A Supplementary Information for "Save the Farms: Nonlinear Impact of Climate Change on Banks' Agricultural Lending"

A.a Conceptual Framework

A.a.1 Timeline and Environment

To illustrate the link between climate change and bank lending to farms, this section provides a conceptual framework[1] of loan contracting based on Chodorow-Reich et al. (2021) and Holmstrom and Tirole (1998), with applications to the distributional assumptions specific to climate change shocks and the importance of farm sizes. In a stylized economy, there is one bank and one farm. The farmer faces uncertain output and lives for only 2 periods. The timeline of the framework is shown in Figure 1. At $t = 0$, the farm applies for a loan (or credit line) with the bank, and this loan is to be used next period. At $t = 1$, due to climate change, the cash-flow shock ρ materializes: to continue operations, the farmer needs to inject ρ per unit of asset, and $\rho \sim F = \mathcal{N}\left(\mu, \sigma^2\right)$. When $\rho > 0$, it means the farm has cash needs. The bank approves or denies the loan, based on the cash-flow shock and uncertain terminal value. If approved, the credit line is $\hat{\rho}$. If the farm has been denied credit, it has to shut down.[2] At $t = 2$, the farm yields payoff $z + \epsilon$ per unit of asset. The shock ϵ is uncorrelated with ρ and has mean zero, and is observable at $t = 1$ if the bank pays a monitoring cost of ξ.

In other words, there are two states in the system: ρ and ϵ. It is worth discussing further the key parameters in the framework, and why it is a simple yet realistic representation of the shocks from climate risks. The two parameters that describe the distribution of ρ are mean μ and standard deviation σ. Science literature generally uses temperature anomaly to measure climate change, and some studies suggest that in recent decades, the bell curve of temperature has changed. More specifically, on a global scale, the mean of temperature anomaly has shifted to the right, and the tails of the curve have become 'fatter'.[3] In other words, the temperature is becoming higher than normal, and it is more likely for extreme temperature to occur. Relating this to the framework, it means that the size of the cash-flow shock that a farmer faces may become bigger and more extreme than historical averages, which has implications for whether and how much the bank provides credit.

Moreover, z is the parameter that contributes to the farm's terminal value per unit of asset at $t = 2$. One can interpret this parameter as the fundamentals or productivity of a farm. Besides, a financial friction exists in the economy such that when applying for credit, the farm can only pledge a fraction, indicated by θ of their terminal value as collateral.

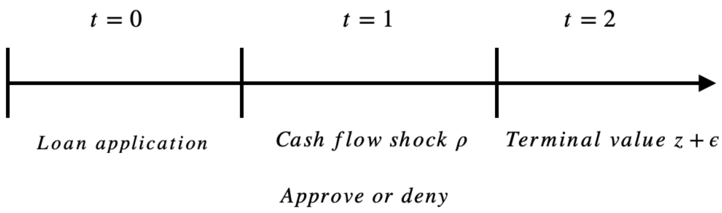
For simplicity, this framework only focuses on discretion as the contractual form. Under discretion, the bank can choose to monitor the farm at $t = 1$. In other words, the bank can terminate the loan/credit line upon observing cash-flow shock ρ or ϵ shock to terminal value. Put another way, even if the initial loan contract is established at $t = 0$, the fund is not disbursed until the next period. Then at $t = 1$, the bank observes the cash-flow shock ρ. The bank can also choose to monitor the shock ϵ to farm by paying a cost of ξ. After considering

[1] The current framework assumes one is agnostic about the bank type. As illustrated in the empirical section, bank size/type plays a role in lending decisions. In future studies, it is worth further developing this model to consider the role of bank type

[2] In other words, we assume that the farm has no other way to raise alternative capital

[3] For a graphical illustration, see Figure 4 of Hansen et al. (2012)

Figure 1: *Timeline of Bank Lending to Farms*



the potential payoff, the bank can choose to abandon the loan contract. In the literature, commitment is another possible contractual form, but empirical studies such as Sufi (2007) show that bad shocks can modify or end credit line. More importantly, the commitment contract is less insightful in illustrating how credit provision varies with both the states of ρ and ϵ, as the bank grants credit only if $\rho < \theta z$ (and monitoring does not exist under the commitment contract).[4]

A.a.2 Equilibrium

To solve for the equilibrium under the discretion contract, the bank simultaneously decides on whether to monitor and whether to approve or deny the loan. The expected value of monitoring is V^M, and of not monitoring V^N.

The bank's lending decision can be characterized as the following:

$$V = \max\{V^M, V^N\} \tag{1}$$

where

$$V^N = \max\{\theta z - \rho, 0\} \tag{2}$$

and

$$V^M = \mathbb{E}[\max\{\theta(z+\epsilon) - \rho, 0\}] - \xi \tag{3}$$

Thus, with monitoring, the bank's decision to lend or not is based on minimizing their losses, namely lending only occurs if $\rho < \theta(z+\epsilon)$.

More detail on the monitoring decision is found in Chodorow-Reich et al. (2021), and the main insight is that monitoring only makes sense when the cash-flow shock is in a range, or $\rho \in [\underline{\rho}, \bar{\rho}]$. In other words, when the cash-flow shock ρ is extremely small, to the left of $\underline{\rho}$, the bank will approve the loan and there is no value in monitoring. On the other hand, when ρ is extremely large, to the right of $\bar{\rho}$, the bank always denies the loan and there is no value in monitoring.

To derive close-form solutions for the these critical values $\underline{\rho}$ and $\bar{\rho}$, assume for simplicity that ϵ takes on 3 values $\{-e, 0, e\}$ with probability $\{q, 1-2q, q\}$.

[4]More specifically, under commitment, the solution to $\hat{\rho} = \mu + \sigma h^{-1}\left(\frac{\mu - \theta z}{\sigma}\right)$, where h^{-1} is the inverse of $h(x) = \phi(x)/\Phi(x)$, the ratio of standard normal probability density function to cumulative density function. For derivation details, see Chodorow-Reich et al. (2021).

When the cash-flow shock ρ is sufficiently small, $\theta(z-e) < \rho < \theta z$, the expected payoff of monitoring is:

$$V^M = \underbrace{\theta z - \rho}_{V^N} + \underbrace{q[\rho - (\theta(z-e)]}_{\text{Monitoring value}} - \underbrace{\xi}_{\text{Monitoring cost}} \tag{4}$$

such that the bank would prefer monitoring if and only if

$$\rho > \underline{\rho} := \theta(z-e) + \xi/q \tag{5}$$

When the cash-flow shock ρ is sufficiently large, $\theta z < \rho < \theta(z+e)$, the expected payoff of monitoring is:

$$V^M = \underbrace{0}_{V^N} + \underbrace{q[\theta(z+e) - \rho]}_{\text{Monitoring value}} - \underbrace{\xi}_{\text{Monitoring cost}} \tag{6}$$

where $V^N = 0$ because without monitoring, the expected payoff $\theta z - \rho$ is negative, and the bank would automatically reject the loan, such that the bank would prefer monitoring if and only if

$$\rho < \bar{\rho} := \theta(z+e) - \xi/q \tag{7}$$

By combining and generalizing the above results, the bank's lending decisions can be graphically illustrated in Figure 2. To summarize, the lending decisions depend on both the states ρ and ϵ. The horizontal axis illustrates the degree of cash-flow shock: the more to the right, the higher a farm's cash needs are. The vertical axis shows the degree of fundamentals that determine the terminal value of the farm (put simply, the positive ϵ illustrates good state, while negative ϵ refers to bad state). θz is the farm's pledgeable terminal value as collateral.

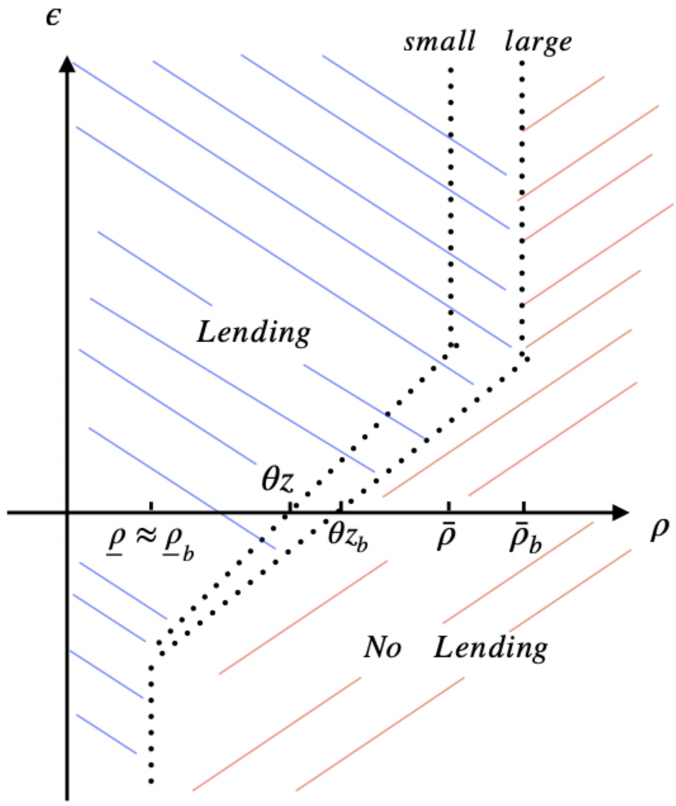
The graph shows that the bank will lend to the farm in two broad cases: 1) ϵ is in good state, and ρ is not too large; 2) ϵ is in bad state, but ρ is very small. On the other hand, the bank will deny lending to the farm in two broad cases: 1) ϵ is in good state, but ρ is too large; 2) ϵ is in bad state, and ρ is sufficiently large.

So far the analysis assumes that there is only one type of farm in the economy. However, studies such as Chodorow-Reich et al. (2021) illustrate that firm size matters for the terms of contract for bank loans. More specifically, within the U.S. farm system, it is possible that there are fundamental differences between large and smaller farmers that affect the key parameters in this stylized framework. For example, regardless of the shock ϵ, large farms have higher z than smaller farms. In fact, there is evidence of differing productivity between large and small farms, as documented by the Economic Research Service (ERS), United States Department of Agriculture (USDA). Moreover, there is emerging evidence from microeconomic studies such as Etwire et al. (2022) suggesting that farm size has a positive relationship with the decision to adopt climate adaptation measures. Put another way, when faced with the identical climate induced-shock ρ, large farms' adaptation capability ensures they have larger terminal value. Finally, due to their market power or name recognition, large farms may have more publicly available information about themselves, thus the bank spends less ξ monitoring large farms.

Assuming that large farms have larger z and smaller ξ, define the critical values for large farms as $\underline{\rho}_b$ and $\bar{\rho}_b$. We can derive from Equations 5 and 7 that $\underline{\rho}_b \approx \underline{\rho}$ and $\bar{\rho}_b > \bar{\rho}$. As seen in Figure 2, the critical range is wider for large farms. Moreover, when faced with large shocks, it is more likely for large farms to be approved for a loan, and the lending region is bigger.

Put simply, large farms have more 'room to maneuver.' Motivated by the predictions of this conceptual framework, the rest of the paper examines the empirical links between climate shocks and bank lending to farms.

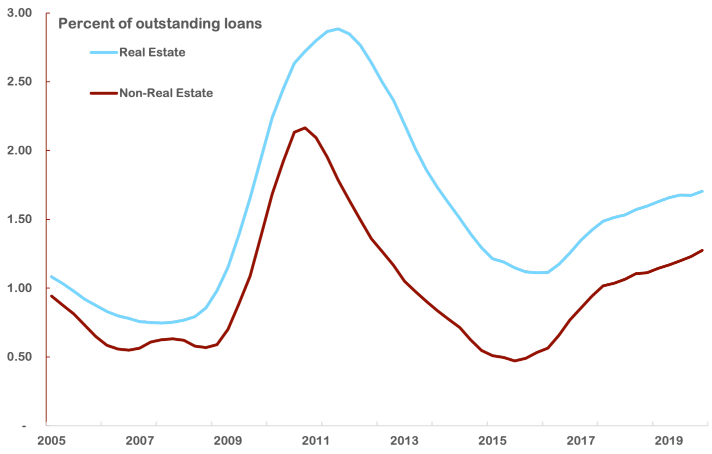
Figure 2: *Lending Regions under Bank Discretion: Small-Medium versus Large Farms*



Note: Compared with smaller farms, the lending region to large farms is wider. ρ stands for the cash-flow shock caused by climate risks as measured by temperature anomaly; ϵ is an independent shock that contributes to a farm's terminal value. The subscript b refers to the scenario in which the farm is large.

A.b Additional Figure

Figure 3: *Non-Performing Farm Loans at U.S. Commercial Banks*



Note: 4-quarter moving average; accruing and non-accruing loans past due 90 or more days

Sources: Bank call reports and Kreitman and Cowley (2020)

A.c Summary Statistics

The analysis in the paper makes an effort to distinguish between the lending to large and to smaller farms. At the same time, CRA lending goes primarily to non-large farms. Thus it is first useful to understand the distribution of farm size and why one should care about the insights from analyzing the CRA lending data.

Using the USDA Agricultural Census 1997 through 2017, I have tabulated the distribution of farm size in Table (1). In the United States, large farms dominate the value of total market production (MacDonald (2021)). But as seen in Table (1), in terms of number of operations, the vast majority of farms are not large. In fact, small farms on average account for over 80% of the country's total farms in the past two decades.[5] Across the years observed, it seems that farms with over \$500 thousand gross sales have increased in shares—in fact, their shares have exactly doubled between 1997 and 2017. At the same, farms in the intermediate range (\$100k to 499k) have dwindled, with the smallest farms (less than \$100k) seeing a small increase across the years observed. While it requires more rigorous testing, it seems the distribution of farm size, in terms of number of operations, has become more bimodal. In summary, based on the Census data, small farms are critical parts of the U.S. agricultural system.

Table 1: *Size and Sales Distribution of U.S. Farms*

		Share of farms (Percent)				
Farm size	***Sales category***	**1997**	**2002**	**2007**	**2012**	**2017**
Small	*< \$100k*	81.9	85.3	83.8	81.5	82.1
Small to Midsize	*\$100k-499k*	14.5	11.3	10.9	11.1	10.7
Midsize	*\$500k-999k*	2.2	2.1	2.8	3.6	3.4
Large	*> \$1 million*	1.4	1.3	2.5	3.8	3.8

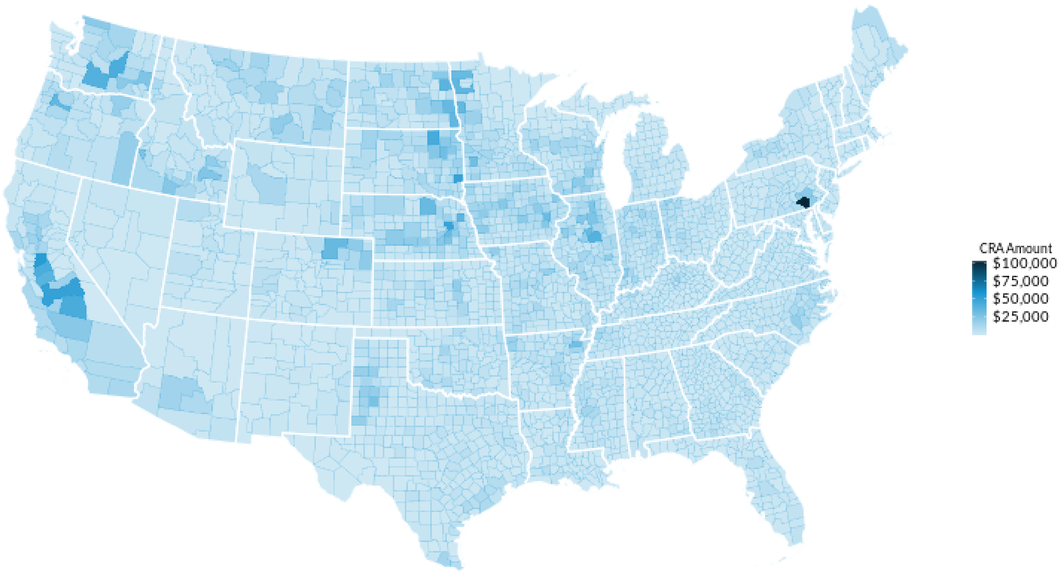
Source: USDA Census 1997-2017, Table 2 "Market Value of Agricultural Products Sold Including Landlord's Share and Direct Sales"

Tables (2) provides summary statistics of CRA loans at the county level in terms of number of loans, and the amount of loans. The table is grouped by lending to large and to small-medium farms. Overall there are 3,106 counties in the CRA dataset across 24 years (1996-2019). As shown by Table (2), due to the nature of CRA, the overall magnitudes of lending to small-medium farms are bigger than to large farms. Section A.d provides additional summary statistics grouped by the loan size thresholds.

To illustrate the geospatial distribution of CRA lending, I have mapped data through Figures (4) and (5) that illustrate the average county values during 1996-2019. At first glance, regions and states that are traditionally major agricultural producers (e.g., parts of California and the Midwest) also tend to receive more financing, both in terms of number and amount of loans. For the rest of the country, CRA lending seems relatively evenly distributed. While Table (1) summarizes the size distribution of farms across years, Figure (6) illustrates the distribution across space. Comparing it with the CRA maps, it seems there are parallels between the high share of larger farms and the bank lending, though the patterns do not hold for all counties.

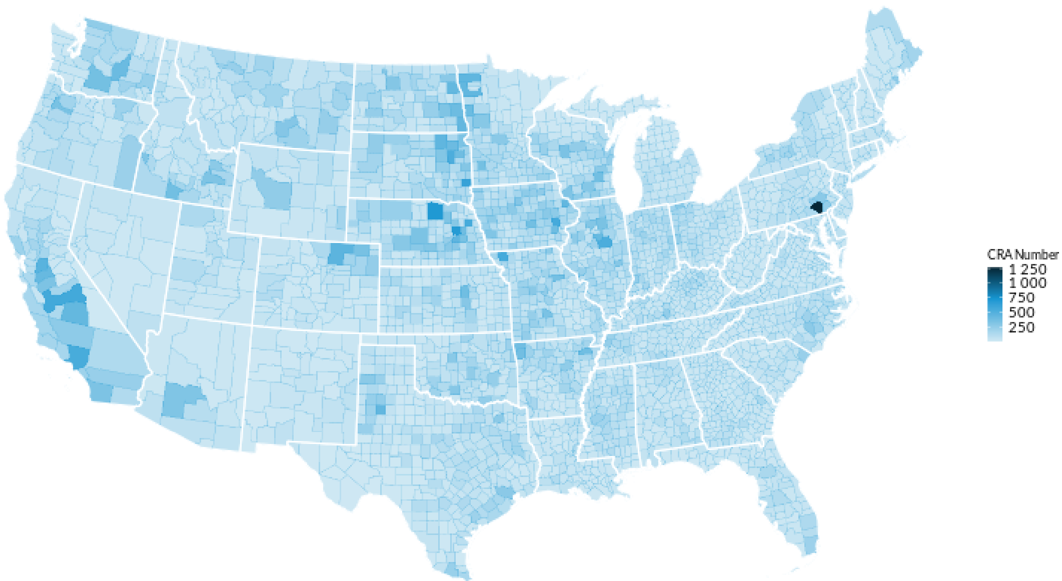
[5]The sales categories in the Census go from \$100k to \$249k, and then \$250k to \$499k. Thus the Census data do not provide a clear cutoff between small and midsize farms—the threshold is \$350k according to ERS.

Figure 4: *Yearly Average Total Amount of CRA Farm Loans, 1996-2019, in thousand 2015 USD*



Source: FFIEC (2021)

Figure 5: *Yearly Average Number of CRA Farm Loans, 1996-2019*

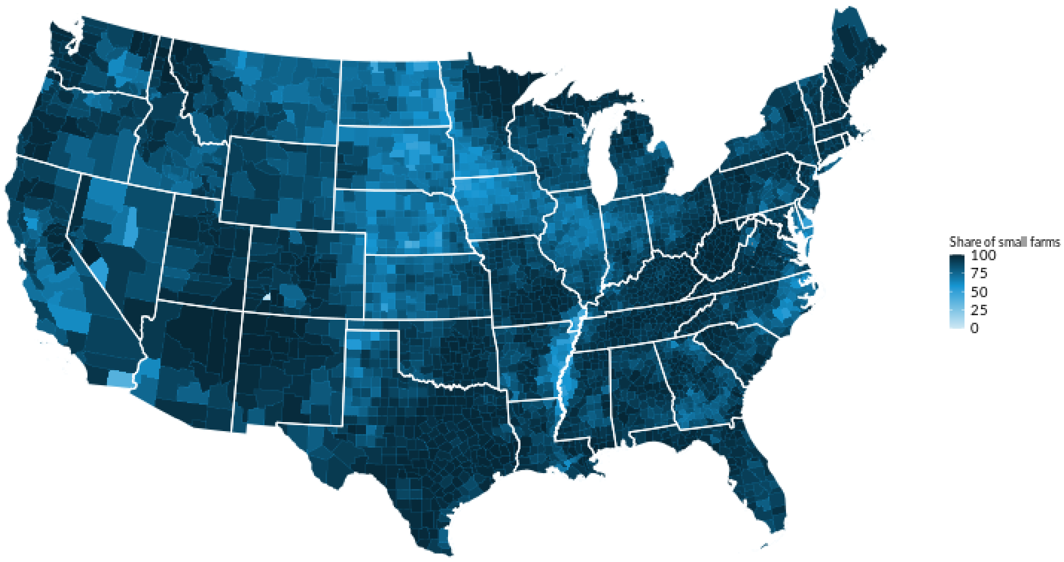


Source: FFIEC (2021)

Table 2: Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
Number of loans	overall	17.07	26.69	1.00	1030.00	N = 64253
to large farms	between		18.24	1.00	245.67	n = 3102
	within		18.75	-166.97	979.99	T-bar = 20.7
Amount of loans	overall	1080.59	2226.96	1.01	40557.89	N = 63983
to large farms	between		1748.34	3.64	27361.08	n = 3101
(thousand 2015 USD)	within		1236.82	-13643.49	26748.78	T-bar = 20.63
Number of loans	overall	52.87	81.44	1.00	1623.00	N = 70914
to small-medium farms	between		64.85	1.00	1101.08	n = 3105
	within		48.25	-416.13	1020.78	T-bar = 22.8
Amount of loans	overall	2890.80	4867.74	1.01	140596.10	N = 70749
to small-medium farms	between		4212.58	1.06	85225.58	n = 3104
(thousand 2015 USD)	within		2322.11	-48932.92	58261.29	T-bar = 22.8

Figure 6: *Share of Small Farms (gross sales < \$250k), 2012-2017*



Source: USDA Census

A.d Summary Statistics

Table 3: *Summary Statistics of Number of CRA Loans, County Level*

Variable		Mean	Std. Dev.	Min	Max	Observations
Number of loans smaller than $100k	overall	54.32	77.09	0.00	1518.00	N = 72834
	between		62.23	0.25	940.21	n = 3106
	within		45.18	-438.10	1058.90	T-bar = 23.45
Number of loans $100k to $250k	overall	8.24	14.43	0.00	349.00	N = 72834
	between		12.55	0.00	204.96	n = 3106
	within		6.98	-103.72	152.28	T-bar = 23.45
Number of loans $250k to $500k	overall	3.97	8.12	0.00	199.00	N = 72834
	between		7.03	0.00	124.13	n = 3106
	within		3.96	-85.16	78.84	T-bar = 23.45

Table 4: *Summary Statistics of Amount of CRA Loans, County Level, in thousand 2015 $*

Variable		Mean	Std. Dev.	Min	Max	Observations
Amount of loans smaller than $100k	overall	1230.26	1844.59	0.00	47299.75	N = 72834
	between		1604.50	0.43	28959.89	n = 3106
	within		894.52	-13151.50	19570.12	T-bar = 23.45
Amount of loans $100k to $250k	overall	1218.87	2178.50	0.00	56579.62	N = 72834
	between		1882.13	0.00	31524.24	n = 3106
	within		1074.01	-20163.81	26274.25	T-bar = 23.45
Amount of loans $250k to $500k	overall	1307.94	2783.98	0.00	72390.09	N = 72834
	between		2348.64	0.00	42286.68	n = 3106
	within		1464.12	-31752.53	31411.35	T-bar = 23.45

A.e Estimation of Effects of Climate Disasters

Climate disasters are the realizations of climate change risks. Thus, examining the effect of climate-related disasters on bank lending establishes helpful baseline understandings.

The econometric specification for the county level analysis is

$$y_{it} = \beta_k \mathbf{disaster}_{it} + \gamma_i trend + \gamma_{i2} trend^2 + u_i + \eta_t + \lambda_{rt} + e_{it} \tag{8}$$

where y_{it} refers to CRA lending variables, with subscript i as county index and subscript t as year. Additionally, each of the county i corresponds to one climate region indexed by r. $\mathbf{disaster}_{it}$ refers to a vector of climate-related disasters reported by FEMA.

Since the evolution of bank lending in relation to climate change may be nonlinear, the linear and quadratic county-specific year trends, denoted as $trend$ and $trend^2$, are both included, to allow for more flexibility in estimation. u_i and η_t are county and year fixed effects. u_i controls for the time-invariant heterogeneities of counties. The year fixed effect controls for global shocks such as commodity cycles in specific years. Moreover, it is likely that the effects of such shocks differ by climate region, thus the region by year (interaction) fixed effect λ_{rt} is included to explicitly control for this. Finally, e_{it} is the error term.

Moreover, there are four main CRA variables used in the analysis: 1) Number of loans to large farms 2) Amount of loans to large farms 3) Number of loans to small-medium farms 4) Amount of loans to small-medium farms.

To measure climate disasters, I count the number of FEMA-declared disasters that are related to climate in each county in each year. It is important to note that such events are all extreme/anomaly events. FEMA, a federal agency, only declares an event as a disaster when local and state governments are unable to cope with it (FEMA (2021)). The main types of FEMA-declared disasters include: 1) coastal storm, 2) flood, 3) freezing, 4) hurricane, 5) landslide, 6) ice storm, 7) storm, 8) snow, 9) and tornado. The disaster events are orthogonal to each other (i.e., no double counting) due to how FEMA categorizes such events. For example, while snow and ice storm may seem related, they are generally distinct events. Additionally, for disaster events such as freezing, ice storm, and snow that occur in winter, it is likely that they occur at the end of a year and thus their effects are lagged compared with other disasters. Thus, in the regression these winter disasters are lagged by 1 year.

Table (5) reports the results from estimation of Equation (8). With the exception of freezing, almost all the disasters have some significant effect on at least one of the CRA variables. In particular, the coefficients for hurricane and storm are negative and significant across all the lending variables. Similarly, the relationship between CRA lending and flood, landslide, ice storm, and snow is generally negative. In other words, for the aforementioned events, the more they occur, the less the level of CRA lending there is. Section A.i reports the same estimations but grouped by the loan size thresholds. Additionally, the results are robust to dropping observations from years 2008-2009 (the Great Recession), reported in Section A.k.

The results of Table (5) suggest that there is a negative link between climate-related disasters and the level of bank lending. Moreover, this relationship holds for loans to both large and small-medium farms. However, one key limitation from the estimation of Equation (8) is that it is difficult to plausibly identify that such climate-related disasters are all occurring due to climate change. Put another way, weather events are not the same as climate change. Therefore in the remainder of the paper, I use temperature and precipitation data as more direct measures of climate change.

Table 5: *CRA Farm Loans and Climate Disasters, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
Coastal Storm	1.65**	73.64	0.01	-14.92
	(0.73)	(61.97)	(1.89)	(148.94)
Flood	-0.82***	-55.33**	-1.71**	-152.44***
	(0.30)	(26.42)	(0.80)	(58.33)
Freezing (lagged)	10.66	720.68**	7.43	513.00
	(8.47)	(294.34)	(8.48)	(384.11)
Hurricane	-0.91***	-27.51***	-0.59*	-37.27*
	(0.15)	(9.48)	(0.31)	(20.20)
Landslide	-8.12***	-289.85	8.17**	399.65
	(1.76)	(242.23)	(3.18)	(284.70)
Ice storm (lagged)	-0.78***	-42.09**	1.50	155.17***
	(0.22)	(18.19)	(0.95)	(59.47)
Storm	-0.32**	-20.91*	-1.48***	-69.71**
	(0.12)	(11.54)	(0.44)	(28.65)
Snow (lagged)	-0.01	-77.10***	-5.61***	-268.72***
	(0.24)	(26.62)	(0.95)	(71.89)
Tornado	-1.12*	33.28	3.39	382.39*
	(0.67)	(73.53)	(2.77)	(206.06)
Observations	69,728	69,728	69,728	69,728
R-squared	0.203	0.051	0.140	0.111
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification for this table is Equation (8) $y_{it} = \beta_k \mathbf{disaster}_{it} + \gamma_i trend + \gamma_{i2} trend^2 + u_i + \eta_t + \lambda_{rt} + e_{it}$. The lending amount variables in real terms (2015 USD)

A.f Robustness Check: Including Precipitation

Besides temperature anomaly, precipitation anomaly is another measurement of climate change. In Burke and Emerick (2016), both mean temperature and precipitation are included in the estimation. At the same time, in the climate process, temperature and precipitation closely interact with each other. Thus the inclusion of precipitation may be unnecessary or could lead to problem of multicollinearity. However, for completeness, I extend the baseline regression to examine how considering precipitation shapes the overall results.

$$y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 P_{it} + \theta_2 P_{it}^2 + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it} \tag{9}$$

where P_{it} refers to precipitation anomaly observed in each county in each year, P_{it}^2 is the quadratic form. Everything else is the same as in Equation (1) in the main text.

Table (6) shows the results: including precipitation does not significantly change the coefficient estimates of temperature, though it does make the coefficient of linear high temperature anomaly in Columns (1) and (2) insignificant. Moreover, precipitation anomaly seems to have positive effect on the amount of loans for both large and small-medium farms. In comparison, both the linear and nonlinear effects on the number of loans to small-medium farms are negative. In short, the patterns revealed by precipitation anomaly is less clear compared with temperature. One possibility is that the NOAA data on precipitation does not distinguish between high or low precipitation. Therefore, for remainder of the paper, I focus on using high temperature anomaly to measure climate change.

Table 6: *CRA Farm Loans and Climate Vulnerability, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temperature anomaly	-0.09	-5.15	1.34***	60.80***
	(0.09)	(6.32)	(0.20)	(13.00)
High temperature anomaly (square)	0.02	1.88	-0.85***	-28.15***
	(0.03)	(2.05)	(0.08)	(4.30)
Precipitation anomaly	0.24**	21.92**	-0.76**	24.23
	(0.12)	(8.72)	(0.34)	(19.16)
Precipitation anomaly (square)	-0.11	14.37**	-0.63***	38.85***
	(0.08)	(5.81)	(0.22)	(13.39)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.093	0.133	0.056
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.g Robustness Check: Seasonal Effects

While the estimation is conducted at annual frequency, it is possible to isolate the seasonal effects of high temperature anomaly. For example, Diffenbaugh et al. (2021) splits the estimation into growing season (April through October) and non-growing season. Thus I follow their approaching by calculating the temperature anomaly for the growing season and the rest of the year, using original, monthly observations of the NOAA NClimDiv dataset. Other than the new measurements of temperature, the specification follows that of Equation (1). Tables (7) and (8) show the results. For small-medium farms, a temperature anomaly shock seems costly during the growing season, compared to what larger farms experience. On the other hand, small-medium farms remain vulnerable during the non-growing season. Yet for large farms, during non-growing season, the impact of a climate shock is mostly statistically insignificant.

Table 7: *CRA Farm Loans and Climate Vulnerability, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temp. anomaly (growing season)	-0.33***	-16.30***	1.12***	11.16
	(0.07)	(5.25)	(0.17)	(10.60)
High temp. anomaly (square, growing season)	-0.01	4.00***	-0.66***	-18.87***
	(0.02)	(1.53)	(0.06)	(3.49)
Observations	72,834	72,834	72,834	72,834
R-squared	0.195	0.094	0.133	0.056
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: *CRA Farm Loans and Climate Vulnerability, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temp. anomaly (non-growing season)	0.11***	0.03	0.67***	44.94***
	(0.04)	(3.30)	(0.12)	(6.42)
High temp. anomaly (square, non-growing season)	0.01	-0.25	-0.22***	-8.92***
	(0.01)	(0.84)	(0.03)	(1.86)
Observations	72,834	72,834	72,834	72,834
R-squared	0.195	0.094	0.133	0.057
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.h Distributed Lag Model

In the paper so far I focus on the contemporaneous relationship between temperature anomaly and CRA lending. However, the impact of climate change may play out over time rather than materializing instantaneously. In this section, I use a distributed lag specification to examine such longer-term effect.

$$y_{it} = \sum_{l=0}^{2} (\beta_l T_{i,t-l}) + \sum_{m=0}^{2} (\theta_m T^2_{i,t-m}) + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it} \tag{10}$$

where the lagged terms (1 and 2 years) of temperature anomaly are added to the baseline specification.

If we assume at time t there is a *permanent* increase of temperature anomaly evaluated at T^*, the effect will materialize this period but also last into the next two periods. Additionally, the cumulative marginal effect of temperature anomaly over time is

$$\sum_{l=0}^{2} \beta_l + \sum_{m=0}^{2} \theta_m = \beta_0 + 2\theta_0 T^* + \beta_1 + 2\theta_1 T^* + \beta_2 + 2\theta_2 T^* \tag{11}$$

In other words, the cumulative effect of a temperature anomaly T^* is a weighted sum of linear and nonlinear effects, both in the present and in two previous periods.

The results from estimating Equation (10) are shown is Table (9). Within each of the columns, it is clear that the contemporaneous effects are still generally significant. However, it is interesting that the coefficient for the amount of loans to small-medium farm is now negative. Besides, for all the CRA variables, especially the lending to small-medium farms, the lagged effects are significant. This provides evidence showing that climate change impact accumulates over time.

Using Equation (11), we can calculate the cumulative effect of a permanent increase of 1 high temperature anomaly—1 degree in Fahrenheit, or about 0.56 Celsius. For large farms, the effect is 0.36 for number of loans, and is 4.83 for the amount of loans. For small-medium farms, the effect is -0.92 for number of loans, and is -31.71 for the amount of loans.

Based on the results, it is clear that small-medium farms are more vulnerable to bank lending cutback due to climate change. With 1 degree in Fahrenheit of temperature anomaly, lending to small-medium in one county would decrease by about 1 loan and $31,710. However, if the anomaly is 3 degrees Fahrenheit (1.5 Celsius), the number of loans cut would be 14 and the amount reduced would be $381,670. While the data here are at the county aggregate level, not farm-level, the magnitudes of effect are not trivial. In contrast, with temperature increasing, large farms will likely experience increase in both number and amount of lending. As the results in Supplementary Information Tables (12) and (13) suggest, at least in terms of amount of loan, the different financial flows that large and small-medium farms experience are likely to due to banks' shift of lending between these types of farms. It is beyond the scope of the paper to explicit account for what may explain the differential outcome, but one possible explanation is that large farms are better able to adapt to climate change. Banks see less risk in such farms and are thus more willing to lend to them.

Table 9: CRA Farm Loans and Climate Vulnerability, Distributed Lag

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temperature anomaly	-0.20**	-24.35***	1.93***	8.75
	(0.10)	(6.71)	(0.21)	(13.53)
High temperature anomaly (lag)	0.11	-19.28***	1.93***	52.55***
	(0.07)	(5.22)	(0.17)	(10.82)
High temperature anomaly (two lags)	0.04	-5.80	1.87***	81.97***
	(0.07)	(5.19)	(0.19)	(11.31)
High temperature anomaly (square)	0.08**	11.00***	-1.31***	-21.50***
	(0.04)	(2.48)	(0.10)	(5.21)
High temperature anomaly (square, lag)	0.09**	9.56***	-1.28***	-39.09***
	(0.04)	(2.48)	(0.10)	(5.13)
High temperature anomaly (square, two lags)	0.03	6.57***	-0.74***	-26.90***
	(0.03)	(2.37)	(0.09)	(5.00)
Observations	66,622	66,622	66,622	66,622
R-squared	0.201	0.091	0.161	0.063
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification for this table is Equation (10), $y_{it} = \sum_{l=0}^{2} (\beta_l T_{i,t-l}) + \sum_{m=0}^{2} \left(\theta_m T_{i,t-m}^2\right) + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$

A.i Estimations by Loan Size Brackets

To further analyze how bank branching plays a role, I conduct additional regressions using a different dimension of CRA lending—loan size bracket: 1) loans less than \$100 thousand 2) loans between \$100 thousand and \$250 thousand 3) loans between \$250 thousand and \$500 thousand.

Estimation by Loan Sizes The CRA dataset does not provide information to compare loan size brackets and lending to large versus small farms. In other words, it is difficult to know whether loans in the smaller bracket are directed primarily towards to small-medium farms. However, it is plausible that in absolute terms, large farms have bigger financing needs and thus may be more likely to have larger loans. Moreover, independently of which type of farms the lending goes to, the sheer size of loans correlates with banks' exposure, and is indicative of how banks may want to manage their exposure in light of climate risks.

Table (10) presents the estimation in terms of amount of loans. As shown by Column (2), the coefficients of temperature for loans less than \$100 thousand mirror those for overall loans to small-medium farms—suggesting a concave curve. In contrast, the coefficients for loans of size \$250 to \$500 thousand have the opposite signs. Moreover, as seen in Column (2), the interaction effect between temperature anomaly and bank branches is highly significant for small loans, suggesting that banks adjust the size of their exposure in relation to climate change. This adjustment may involve substitution between loan sizes, as suggested by Column (1), there is no significant impact of temperature on the total amount of loans.

Similarly, Table (11) shows the results for the number of loans. The effects of temperature on loans smaller than \$100 thousand are similar to Column (2) of Table (10). However, temperature has almost no impact on the number of loans of size \$250 to \$500 thousand. Additionally, while statistically significant, the coefficients for loans of \$100 to \$250 thousand have the same signs as Column (2), as are total number of loans in Column (1). In contrast to Table (10), in terms of number of loans, Table (11) shows that there does not seem to be substitution between different sizes of lending. Rather, climate change, measured in terms of

Table 10: *CRA Farm Loan Amount and Climate Vulnerability, Loan Size Bracket*

VARIABLES	(1) Total Amt.	(2) Amt. (less 100k)	(3) Amt. (100k to 250k)	(4) Amt. (250k to 500k)
High temperature anomaly	47.18***	37.51***	20.20***	-10.53
	(14.00)	(4.97)	(5.50)	(6.61)
High temperature anomaly (square)	-25.90***	-21.22***	-8.37***	3.69
	(5.21)	(1.82)	(2.02)	(2.51)
Total number of bank branches	2.61	6.23***	-1.12	-2.49
	(3.10)	(1.24)	(0.89)	(2.05)
Temp. anomaly x Bank Branches	-1.42*	-0.08	-0.39	-0.96**
	(0.81)	(0.38)	(0.25)	(0.47)
Temp. anomaly (square) x Bank Branches	0.49	-0.73***	0.40**	0.81
	(0.64)	(0.24)	(0.20)	(0.60)
Observations	72,447	72,447	72,447	72,447
R-squared	0.049	0.082	0.046	0.076
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification for this table is Equation (**??**), $y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 branch_{it} + \theta_2 T_{it} \cdot branch_{it} + \theta_3 T_{it}^2 \cdot branch_{it} + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$, where y_{it} is the loan variable based on loan size bracket.

Table 11: *CRA Farm Loan Frequency and Climate Vulnerability, Loan Size Bracket*

VARIABLES	(1) Total Num. of Loans	(2) Number of loan (less 100k)	(3) Number of loan (100k to 250k)	(4) Number of loan (250k to 500k)
High temperature anomaly	1.40***	1.30***	0.13***	-0.02
	(0.21)	(0.18)	(0.03)	(0.02)
High temperature anomaly (square)	-0.83***	-0.78***	-0.06***	0.01
	(0.08)	(0.07)	(0.01)	(0.01)
Total number of bank branches	0.43***	0.44***	-0.00	-0.01
	(0.04)	(0.04)	(0.01)	(0.01)
Temp. anomaly x Bank Branches	-0.03	-0.03	-0.00	-0.00**
	(0.04)	(0.04)	(0.00)	(0.00)
Temp. anomaly (square) x Bank Branches	-0.04***	-0.04***	0.00*	0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Observations	72,447	72,447	72,447	72,447
R-squared	0.080	0.087	0.046	0.073
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification for this table is Equation (**??**), $y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 branch_{it} + \theta_2 T_{it} \cdot branch_{it} + \theta_3 T_{it}^2 \cdot branch_{it} + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$, where y_{it} is the loan variable based on loan size bracket.

increasing high temperature anomaly, has overall negative impact on the total number of loans.

A.j Alternative Measures of Temperature Anomaly

***Table 12:** CRA Farm Loans and Climate Vulnerability, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temperature anomaly (50 years)	-0.14	-10.59	2.08***	78.13***
	(0.09)	(6.91)	(0.22)	(13.58)
High temperature anomaly (square, 50 years)	0.00	1.51	-0.80***	-27.84***
	(0.03)	(2.09)	(0.08)	(4.22)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.093	0.132	0.056
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table 13:** CRA Farm Loans and Climate Vulnerability, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temperature anomaly (70 years)	-0.16*	-11.29	2.20***	83.78***
	(0.09)	(7.14)	(0.23)	(14.01)
High temperature aneromaly (square, 70 years)	0.01	1.81	-0.76***	-27.86***
	(0.03)	(2.11)	(0.07)	(4.18)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.093	0.132	0.056
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table 14:** CRA Farm Loans and Climate Vulnerability, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temperature anomaly (100 years)	-0.15	-10.34	2.01***	79.20***
	(0.09)	(7.03)	(0.22)	(13.52)
High temperature anomaly (square, 100 years)	0.01	1.17	-0.66***	-26.22***
	(0.03)	(2.08)	(0.07)	(3.94)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.093	0.132	0.056
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table 15:** CRA Farm Loans and Climate Vulnerability, County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temperature anomaly (since 1895)	-0.17*	-10.85	2.13***	85.48***
	(0.10)	(7.38)	(0.23)	(14.11)
High temperature anomaly (square, since 1895)	0.02	1.26	-0.61***	-25.01***
	(0.03)	(2.03)	(0.07)	(3.80)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.093	0.132	0.056
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.k Dropping Years 2008 and 2009

Table 16: *Number of CRA Farm Loans and Climate Vulnerability, County Total*

	(1)	(2)	(3)	(4)
VARIABLES	Num. to large farms	Amount to large farms	Num. to small-mid farms	Amount to small-mid farms
High temperature anomaly	-0.18**	-3.10	1.20***	57.99***
	(0.08)	(6.74)	(0.20)	(12.76)
High temperature anomaly (square)	0.00	0.79	-0.84***	-28.54***
	(0.03)	(2.06)	(0.08)	(4.26)
Observations	66,748	66,748	66,748	66,748
R-squared	0.204	0.099	0.135	0.059
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

A.1 Lagged and Growth Effect

Table 17: *CRA Farm Loans and Climate Vulnerability (Lagged), County Total*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
High temperature anomaly (lag)	0.26***	-0.19	1.65***	82.98***
	(0.07)	(5.44)	(0.18)	(11.03)
High temperature anomaly (square, lag)	-0.00	-0.91	-0.94***	-43.24***
	(0.03)	(1.98)	(0.08)	(4.21)
Observations	69,728	69,728	69,728	69,728
R-squared	0.202	0.092	0.142	0.059
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: *CRA Farm Loans (growth) and Climate Vulnerability, County Total*

VARIABLES	(1) Num. of loans to large farms (%)	(2) Amount of loans to large farms (%)	(3) Num. of loans to small-medium farms (%)	(4) Amount of loans to small-medium farms (%)
High temperature anomaly	0.30***	7.12	-0.54***	-8.04
	(0.06)	(4.66)	(0.13)	(9.38)
High temperature anomaly (square)	0.07**	-3.79**	0.01	-1.14
	(0.03)	(1.84)	(0.04)	(3.07)
Observations	69,728	69,728	69,728	69,728
R-squared	0.053	0.031	0.049	0.045
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: *CRA Farm Loans (growth) and Climate Vulnerability (lag), County Total*

VARIABLES	(1) Num. of loans to large farms (%)	(2) Amount of loans to large farms (%)	(3) Num. of loans to small-medium farms (%)	(4) Amount of loans to small-medium farms (%)
High temperature anomaly (lag)	0.26***	6.52	0.13	-1.35
	(0.07)	(5.42)	(0.14)	(10.02)
High temperature anomaly (square, lag)	-0.04	-3.95**	-0.03	-6.42*
	(0.03)	(1.91)	(0.05)	(3.38)
Observations	69,728	69,728	69,728	69,728
R-squared	0.053	0.031	0.049	0.045
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.m Results by Census Regions

Table 20: *CRA Farm Loans and Climate Vulnerability, Low Income Areas*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
Temp. anomaly	-0.05	-1.98	0.17**	-0.73
	(0.04)	(3.54)	(0.07)	(6.53)
Temp. anomaly (square)	0.01	0.28	-0.09***	-3.01
	(0.02)	(1.71)	(0.03)	(2.91)
Observations	5,129	5,129	5,129	5,129
R-squared	0.045	0.033	0.067	0.052
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification for this table is Equation (**??**), $y_{ict} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ict}$, but only for the sample of low income areas.

Table 21: *CRA Farm Loans and Climate Vulnerability, Moderate Income Areas*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
Temp. anomaly	-0.07	-0.38	0.47***	12.34*
	(0.04)	(3.87)	(0.11)	(7.23)
Temp. anomaly (square)	0.01	2.05	-0.23***	-4.48
	(0.02)	(1.31)	(0.06)	(3.57)
Observations	31,702	31,702	31,702	31,702
R-squared	0.060	0.014	0.069	0.041
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: *CRA Farm Loans and Climate Vulnerability, Middle Income Areas*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
Temp. anomaly	-0.36***	-27.07***	2.10***	34.26***
	(0.07)	(6.14)	(0.21)	(12.79)
Temp. anomaly (square)	0.16***	11.39***	-0.87***	-9.49*
	(0.03)	(2.24)	(0.09)	(5.19)
Observations	65,603	65,603	65,603	65,603
R-squared	0.172	0.078	0.130	0.049
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: *CRA Farm Loans and Climate Vulnerability, High Income Areas*

VARIABLES	(1) Num. to large farms	(2) Amount to large farms	(3) Num. to small-mid farms	(4) Amount to small-mid farms
Temp. anomaly	0.03	-1.68	0.21	-1.32
	(0.07)	(7.59)	(0.14)	(10.53)
Temp. anomaly (square)	0.01	4.22*	-0.22***	3.90
	(0.03)	(2.22)	(0.07)	(5.39)
Observations	29,308	29,308	29,308	29,308
R-squared	0.154	0.060	0.054	0.026
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification for Tables 21 to 23 is Equation (**??**), $y_{ict} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ict}$, and for the sample of moderate income area, middle income area, and high income area respectively.

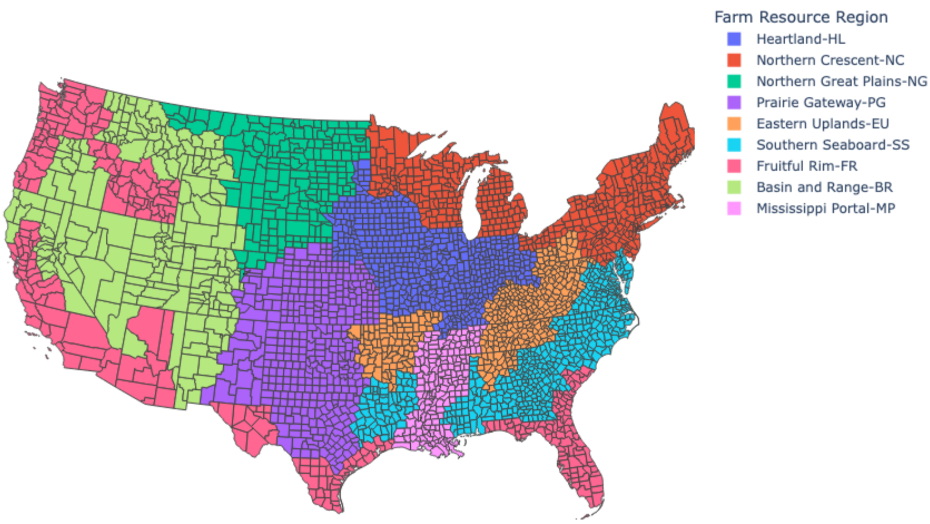
A.n Regional Heterogeneity

The analysis thus far examines farms in the United States as a whole, controlling for unobserved county fixed effects. But these farm systems are not monolithic, and it is useful to examine their heterogeneity. In this section, I conduct such analysis using the Farm Resource Regions categorized by USDA Economic Research Service (ERS). Such regions are constructed based on similarities in land resources, clusters of farming characteristics, and dominant and specialty crops (USDA (2000)). The main reason for such analysis using Farm Resource Regions is to account for the possibility that climate change impact on lending to farm areas is not homogeneous. For example, depending on the dominant crops, the degree of vulnerability in terms of production loss differs between regions, thus potentially leading to differential lending outcomes.

As illustrated by Figure (7), the Farm Resource Regions include: 1– Heartland (HT), 2– Northern Crescent (NC), 3– Northern Great Plains (NG), 4– Prairie Gateway (PG), 5– Eastern Uplands (EU), 6– Southern Seaboard (SS), 7– Fruitful Rim (FR), 8– Basin and Range (BR), 9– Mississippi Portal (MP).

Following Equation (2) in the main text, I estimate the marginal effects for different ERS regions in the medium term (2041-2060) and under the climate scenario of 'net zero by 2100' (SSP2-4.5), equivalent to increase of high temperature by 2.2 Celsius or 3.96 Fahrenheit. The results are in shown Figure (8). Compare with Figure (2) in the main text, the results here are overall consistent: small-medium farms suffer negative impact, while the effects large farms are small and even positive in some cases. However, there are also considerable regional heterogeneity. For example, for all farms in Northern Crescent (NC), increase in temperature anomaly have only positive impact. In contrast, the impact is negative across all categories for the regions of Basin and Range (BR) and Southern Seaboard (SS).

Figure 7: *Farm Resource Regions*



Source: USDA ERS

By matching each county with its region category, I also run the regression specified in Equation (10) for each of the farm regions. The region "Fruitful Rim" is quite broad, encompassing not only western United States, but also Texas and Florida. However, they are in different climate regions. Thus the analysis decomposes this region into: 1) parts of Texas and Florida; 2) the rest of the fruitful rim.[6]

Here I focus on discussing the cumulative effects, calculated using Equation (11). Table (24) presents the calculations based on the scenario in which there is a permanent increase of 3 Fahrenheit degrees of temperature anomaly. The results for small-medium farms are shown in Columns (3) and (4). In terms of the number of loans, there are reductions in almost all the regions except the Northern Crescent. As suggested by the previous results in Table (9), the national average of reduced loan number is 14. It seems that the two regions that experience the most drastic decrease are: Northern Great Plains; the Texan and Floridan parts of the Fruitful Rim. The results for the amounts of loans to small-medium farms are more mixed. The effect of temperature anomaly is small or positive for four of the regions. For regions that experience reduction in amount of loans, the effect is particularly pronounced for the Fruitful Rim overall. In sharp contrast, as shown in Columns (1) and (2), for large farms, half of all the regions experience an increase in amount of loans, and 40% of the regions experience increase in the number of loans.

Table (24) illustrates the regional heterogeneity of bank lending, and is broadly consistent with the national results in Table (9): 1) The effect of climate change on lending to small-medium farms is generally negative; 2) In contrast, large farms seem to fare better; 3) There seems to be shift of lending from small-medium to large farms in regions such as the Northern Great Plains, southeastern parts of the Fruitful Rim, and the Mississippi Portal;

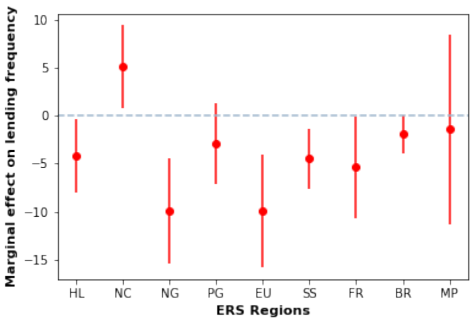
Table 24: *Cumulative Effects of 3 Fahrenheit Degrees of High Temp. Anomaly*

Region	(1) **Num. to large**	(2) **Num. to small-mid**
Heartland	2.4	-6.45
Northern Crescent	2.27	8.22
Northern Great Plains	4.24	-25.17
Prairie Gateway	-4.5	-10.46
Eastern Uplands	-0.53	-9.25
Southern Seaboard	-5.49	-8.3
Fruitful Rim (TX and FL)	-4.82	-17.48
Fruitful Rim (remaining)	-13.96	-12.78
Basin and Range	-1.79	-8.21
Mississippi Portal	3.91	-2.54

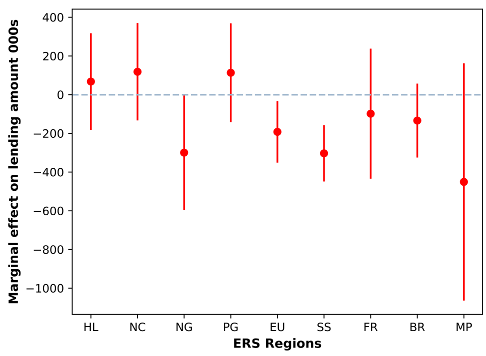
Note: Results calculated using Equation (11), $\sum_{l=0}^{2} \beta_l + \sum_{m=0}^{2} \theta_m = \beta_0 + 2\theta_0 T^* + \beta_1 + 2\theta_1 T^* + \beta_2 + 2\theta_2 T^*$

[6] The regression tables for individual regions are all reported in available upon request.

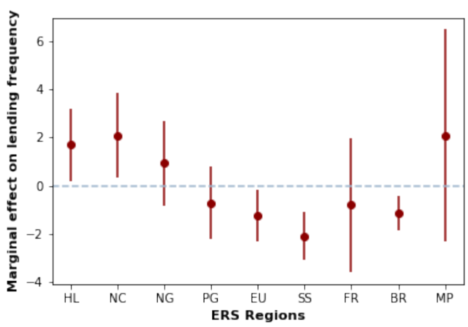
Figure 8: Marginal Effect of Temperature on CRA Lending, Regional Heterogeneity



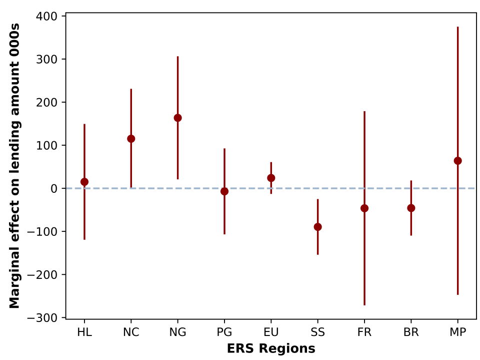
(a) Frequencies to Small-Medium Farms



(b) Amount to Small-Medium Farms



(c) Frequencies to Large Farms



(d) Amount to Large Farms

Note Climate scenario: medium term (2041-2060) and 'net zero by 2100' (SSP2-4.5), equivalent to 2.2 °C/ 3.96° F. Marginal effects with 95% confidence intervals, calculated based on Equation (**??**); The projected temperature estimates are from IPCC. The projections are specific to continuous United States, and refer to permanent increase of annual maximum temperature. The projections are based on CMIP6 Model, taking into account emission uncertainty, and use 1986- 2005 as baseline.

A.0 Climate Change Measured by Temperature Anomaly: Bank-County Level

Previous sections focus on the county-level aggregate frequencies and amounts of bank lending. The results in this section further answer the research question from a different perspective: bank-county level pair.[7] In other words, what is being estimated here is more granular: for a banking institution, whether there is difference in their lending to farms according to not only farms' exposure to climate risks, but also to bank-specific operations and market shares. The point of this bank-county pair section is to demonstrate that banks' own characteristics such as size, play a role in the impact, complementing the main results of the aggregate estimates.

More specifically, I classify banks by their sizes based on CRA definitions[8]: 1) very small banks: asset value less than $300 million; 2) small-mid banks: asset value between $300 million and $1.2 billion; 3) large banks: asset value over $1.2 billion. It is important to point out the composition of the lending data: the vast majority of banks in the CRA dataset are large banks, and very small banks make up the smallest share.

The loan size also matters in understanding the banks' lending behavior. The CRA dataset categorize loans into three brackets based on their sizes: 1) smaller loans ('100k loans'): less than $100 thousand per origination; 2) medium loans ('250k loans'): between $100 and 250 thousand; 3) larger loans ('500k loans'): between $250 and 500 thousand. Given their market share in general, it is reasonable to assume the majority of the CRA loans originate from large banks. However, it is somewhat surprising that large banks are also dominant in lending out loans of less than $100 thousand. For such small loans, almost 73% of the total number of loan originations is made by large banks, whereas the shares for small and medium banks are 5% and 22% respectively.[9]

The intersection of large banks and smaller farms loans (size of less than $100k) provides an important clue in understanding why different types of farms fare differently in terms of financial access, as these smaller loans make up the biggest share of total loan origination frequencies in years 1996-2019. The CRA dataset is not granular enough to decompose loans by farm type *and* simultaneously by loan size brackets. In other words, it is difficult to say how much of the smaller loans go to a certain type of farms. Yet it is plausible that small farms are most likely the recipients of these smaller loans. Thus the effects of climate risks on loans of smaller sizes are especially relevant to these small farms, both qualitatively and quantitatively.

To uncover the lending patterns at the bank-county level, I first set the scene through regressions by loan sizes. These results provide important contexts in understanding the ensuing estimations of loans to small and large farms, and for connecting the bank-county level results with the county-aggregate results.

[7]The bank level here refers to the bank entity level, not bank branch level. The bank-county level pair is not necessarily equivalent to bank branch in that county.

[8]The categories are based on a 2014 CRA fact sheet. As of now, the bank asset data in the estimates are in nominal values

[9]The dominance of large banks in providing small loans mirrors the findings by DiSalvo (2021) that examines the patterns of small business loans in metropolitan areas. Existing studies such as Mkhaiber and Werner (2021) suggest that large banks tend to lend to large firms. But the interaction between large banks and small farms/firms is worth further investigation

Taking into account the interaction between bank size and temperature anomaly, the econometric specification in this section is

$$\begin{aligned} y_{ibt} =& \beta_1 T_{it} + \beta_2 T_{it}^2 + (a_1 + a_2 T_{it} + a_2 T_{it}^2) small + (b_1 + b_2 T_{it} + b_3 T_{it}^2) medium \\ &+ (c_1 + c_2 T_{it} + c_3 T_{it}^2) large + u_i + \psi_b + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ibt} \end{aligned} \tag{12}$$

Compared with Equation (1) in the main text, the main difference of Equation (12) is that the lending variables are at the bank entity level (with subscript b) in a specific county, with the additional ψ_b as bank-level fixed effects. In short, what is being estimated here is that given the county and year, how a bank makes lending decisions, controlling for bank characteristics. Moreover, bank-size dummy variables are included: *small* (asset less than \$300 million), *medium* (asset between \$300 million and \$1.2 billion), and *large* (asset over \$1.2 billion)). Additionally, these bank-size dummies interact with the linear and quadratic temperature anomaly terms.

The first set of regression using Equation (12) is at the loan bracket level, and the results for the effects on loan origination frequencies are illustrated in Figure (9). Due to the interpretation challenge posed by the multitude of interaction terms, the full results of the regressions are reported in Table (27) in Supplementary Information, where the vast majority of main and interaction terms are highly significant. To facilitate interpretation, I estimate the average marginal effects, reported in Figure (9).[10]

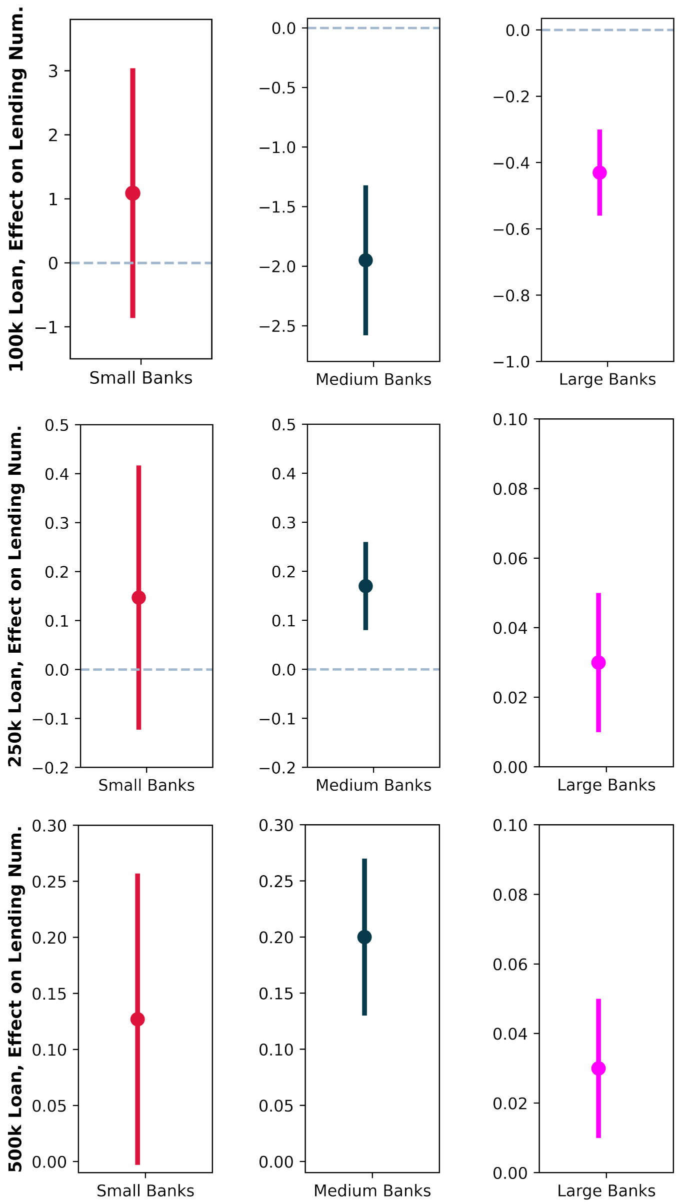
In response to climate risks, the contrast between how banks make 100k loans and the other two sizes is stark. As shown by the first row of graphs of Figure (9), holding all else constant, small banks will make more 100k loans to farms. In comparison, it is much more likely for medium and large banks to reject such loan applications. In terms of magnitude, the mean marginal effect of medium banks is much bigger than that of large banks. It is worth emphasizing the contrast of lending behavior here. As discussed previously, small farms are most likely the recipients of these smaller, 100k loans. With respect to the increase of climate risks, small banks actually want to provide more of such loans, likely due to small farms being important clients for them. However, medium substantially reduce funding access to the 100k loans. Most importantly, large banks also respond by lending less, and their dominance in the smaller loan market likely add up. Put another way, while small banks want to support (mostly small) farms who apply for 100k loans, their market share is not substantial enough to compensate for the withdraw of funding from large banks.

The second and third rows of Figure (9) provide further evidence of heterogeneous effects by loan size. For the 250k and 500k loans, all banks, including medium and large banks respond to increased temperature anomaly by lending more, and such larger loans are more likely to go to large farms. The lending behavior by bank type can also be viewed vertically. In general, small banks do not decrease funding access. In comparison, larger banks deny loans only of smaller sizes, but will approve larger size loans.

Additional estimations are conducted in terms of loan amount, and the full results are reported in Table (29) in Supplementary Information. Figure (10) illustrates the estimates

[10] The calculation procedure is similar to that in Equation (**??**). Note due to the peculiarity of how Stata calculates marginal effects, there may be slight differences between the results reported in the graph and those calculated by hand.

Figure 9: Marginal Effect of Temperature Anomaly on CRA Lending Frequency, by Loan Size



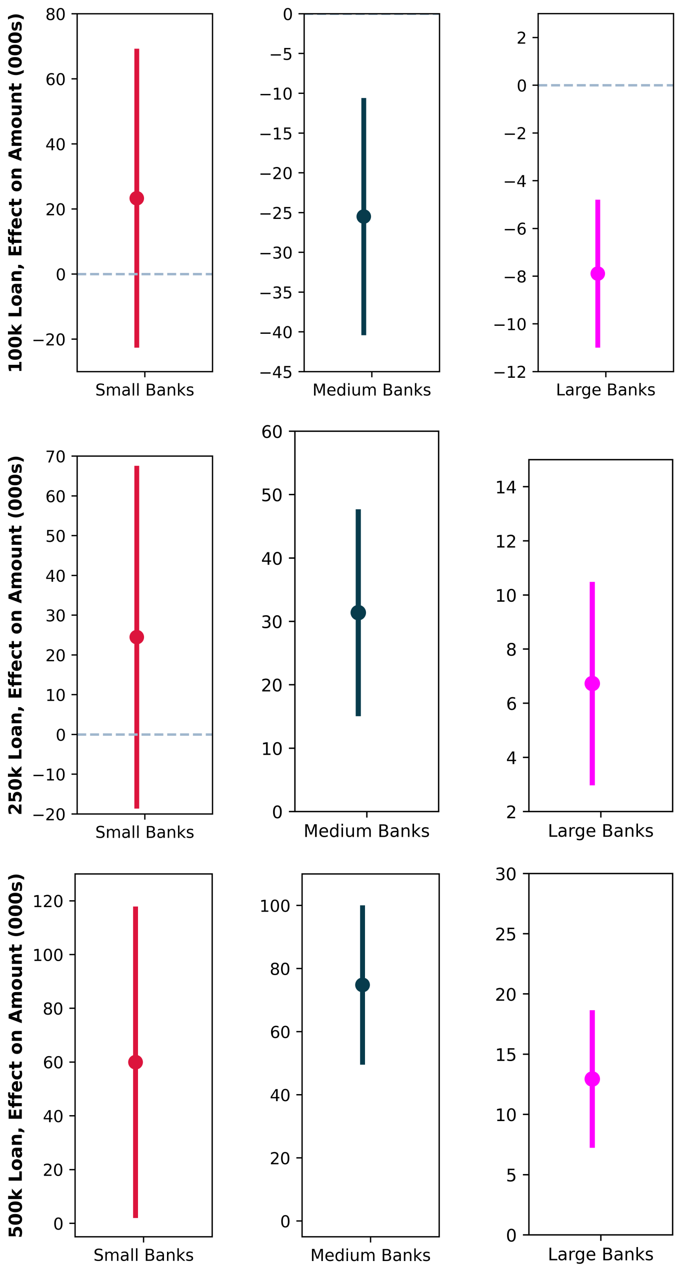
Note: Average marginal effects with 95% confidence intervals, assuming a temperature anomaly of 2.8 °C / 5.04° F. This is consistent with an adverse climate scenario, or'3X CO2 by 2100' (SSP5-8.5). The regression results corresponding to this graph are in Table (27) in Supplementary Information

of average marginal effects, and the results are consistent with Figure (9) in terms of the directions of impact.

With the results of loan size providing contexts, I use Equation (12) to run regressions on the loans to small and large farms. The results of loan frequencies are illustrated in Figure (11), and those of loan magnitudes shown in Figure (12) (regression results shown in Table (29) in Supplementary Information; most of the main and interaction coefficients are significant). Additionally, the results are estimated for two climate scenarios: moderate and severe.

The first row of Figure (11) illustrates the results for small farms, while the second row shows the results for large farms. For small farms, the contraction of lending frequencies from medium and large banks are noticeable, and the magnitude of impact from medium banks is particularly large. Small banks do increase their lending frequencies to small farms. But such increased support is unlikely to overturn the overall loss of lending access that small farms experience, simply due to small banks' very limited market share.

Figure 10: *Marginal Effect of Temperature Anomaly on CRA Lending Amount, by Loan Size*



Note: Average marginal effects with 95% confidence intervals, assuming a temperature anomaly of 2.8 $^\circ C$/ 5.04$^\circ F$. This is consistent with an adverse climate scenario, or'3X CO2 by 2100' (SSP5-8.5). The regression results corresponding to this graph are in Table (27) in Supplementary Information

In contrast, for large farms, the impact of lending frequencies from small and medium banks are negligible or even positive at times. Only large banks noticeably reduce lending frequencies to large farms. One way to interpret these results is that as farms' climate vulnerability increase, small farms do not seem to drastically reduce their perceived risk exposure. Instead, they increase lending to small farms likely due to that they rely on this type of farms as clients. Medium banks try to reduce their exposure to small farms by reducing loan frequencies, while maintaining relatively similar level of lending activities to large farms. Thus medium banks de-risk by lending less to small farms. Other than that, they largely maintain their lending activities within the same county. Moreover, since large banks reduce their lending frequencies to both small and large farms, it is plausible that these large banks de-risk by moving their farm lending to other less-risky counties (the only other valid interpretation is that large banks reduce their farm lending altogether). Thus, for large banks, there may be leakage of lending across counties. This is plausible as such banks have more extensive branches and operations than smaller-sized banks.

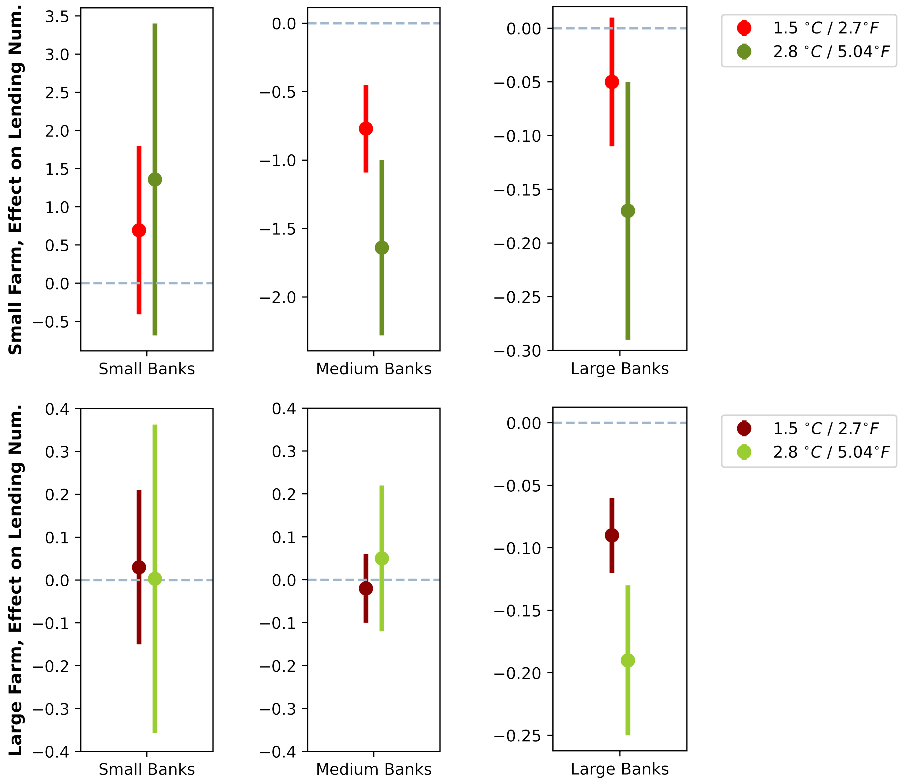
Figure (12) shows the results for the estimation of lending magnitudes, which is based on the bank-county level estimation showing the effect *conditional on* the loans already being approved. The qualitative model of the paper predicts that as climate risks increase, farms' financing needs also increase. Therefore it is reasonable to expect that the actual amount of lending will increase. This is exactly what is shown in Figure (12). Conditional on already being approved for loans, both small and large farms obtain increased amount of lending. It is interesting that the magnitudes of impact are more pronounced for small farms. But this is not surprising, if one assumes that small farms want to access more funding to improve their climate resilience. It is important to first point out the difference of the results here versus county-level estimations of lending amount. For the county-level regression results shown earlier in the paper, the results are underpinned by the composition effect: there is a multitude of banks operating within a county, and on aggregation the effect could be negative for a county.

Besides the aforementioned results, I have estimated additional regressions separately for three groups of banks: very small, small-mid, and large. For the sake of brevity, Tables (30-32) appear in the Supplementary Information. The results are largely the same as in the estimations with bank dummies and interaction effects.[11]

While more analyses are needed, one potential mechanism at work is a bank's ability to relocate their operations or businesses. The large banks in the sample are generally national entities with operations in many counties. Thus they have more leeway to move their businesses elsewhere, should the lending activities in a few locations are anticipated to be less profitable due to climate risks. In comparison, smaller banks, and especially those very small banks are much more localized. For some of them, their entire operations are constrained to one county, and do not have the flexibility as large banks for geographic risk-sharing or arbitrage. For small-mid banks, it is possible that they anticipate large farms to be more

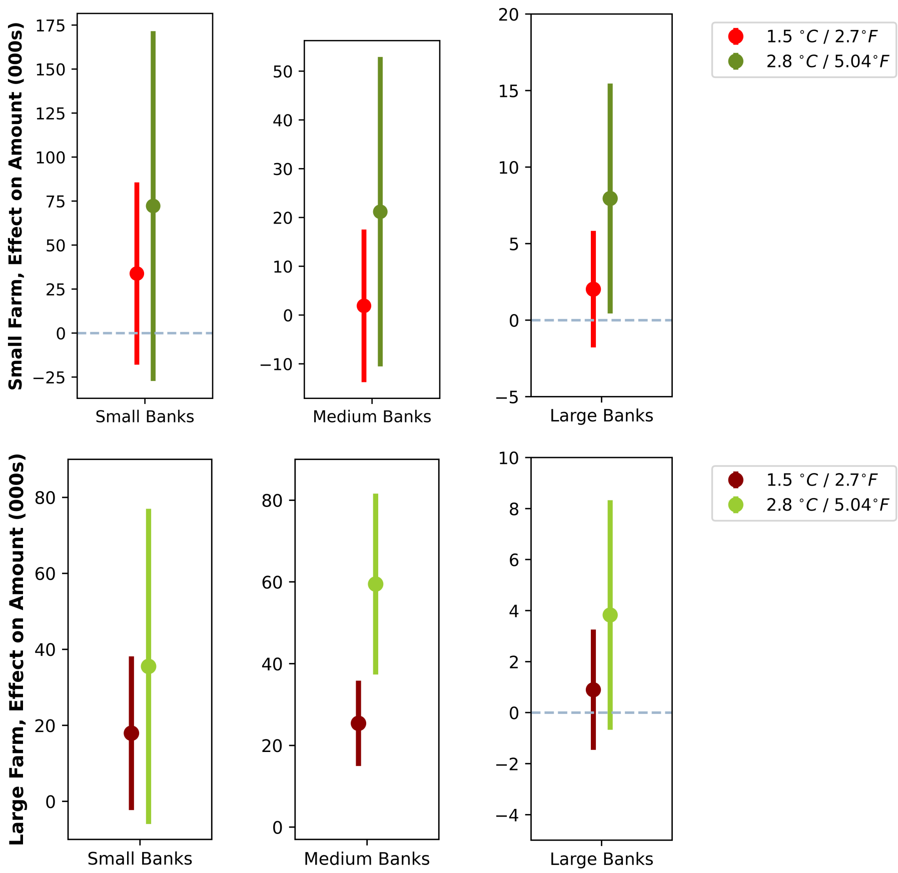
[11] In Supplementary Information, Tables (30-32) show results from the estimation, with bank-level fixed effects included. As seen in Table (30), very small banks' lending do not change in a significant way in response to farms' climate risks. What is more interesting is that as such risks increase, the lending to smaller farms actually increase, both in terms of frequency and amount. In contrast, as Table (30) shows, for small to midsize banks, their lending to small farms shrinks, while the amount of lending to large farms increases. As farms' exposure to climate risks increase, large banks in general are less willing to lend to farms, regardless of farm size, the magnitude of the effect seem slightly larger for small-medium farms.

Figure 11: Marginal Effect of Temperature Anomaly on CRA Lending Frequencies, by Farm Size



Note: Average marginal effects with 95% confidence intervals, with two scenarios: i). temperature anomaly of 1.5 °C / 2.7° F; ii). temperature anomaly of 2.8 °C / 5.04° F; The first is consistent with a moderate climate scenario, or 'net zero by 2075' (SSP1-2.6). The second is consistent with an adverse climate scenario, or'3X CO2 by 2100' (SSP5-8.5). The regression results corresponding to this graph are in Table (29) in Supplementary Information.

Figure 12: Marginal Effect of Temperature Anomaly on CRA Lending Amount, by Farm Size



Note: Average marginal effects with 95% confidence intervals, with two scenarios: i). temperature anomaly of 1.5 °C / 2.7° F; ii). temperature anomaly of 2.8 °C / 5.04° F; The first is consistent with a moderate climate scenario, or 'net zero by 2075' (SSP1-2.6). The second is consistent with an adverse climate scenario, or'3X CO2 by 2100' (SSP5-8.5). The regression results corresponding to this graph are in Table (29) in Supplementary Information.

climate-resilient, thus continue lending to them. For very small banks, their lending decision could be more dictated by their established relations with small-medium farms, or they are liquidity-constrained such that they cannot meet the financing needs of large farms.

In summary, results in this section provide richer insights into how lending decisions are made at the bank level with each county. Even though the analysis is conducted at a more granular dimension, many results here are highly consistent with those in the county level results. More specifically, there continues to be a wide gap of how large farms and smaller farms fare in terms of financial access—smaller farms generally have a harder time getting a loan approved in response to increased climate risks. Conditional on getting a loan, however, both smaller and large farms do receive financial support. The bank-county level analysis also reveal additional insights in that banks bear the different levels of burden of financing: large (likely national, multi-branch) banks tend to de-risk by withdrawing funding, as is the often the case for medium size banks. It is more likely for the localized, small banks to continue lending to small farms. While this is not a paper about the financial risks arising from climate change, the results here do point to concerning signs that the sharing of risks among banks is not distributed equally.

A.o.1 Extension: Bank-County Level–Census Tract Income Areas

The analyses of bank-county pair can be expanded further by considering which income areas farms are located in. Thus the unit of analysis here becomes bank-county-income group pair. The econometric specification becomes

$$y_{ibct} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \psi_b + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ibct} \tag{13}$$

The estimation now includes more granular data of how much a bank b lends in income area c of county i, and income group fixed effect ξ_c is included.

The results for all income groups,[12] estimated by bank sizes[13], are mostly identical to the results in Tables (28-30). In short, large banks in general are less willing to lend, small-mid banks lend less to small farms and more to large farms, and very small banks lend more to small farms.

As suggested by similar analysis in Section III in the main text, it is necessary to understand the heterogeneity of impact by income groups: in general, farms located middle income areas of counties bear the brunt the effect of climate risks. The results in Section III are at county level. This pattern continues to hold here at bank-county-income group level, as seen in additional tables in Appendix A.p.

In summary, the results in this section confirm that at bank level, farms' vulnerability to climate risks still matter for lending. More specifically, as climate risks increase, very small banks maintain or lend more to small farms. Small-mid size banks lend more to large farms, and lend less to small farms. Large banks uniformly lend less to big and small farms in terms of frequencies. The results are largely consistent with the aggregate county-level data, but with richer details by bank characteristics.[14]

[12] The tables of the results are upon request

[13] Note the current estimation includes bank income group fixed effect, not bank-level fixed effect. The income group is classified based on the yearly decile distribution of banks' assets (of the prior year)

[14] The correspondence between the county-level and bank-county level results is not immediately straightforward. A paper by Blickle et al. (2021) suggests banks themselves are fairly resilient to natural disasters: in general, their balance sheets are not hit hard in a significant way. In short, analysis of climate effect at bank level does not always point to significant results.

A.p Tables of Bank Level Estimates

Table 25: *Number of CRA Farm Loans and Climate Vulnerability, Bank-County Level by Loan Size*

VARIABLES	(1) Total Num. of Loans	(2) Number of loan (less 100k)	(3) Number of loan (100k to 250k)	(4) Number of loan (250k to 500k)
High temperature anomaly	0.12	0.25***	-0.07***	-0.06***
	(0.08)	(0.07)	(0.01)	(0.01)
High temperature anomaly (square)	-0.17***	-0.22***	0.02***	0.03***
	(0.04)	(0.04)	(0.01)	(0.00)
Mid-size bank = 1	2.62***	1.87***	0.48***	0.26***
	(0.61)	(0.55)	(0.08)	(0.05)
Large-size bank = 1	3.72***	1.53**	1.34***	0.85***
	(0.74)	(0.67)	(0.11)	(0.07)
Small bank × Temperature	-0.12	-0.22	0.07**	0.02*
	(0.20)	(0.18)	(0.03)	(0.01)
Small bank × Temperature (square)	0.30***	0.32***	-0.01	-0.01
	(0.11)	(0.11)	(0.02)	(0.01)
Large bank × Temperature	-0.00	-0.10	0.06***	0.04***
	(0.08)	(0.07)	(0.01)	(0.01)
Large bank × Temperature (square)	0.12***	0.16***	-0.02***	-0.02***
	(0.04)	(0.04)	(0.01)	(0.00)
Observations	480,898	480,898	480,898	480,898
R-squared	0.018	0.023	0.011	0.016
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: *Amount of CRA Farm Loans and Climate Vulnerability, Bank-County Level by Loan Size*

VARIABLES	(1) Total Amt. of Loans	(2) Amount of loan (less 100k)	(3) Amount of loan (100k to 250k)	(4) Amount of loan (250k to 500k)
High temperature anomaly	-40.80***	-3.99***	-14.95***	-21.86***
	(5.50)	(1.49)	(2.05)	(3.11)
High temperature anomaly (square)	15.95***	-0.11	5.96***	10.10***
	(2.54)	(0.65)	(0.96)	(1.51)
Small-size bank = 1	-240.40***	-69.47***	-81.66***	-89.27***
	(36.54)	(10.90)	(13.04)	(18.35)
Large-size bank = 1	477.37***	79.01***	168.99***	229.38***
	(31.97)	(8.08)	(12.16)	(15.79)
Small bank × Temperature	22.71**	4.53	11.96***	6.22
	(10.74)	(3.55)	(4.08)	(4.87)
Small bank × Temperature (square)	-5.05	2.06	-3.38	-3.72
	(5.89)	(1.92)	(2.12)	(2.84)
Large bank × Temperature	29.03***	4.64***	10.65***	13.73***
	(4.99)	(1.42)	(1.90)	(2.79)
Large bank × Temperature (square)	-12.86***	-0.47	-4.63***	-7.76***
	(2.54)	(0.66)	(0.97)	(1.50)
Observations	480,898	480,898	480,898	480,898
R-squared	0.025	0.009	0.020	0.028
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27: *CRA Farm Loans and Climate Vulnerability, Bank-County Level*

VARIABLES	(1) Num. of loans to large farms	(2) Amount of loans to large farms	(3) Num. of loans to small-medium farms	(4) Amount of loans to small-medium farms
High temperature anomaly	-0.10***	-13.64***	0.22***	-27.16***
	(0.03)	(2.59)	(0.08)	(4.03)
High temperature anomaly (square)	0.01	7.28***	-0.18***	8.67***
	(0.01)	(1.30)	(0.04)	(1.74)
Mid-size bank (= 1 if yes)	-0.15	38.43***	2.77***	201.97***
	(0.16)	(13.99)	(0.59)	(28.58)
Large-size bank (= 1 if yes)	0.49**	186.18***	3.23***	531.59***
	(0.20)	(19.92)	(0.71)	(38.12)
Small bank × Temperature	0.17***	10.02**	-0.29	12.69
	(0.05)	(4.00)	(0.19)	(8.37)
Small bank × Temperature (square)	-0.02	-3.85*	0.33***	-1.20
	(0.02)	(2.08)	(0.11)	(4.66)
Large bank × Temperature	0.12***	10.71***	-0.12*	18.31***
	(0.03)	(2.35)	(0.07)	(3.71)
Large bank × Temperature (square)	-0.04***	-6.55***	0.16***	-6.31***
	(0.01)	(1.30)	(0.04)	(1.74)
Observations	480,898	480,898	480,898	480,898
R-squared	0.005	0.021	0.025	0.016
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 28: *CRA Farm Loans and Climate Vulnerability, Very Small Banks*

VARIABLES	(1) Num. of loans to large farms	(2) Amount of loans to large farms	(3) Num. of loans to small-medium farms	(4) Amount of loans to small-medium farms
High temperature anomaly	-0.09	-4.51	0.15	9.68
	(0.13)	(4.38)	(0.34)	(13.20)
High temperature anomaly (square)	0.03	1.70	0.13	7.06
	(0.04)	(3.34)	(0.14)	(5.34)
Observations	14,055	14,055	14,055	14,055
R-squared	0.023	0.037	0.024	0.057
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 29: *CRA Farm Loans and Climate Vulnerability, Small-Mid Banks*

VARIABLES	(1) Num. of loans to large farms	(2) Amount of loans to large farms	(3) Num. of loans to small-medium farms	(4) Amount of loans to small-medium farms
High temperature anomaly	0.02	3.46	-0.14	-8.92
	(0.04)	(2.77)	(0.11)	(5.51)
High temperature anomaly (square)	-0.00	0.32	-0.14***	-0.66
	(0.01)	(1.11)	(0.05)	(2.05)
Observations	66,647	66,647	66,647	66,647
R-squared	0.014	0.074	0.036	0.039
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 30: *CRA Farm Loans and Climate Vulnerability, Large Banks*

VARIABLES	(1) Num. of loans to large farms	(2) Amount of loans to large farms	(3) Num. of loans to small-medium farms	(4) Amount of loans to small-medium farms
High temperature anomaly	0.04***	-0.57	0.08***	-4.64***
	(0.01)	(0.76)	(0.02)	(1.24)
High temperature anomaly (square)	-0.03***	0.14	-0.03***	0.45
	(0.00)	(0.25)	(0.01)	(0.40)
Observations	400,196	400,196	400,196	400,196
R-squared	0.008	0.011	0.033	0.006
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Region x Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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