.104)
LNLOANSIZE	-19.775***	-20.177***
	(4.078)	(4.127)
LNMAT	3.535	3.761
	(5.111)	(5.144)
SECURED	50.764***	51.556***
	(12.707)	(12.868)
STRICT	9.175	8.311
	(8.030)	(8.033)
REVOLVER	-24.879***	-24.909***
	(5.291)	(5.303)
Constant	394.253***	397.641***
	(110.292)	(107.211)
Macro variables	Yes	Yes
Loan purpose dummies	Yes	Yes
Rating dummies	Yes	Yes
Industry dummies	Yes	Yes
Observations	1,190	1,190
Adj R-squared	0.649	0.647