Climate Risk in Local Credit Markets: Some Preliminary Evidence from Mexico

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The views expressed are those of the authors and not necessarily those of the Bank of Mexico

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- Climate models: predictions on temperature/rainfall at fine geographical level
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- Our focus: bank credit to the agricultural sector

  $\rightarrow$ Is exposure to climate-related risks reflected in local credit markets?

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- Study bank lending response to weather shocks (drought)
  - Role of predictions from climate models about future drought conditions

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  - Large agricultural employment share + prone to droughts
  - 2012 "climate change law" $\rightarrow$ INECC: local climate-risk exposure measures
  - Detailed credit registry data on bank loans to agriculture

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  - Detailed credit registry data on bank loans to agriculture
- Empirics
  - Municipality-level variation:
    1. meteorological drought shocks (SPEI)
    2. expected **change** in meteorological dryness based on climate models from INECC
  - Study effects of (1) and (1) $\times$ (2) on price and quantity of new loans

Some very preliminary findings

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- Do dryness shocks increase default on agricultural loans? (*Yes*)
- Does climate-risk exposure predict persistence in dryness? (*Yes*)
- Is climate-risk exposure reflected in new bank loans? (*No*)
- Would including climate-risk exposure help to better predict future default? (*Yes*)

Background

- 2012 Mexico law on climate change creates research institute INECC
- INECC:
  - municipality-level measures of vulnerability of agri activities to dryness
  - vulnerability = f(exposure, sensitivity, adaptive capacity)

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  - exposure = f(rainfall seasonality index, Lang aridity index)
    - current: 1981-2010
    - future: 2021-2040, 2041-2060, 2061-2080

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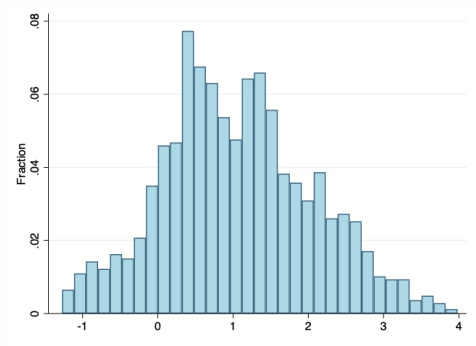
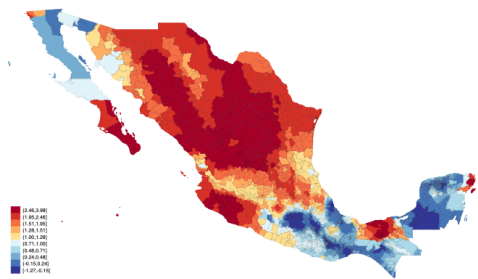
  - exposure = f(rainfall seasonality index, Lang aridity index)
    - current: 1981-2010
    - future: 2021-2040, 2041-2060, 2061-2080
- We construct a **change** in exposure (expected increase in drought conditions) as:

$$\Delta exposure = \underbrace{exposure_{2021-2040}}_{\text{future}} - \underbrace{exposure_{1981-2010}}_{\text{current}}$$

Figure: Predicted increase in drought conditions: 2021-2040 minus 1980-2010
Raw data





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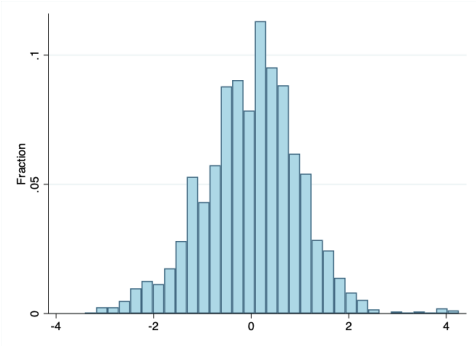

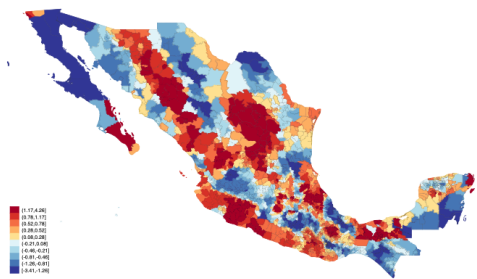

Data

1. Climate
   - municipality level exposure of agri activities to water stress
     - source: "National Atlas of Vulnerability to Climate Change" (INECC)
   - SPEI: Standardized Precipitation and Evapotranspiration Index
     - source: Vicente-Serrano et al. (2010)
     - measure of meteorological dryness, inputs: temperature, rainfall, sun hours
     - standard deviations of dryness from long-term baseline average (1905-2000)

2. Credit registry of Central Bank of Mexico
   - all loans to agricultural sector originated by commercial banks
   - loan-level data on: interest rate, balance, default, maturity, collateral, purpose
   - today: preliminary results based on 10% random sample

3. Municipality-level data
   - Agriculture: Statistical Yearbook of Agricultural Production (Crops + Livestock)
   - Controls: income, population, human capital from Pop Census

Agriculture

	N	Mean	Median	SD
log(value per ha)	43,696	9.09	9.06	0.94
log(value per ha), irrigated	32,341	10.22	10.12	1.01
log(value per ha) , rain fed	42,198	8.61	8.61	0.93
Share of irrigated agricultural area	43,812	0.34	0.18	0.35

- Top agri activities by revenues: corn, sugarcane, livestock, tomato, sorghum and avocado

Figure: Log(Value per ha)

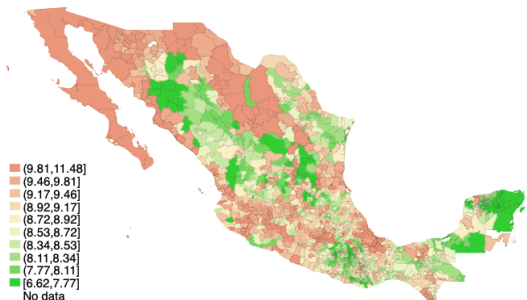

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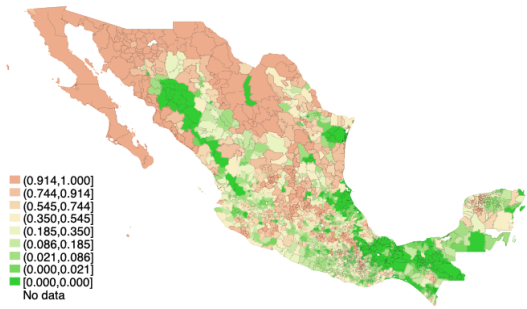
Figure: Share of Irrigated Agri

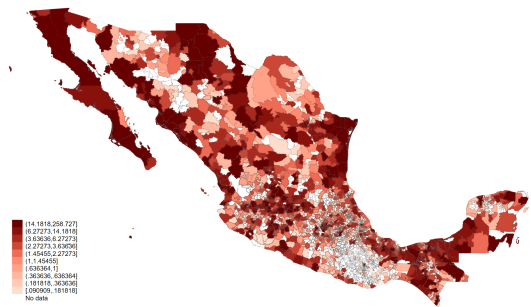


Average value for the period 2003-2010

Data: Credit Registry

	N	Mean	Median	Sd
Stock loans				
Log loan amount	85,868	13.27	13.38	2.56
Default	85,868	0.17	0.00	0.37
Firm size (employees)	85,864	27.59	5.00	86.96
New loans				
Interest rate	20,577	11.73	11.00	4.94
Log loan amount	20,577	0.92	0.45	1.11
Collateral	20,577	0.37	0.00	0.44
Maturity	20,577	21.92	11.69	21.45

Figure: N agri firms



Effect of droughts on agriculture

$$y_{m(r)t} = \alpha_m + \alpha_{rt} + \beta \mathit{dryness}_{m(r)t} + \lambda_t X_{m(r),t=0} + \varepsilon_{m(r)t}$$

m: municipality, r: region, t: year, *dryness*: -SPEI

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	log(value per ha)		
	(1)	(2)	(3)
dryness	-0.0661***	-0.0527***	-0.0549***
	(0.00397)	(0.00539)	(0.00561)
Observations	43,695	43,695	43,687
R-squared	0.859	0.865	0.867
County and year FE	y	y	y
County controls × year FE	n	y	y
Region FE × Year FE	n	n	y

Notes: Significance level: *** p<0.01, ** p<0.05, * p<0.1.

- 1 sd higher dryness → agri average revenue productivity of land decreases by 5.5%

Does Δ Exposure help predict drought persistence?

$$dryness_{m(r)t} = \alpha_m + \alpha_{rt} + \beta_1 dryness_{m(r)t-1} + \beta_2 dryness_{m(r)t-1} \times \Delta Exposure_m + \lambda_t X_{m(r),t=0} + \varepsilon_{m(r)t}$$

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	(1) $dryness_t$	(2) $dryness_t$	(3) $1(drought)_t$	(4) $1(drought)_t$
$dryness_{t-1}$	0.234***	0.163***		
	(0.00556)	(0.00609)		
$dryness_{t-1} \times \Delta$ Exposure		0.136***		
		(0.0100)		
$1(drought)_{t-1}$			0.0717***	0.0348***
			(0.00644)	(0.00855)
$1(drought)_{t-1} \times \Delta$ Exposure				0.0579***
				(0.0116)
Observations	41,446	41,446	41,446	41,446
R-squared	0.772	0.774	0.464	0.465
county and year FE	y	y	y	y
county controls × year FE	y	y	y	y
region × year FE	y	y	y	y

Notes: Significance level: *** p<0.01, ** p<0.05, * p<0.1.

- in municipalities with 1 sd higher change in exposure, past dryness is twice as persistent

Does Δ Exposure help predict drought persistence?

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- in municipalities with 1 sd higher change in exposure, past dryness is twice as persistent
- drought = SPEI < -1 (moderate and above)
- past droughts strong predictor of current droughts

Effect of droughts on default of agricultural loans

$$Pr(default)_{im(r)t} = \alpha_i + \alpha_{rt} + \beta dryness_{m(r)t} + \lambda_t X_{m(r),t=0} + \varepsilon_{im(r)t}$$

i: firm, default: 90+ days late

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i: firm, default: 90+ days late

	default probability	
	(1)	(2)
dryness	0.00754**	0.00794**
	(0.00327)	(0.00367)
Observations	85,868	85,868
R-squared	0.675	0.680
Mean dep. var	.167	.167
Municipality FE	n	n
Year FE	y	y
County characteristics × year FE	n	y
Firm characteristics	y	y
Region FE × Year FE	n	y
Firm FE	y	y

Notes: Significance level: *** p<0.01, ** p<0.05, * p<0.1.

- firms in municipalities with 1 sd higher dryness, probability of default increases by 0.8pp (4.8%)

Interest Rate and Amount of New Loans

$$y_{im(r)t} = \alpha_i + \alpha_{rt} + \beta_1 dryness_{m(r)t} + \beta_2 dryness_{m(r)t-1} + \lambda_t X_{m(r),t=0} + \varepsilon_{im(r)t}$$

focus: new loans

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focus: new loans

	interest rate on new loans		amount borrowed	
	(1)	(2)	(3)	(4)
$dryness_t$	0.0178	-0.0117	-0.00912	-0.00605
	(0.0555)	(0.0438)	(0.0140)	(0.0132)
$dryness_{t-1}$	0.179***	0.109*	-0.00559	0.00825
	(0.0660)	(0.0558)	(0.0126)	(0.0111)
Observations	20,576	20,576	20,576	20,576
R-squared	0.392	0.841	0.348	0.872
Mean dep. var	11.726	11.726	.888	.888
Municipality FE	y	n	y	n
Year FE	y	y	y	y
County characteristics × year FE	y	y	y	y
Firm characteristics	y	y	y	y
Region FE × Year FE	n	y	n	y
Firm FE	n	y	n	y

Notes: Significance level: *** p<0.01, ** p<0.05, * p<0.1.

- control for firm characteristics, including past default
- firms in municipalities with 1 sd higher dryness last year, interest rate on new loans increases 0.11-0.18 pp (1-1.5%)
- no effect on amount borrowed

Interest Rate and Amount of New Loans

heterogeneous effects by exposure to predicted changes in dryness

$$y_{im(r)t} = \alpha_i + \alpha_{rt} + \beta_1 dryness_{m,t-1} + \beta_2 dryness_{m,t-1} \times \Delta \text{exposure}_m + \lambda_t X_{m(r),t=0} + \varepsilon_{im(r)t}$$

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	interest rate on new loans		amount borrowed	
	(1)	(2)	(3)	(4)
$dryness_t$	0.0285	-0.00118	-0.00694	-0.00696
	(0.0561)	(0.0446)	(0.0143)	(0.0135)
$dryness_{t-1}$	0.186***	0.112**	-0.00499	0.00868
	(0.0684)	(0.0545)	(0.0130)	(0.0113)
$dryness_t \times \Delta$ Exposure	0.0267	-0.0394	0.00156	0.00516
	(0.0400)	(0.0323)	(0.00643)	(0.00536)
$dryness_{t-1} \times \Delta$ Exposure	-0.0621	-0.0263	-0.00999	-0.000810
	(0.0385)	(0.0263)	(0.00831)	(0.00554)
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Notes: Significance level: *** p<0.01, ** p<0.05, * p<0.1.

- focus on the interaction coefficient between past dryness and Δ Exposure
- no differential effect of past dryness on interest rate of new loans for firms in municipalities with different predicted increases in dryness

Probability of default on existing balance

heterogeneous effects by exposure to predicted changes in dryness

$$y_{im(r)t} = \alpha_i + \alpha_{rt} + \beta_1 dryness_{m,t-1} + \beta_2 dryness_{m,t-1} \times \Delta \text{exposure}_m + \lambda_t X_{m(r),t=0} + \varepsilon_{im(r)t}$$

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	default probability	
	(1)	(2)
$dryness_t$	0.00622*	0.00746**
	(0.00344)	(0.00369)
$dryness_{t-1}$	-0.00121	0.00369
	(0.00350)	(0.00378)
$dryness_t \times \Delta$ Exposure	0.000431	0.000288
	(0.00198)	(0.00191)
$dryness_{t-1} \times \Delta$ Exposure	0.00522***	0.00347*
	(0.00186)	(0.00189)
Observations	85,868	85,868
R-squared0	0.676	0.680
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- current dryness shock predicts current default: 0.6-0.7pp for 1sd

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- current dryness shock predicts current default: 0.6-0.7pp for 1sd
- region with Δexposure $= 0$, past dryness has no predictive power on future default
- region with Δexposure $= 1$, 1sd higher past dryness increased default probability 0.35-0.52pp

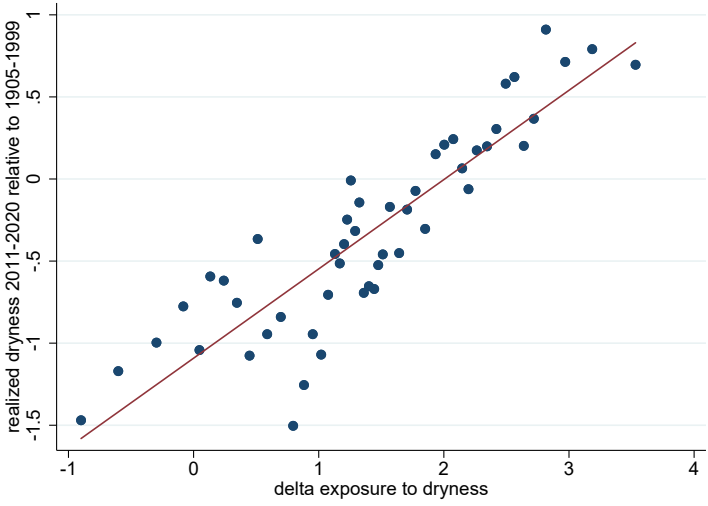
Lots of open questions

Additional open questions/challenges:

- Disentangle supply vs demand forces?
- Do effects depend on maturity?
- Do effects depend on type of investing (e.g. adaptation technologies)?
- Do effects vary across banks depending on their "specialization" in agri?
- How big is the mispricing of risk?
- How costly would it be for banks to just learn via realized default?

Δ Exposure and Realized Meteorological Dryness

- Δ Exposure is a good predictor of increase in meteorological dryness observed in 2011-2020 relative to previous century (1905-1999)



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