Title
Essays in Economic Policy and Climate Change

Author
Liu, Teng

Publication Date
2023

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
SANTA CRUZ

ESSAYS IN ECONOMIC POLICY AND CLIMATE CHANGE

A dissertation submitted in partial satisfaction of the
requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Teng Liu

June 2023

The Dissertation of Teng Liu
is approved:

Professor Galina Hale, Chair

Professor Weishi Steadmon

Professor Jeremy West

Peter Biehl
Vice Provost and Dean of Graduate Studies

Table of Contents

List of Figures

List of Tables

Abstract

ESSAYS IN ECONOMIC POLICY AND CLIMATE CHANGE

by

Teng Liu

In this dissertation, I study the financial impact of climate change through bank lending, sovereign default risks, and household consumption behavior. With intensifying climate change risks, financial institutions minimize potential losses by lending less to borrowers with higher vulnerability to such risks. These borrowers include not only businesses, but also national governments. Chapters 1 and 3 illustrate the credit contraction and financial distress that borrowers may experience. In particular, certain sovereign borrowers' difficulty in accessing funding is exacerbated by their inability to effectively adjust revenue and expenditure. While the results documenting the effects of climate change are about the financial sector, the impact may spill over into other parts of the economy as well. Chapter 2 results show that when sovereign default risks rise, there is likely household consumption loss. Chapters 2 and 3 together suggest that when climate change increases sovereign default risks, there are important implications for household behavior as well.

The agricultural sector is particularly susceptible to the impact of climate change. In Chapter 1, I investigate how vulnerability to climate change affects U.S. farms' credit access, and demonstrates that such impact is unequally distributed across farms. I first construct a theoretical framework of bank lending to farms faced with

climate risks, and the model helps discipline ensuing empirical analyses that use novel panel datasets at county and at bank levels. I find that higher exposure to climate change, measured by temperature anomaly, reduces bank lending to farms. Such impact is persistent, nonlinear, and heterogeneous. Small and medium farms almost always experience loss of loan access. In comparison, large farms see less severe credit contraction, and in some cases may even see improvement in funding. While small banks continue to lend to small farms, their limited market share cannot compensate for the reduction of lending from medium and large banks. These results suggest that factors such as farm size and bank type can amplify the financial impact of climate change.

In Chapter 2, I uncover how sovereign debt default risks spill over into household consumption behavior through the fiscal channel. Existing studies have sparsely documented the consumption implications of sovereign default. During sovereign financial distress, a government typically conducts fiscal adjustment in areas such as pension and food assistance. Thus for households who benefit from public transfers, the adjustment of public expenditures matter for their consumption behavior. Using micro-level data of the National Survey of Household Income and Expenditure (ENIGH) of Mexico, I measure household consumption changes resulting from fiscal adjustment and from sovereign risks. The analyses consist of state-level and household-level estimates, and provide nuanced views of the default-consumption link by exploiting micro variables such as household income distribution, wealth, and socio-demographic characteristics. Both the state-level and household-level results suggest that in many cases, the link between default risk and household consumption is negative and significant, especially through the adjustment of pension expenditure.

Responding to climate change poses increasingly high fiscal costs. In Chapter 3, I examine how climate change affects sovereign default risks and fiscal policy through a set of empirical results and a stylized model. Using panel data of 135 countries over 1995-2018, I first show that 1 percentage increase of vulnerability to climate risks can increase sovereign default probability by around 5 percentage points, and such default risks may differ by fiscal conditions. More specifically, fiscal conditions refer to whether and how a government can conduct tax and expenditure adjustment to respond to aggregate shocks. The stylized model of sovereign default also shows that the risks of climate change raise default probability. Moreover, if a government has high fiscal rigidity, it also raises the default probability, thus potentially amplifying the costs of climate risks. Such results point to the importance of structural reform to reduce a government's debt vulnerability resulting from climate change.

To my family

Acknowledgments

While obtaining the Ph.D. is an individual achievement, many people have helped me get here. I would like to especially thank members of my committee for their advice and support in pursuing innovative research questions to answer. Professor Galina Hale first gave me the courage to work on climate change, and has helped me become a better researcher through our close collaborations and co-authoring of papers. Professor Grace Gu guided me in my second year paper (Chapter 2 of the dissertation), and gave me confidence to work with micro and banking data that became crucial for the dissertation. Professor Jeremy West taught me in Applied Microeconomics, and he imparted to me understandings of causal inference that are invaluable for credible identification in my work. I truly would not be successful today without their guidance.

Many thanks to other members of the economics department who have helped me during my research and job market: Alonso A Villacorta, Brenda Samaniego de la Parra, Chenyue Hu, Natalia Lazzati, Gueyon Kim, Kristian Lopez Vargas. I also express my gratitude to other UCSC professors: Michael W. Beck, Kai Zhu, Stacy M Philpott, and J. Elliott Campbell. I am thankful for my classmates for the support and encouragement, including Yilin Li, Anirban Sanyal, Bhavyaa Sharma, Harrison Shieh, Guanghong Xu, and Yusuf Yildirim. I am also grateful for the financial support of the Food System Research Fund (FSRF) and the Hammett Fellowship of UCSC for Chapter 1 of the dissertation. Special thanks to the program coordinators Sandra Reebie and Meenoo Kohli for ensuring that the PhD process is smooth from start to finish.

Chapter 1

Save the Farms: Nonlinear Impact of Climate Change on Banks' Agricultural Lending

1.1 Introduction

The acceleration of climate change in the United States has materialized as increasing frequency and severity of extreme weather conditions, especially since year 2010.[1] Such weather extremes and disasters contribute to economic losses: the National Oceanic and Atmospheric Administration (NOAA) estimate that since 1980, the U.S. has experienced large-scale climate disasters with loss of over $1.875 trillion, and over 48% of which occurred during 2010-2020.[2] The agricultural sector is especially vulnera-

[1] U.S. Climate Extremes Index (CEI)
[2] Billion-Dollar Weather and Climate Disasters

ble to the risks of climate change and disasters, and the issue has received considerable academic and policy attention. For instance, Walthall *et al.* (2012) assess that increasing temperature and extreme precipitation can reduce U.S. farms' crop productivity. Despite increasing understandings of the economic implications of climate change, not enough attention has focused on the role of financial institutions in this context, particularly with respect to the U.S. agricultural sector.

At the same time, commercial banks play a nontrivial role in financing farms' production and operations, accounting for around 40% of total U.S. farm debt as of 2020.[3] Yet U.S. farms seem to be facing increasing financial challenges since 2015, as demonstrated by the growing shares of non-performing loans.[4] A number of studies examine the effect of natural disasters on general bank lending, such as Ivanov *et al.* (2020), Koetter *et al.* (2020), Garbarino & Guin (2021), Schüwer *et al.* (2018), Petkov (2019), Brei *et al.* (2019), and Cortés & Strahan (2017).[5] Yet few of these studies specifically focus on bank loans to the U.S. agricultural sector.

My chapter contributes to the literature by examining how farms' credit access is affected by their exposure to climate change and disasters. Compared with companies in other sectors, farms absorb the financial impact of climate change more directly: farms that have crop or livestock failures due to climate change will experience revenue loss, thus are likely to default on their bank loans. It is also generally not feasible for

[3]See this article by Willingham (2021)

[4]See Figure 1.14 in the Appendix

[5]In particular, Ivanov *et al.* (2020) is similar in that they examine how banking networks amplify the effect of natural disasters. Two key differences with my chapter: 1). Ivanov *et al.* (2020) use the restricted access Shared National Credit data, focusing on syndicated loans. 2). Their paper does not explicitly measure the vulnerability to climate change

farms to relocate. At the same time, understanding whether the agricultural sector has adequate financing is important to build a resilient food system in response to climate change.[6] To the best of my knowledge, this chapter is one of the first studies that detect the impact of climate change vulnerability on agricultural lending, and the results pay careful attention to the distribution of such effects. More specifically, the analyses reveal that the impact varies by farm size, income area, agricultural region, and bank size.

In order to help answer the research question, I first construct a two-period model of bank lending to farms. The framework provides qualitative predictions on the directions of impact of climate risks, and guides the interpretation of results in the empirical section. In this simple, stylized economy, the farm seeks a loan from the bank, in anticipation of larger financing needs due to climate change. When evaluating whether to provide a loan, the bank assesses the farm's expected payoff, taking into account factors such as the farm's productivity. If assuming that a larger farm has higher productivity, the model predicts that the bank is more likely to lend to the larger farm than small farm, even if their exposure to climate change is identical.

To uncover differences in farms' credit access empirically, I focus on exploiting county-level and bank-level variations. The key variable in this chapter is banks' lending to farms, which is measured using data from the Community Reinvestment Act (CRA) housed at the Federal Financial Institutions Examination Council (FFIEC). While a

[6] Answering the credit access question is important, as it lays the foundation for further understanding U.S. farms' climate resilience: after a climate-related disaster, it is possible that farms in U.S. counties with more bank lending recover faster than counties with less bank financing, and they may also adapt better to climate change. Thus there may be systematic differences in counties' adaptability to climate risks, which can partly be explained by bank lending.

few papers like Bord *et al.* (2021) have used such data to examine questions related to local banking, CRA agricultural lending is a novel dataset to use for questions related to climate change. It is publicly available, and offers geographic and temporal variations that are necessary to identify the effects of climate change. Then the bank lending data are merged with measures of climate change vulnerability. The main measurement in this chapter is the county-specific temperature anomaly, typically used in the scientific literature to proxy for climate change.

Following existing studies such as Burke *et al.* (2015), I use nonlinear econometric specifications to estimate the effects of climate change on bank lending to farms. The analysis differentiates between lending to large farms and that to smaller farms, as these groups may be fundamentally different in their production structure and financial capabilities. The results from Section 1.4.2 at the county-level confirm the predictions from the conceptual framework: given the same county-specific temperature anomaly, it is more likely for smaller farms to be denied loans than large farms. While such overall patterns are statistically significant for all U.S. counties, there is also a range of regional heterogeneity. For example, the divergent effects on small and large are most clearly seen in northern states such as the Dakotas and southern states such as Mississippi and Louisiana. Additionally, farms located in Census-designated middle income areas experience the impact most significantly, compared with those in lower and high income areas.

Further, the bank-level estimation in Section 1.4.3 is consistent with county-level results, and also reveals that the size of banks also plays a role in lending patterns.

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. Due to the dominance of large banks in smaller loans, on which small farms most likely rely, the reduction of this type of lending may explain the credit access loss that small farms experience at the county aggregate level.

Based on the econometric estimation, I also conduct scenario analysis of the impact of future climate scenarios at county and bank levels. More specifically, I calculate marginal effects of a given temperature anomaly (of a given climate scenario) on lending patterns. As a climate scenario becomes more pessimistic (higher temperature), the magnitudes of effects become larger, as do the divergent impact across farm types.

The chapter proceeds as follows. Section 1.2 delineates the two-period model and its qualitative predictions. Section 1.3 describes the datasets, why particular temperature measurements are used, and summary statistics. Section 1.4 shows the econometric framework, and presents the results at the county-aggregate level and bank-level. Section 1.5 concludes and discusses the implications of the results.

1.2 Conceptual Framework

Timeline and Environment

To illustrate the link between climate change and bank lending to farms, this section provides a conceptual framework[7] of loan contracting based on Chodorow-Reich

[7] 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. I plan to further develop this model to consider the role of bank type

et al. (2021) and Holmstrom & 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 1.1. 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.[8] 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. 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'.[9] 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

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

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

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 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).[10]

[10] 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).

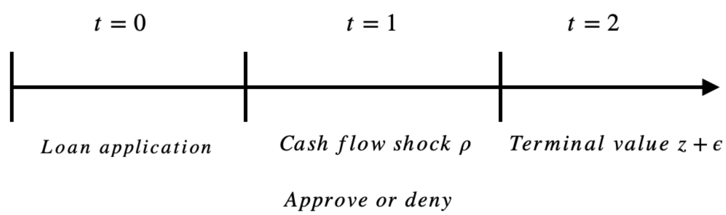


Figure 1.1: Timeline of Bank Lending to Farms

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:

$$V = \max\{V^M, V^N\} \tag{1.1}$$

where

$$V^N = \max\{\theta z - \rho, 0\} \tag{1.2}$$

and

$$V^M = \mathbb{E}[\max\{\theta(z + \epsilon) - \rho, 0\}] - \xi \tag{1.3}$$

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 $\{q, 1-2q, q\}$.

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

$$V^M = \underbrace{\theta z - \rho}_{V^N} + \underbrace{q[\rho - (\theta(z-e)]}_{\text{Monitoring value}} - \underbrace{\xi}_{\text{Monitoring cost}} \tag{1.4}$$

such that the bank would prefer monitoring if and only if

$$\rho > \underline{\rho} := \theta(z-e) + \xi/q \tag{1.5}$$

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

$$V^M = \underbrace{0}_{V^N} + \underbrace{q[\theta(z+e) - \rho]}_{\text{Monitoring value}} - \underbrace{\xi}_{\text{Monitoring cost}} \tag{1.6}$$

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

$$\rho < \bar{\rho} := \theta(z+e) - \xi/q \tag{1.7}$$

By combining and generalizing the above results, the bank's lending decisions can be graphically illustrated in Figure 1.2. 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 1.5 and 1.7 that $\underline{\rho}_b \approx \underline{\rho}$ and $\bar{\rho}_b > \bar{\rho}$. As seen in Figure 1.2, 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 chapter examines the empirical links between climate shocks and bank lending to farms.

1.3 Data and Measurements

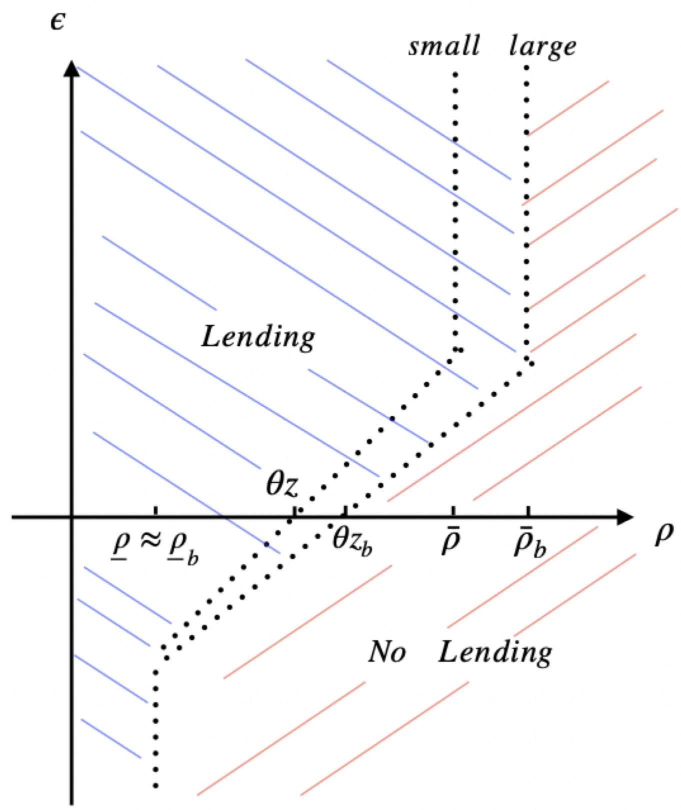
The chapter employs three main types of data: bank lending to farms; climate risks and disasters; agriculture production and other banking variables. The data are observed at U.S. county level and on an annual frequency.

Bank Financing

Accurately capturing lending to U.S. farms is a challenge, as such data at loan level tend to be confidential. While bank call reports include information about farm loans, such data are only available at bank institution level, and not at bank branch level. Therefore, these data do not have geographic variations that are necessary to identify how climate change vulnerability relates to farm lending in different regions. To the best of my knowledge, the Community Reinvestment Act (CRA) dataset[11] is

[11] See `https://www.ffiec.gov/cra/craproducts.htm`

Figure 1.2: 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 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.

the only publicly available source that provides a relatively comprehensive view of farm lending for the United States.

The CRA is a federal law enacted to encourage banks to lend to rural as well as low- and middle-income communities.[12] The dataset covers years 1996 to 2019, and loans to small farms by county as well as by bank institutions. For the purpose of the

[12]Keenan & Mattiuzzi (2019)

chapter, I use information of small farm loan originations, both in terms of the total number and amount of loans. Additionally, the original CRA database is disaggregated by several overlapping levels of measurements: loan size, banking institution, and income characteristics of recipients. The analysis focuses on total of loans in each county. In other words, the unit of analysis is the total amount of CRA financing in each county. It results in a panel dataset at county level across years.

More specifically, two types of CRA variables are used: number of CRA loans; total amount of such loans. All the loan variables are converted to real terms (2015 dollar). Additionally, I categorize the loans based on farm groups: 1) loans to small-medium size farms (less than $1 million gross revenue); 2) loans to large farms (more than $1 million gross revenue).

The CRA dataset identifies loans to farms with less than $1 million of gross annual revenue. Thus the funding that goes to large farms can be derived from this variable. This categorization is broadly consistent with the classifications of the Economic Research Service (ERS) of USDA (2021). The ERS classification is based on farm gross revenue as well: 1) small farms have less than $350 thousand gross revenue; 2) midsize farms have $350-999 thousand gross revenue; 3) large farms have more than $1 million gross revenue.

While the CRA dataset is insightful, it is limited in its scope and coverage. First, it does not encompass all the farm lending that banks provide, as not all U.S. financial institutions are subject to CRA reporting requirements. For example, credit unions, which are not backed by the Federal Deposit Insurance Corporation (FDIC), are not included in the dataset. Moreover, the dataset is only for farm lending that is small in terms of amount. According to the CRA reporting guidelines shown in FFIEC (2015), a small farm loan is defined as one with amount less than $500,000, and can be either for farm land or production purpose. While CRA lending goes to farms of all sizes, it is likely that the lending to large farms are not representative of all the financial flows to such farms.

Climate Change Measures

To measure vulnerability to climate change, I use two types of variables: 1) county-level climate-related disasters; 2) county-level records of extreme climate conditions. The data on climate-related disasters come from the Disaster Declarations Summary by the Federal Emergency Management Agency (FEMA).[13] Publicly available, this dataset records the dates and types of natural disasters (e.g., hurricane; flood) at the county level. The year coverage is 1953 to present. However, extreme weather events are not equivalent to climate change.

Thus I also use the temperature and precipitation data that NOAA collects from year 1895 to present. More specifically, I use NOAA Monthly U.S. Climate Divisional Database (NClimDiv). Using such data, I measure climate anomaly that each county experiences in each year compared to its long-run average (e.g., 30 years).[14] Essentially this anomaly variable is the difference between yearly observed value and the

[13] See `https://www.fema.gov/openfema-dataset-disaster-declarations-summaries-v2`

[14] In the climate literature, there does not seem to be consensus on what the "correct" baseline is, studies use anywhere between the past 30 years and the preindustrial years as reference periods. See Moore *et al.* (2019)

county's mean value in record.[15] Finally, I also categorize counties into climate regions using the 2012 International Energy Conservation Code created by the International Code Council.

It is worth discussing the primary choice of temperature measurement in this chapter—maximum temperature (observed daily but extrapolated to yearly for analysis in the chapter). While mean temperature and its increase are often discussed in relation to climate change, it is problematic as an empirical measure as it has a clear trend. Additionally, temperature extremes are likely more indicative of the unexpected "shocks" posed by climate change, therefore likely have more exogenous variation. For example, it is likely easier for agents to predict mean temperature than temperature extremes based on historical observations—the mean temperature is the first moment, whereas temperature extremes are related to higher moments. In other words, temperature extremes are likely to be unanticipated by economic agents, thus truly exogenous to the economic behavior one tries to explain.

Thus the choice comes down to maximum versus minimum temperature, and the maximum measurement is the primary metric used in the chapter. The main reason for this choice is that at least within the United States, record high temperatures are becoming more common than record low temperatures. For instance, one report by the Environmental Protection Agency (EPA) shows that the frequency distribution of extreme highs and lows are uneven in the past few decades; in particular, in the 2000s extreme highs had twice as many occurrences as extreme lows. One way of

[15]The original NOAA data are monthly observations, and I took average of the monthly observations to obtain the annual observations

interpreting this unevenness is that it is more likely for climate change to materialize as maximum than minimum temperature. Besides the factor of frequency, studies by Vose *et al.* (2017) for the National Climate Assessment project that throughout the century, the intensity of extreme highs are going to increase, while that of extreme lows will decrease—more severe heat waves, and less severe cold waves. Finally, recent studies such as Diffenbaugh *et al.* (2021) that examine how climate change affects the economics of agriculture use daily maximum temperature as the primary measurement. However, in this chapter, minimum temperature and precipitation data are included as controls or used as alternative measurements in robustness tests.

Agricultural and Other Banking Variables

Estimations in the chapter are supplemented by variables that illustrate the characteristics of agricultural production and banking in each county. The farm-related data mainly come from USDA Agricultural Census, which is generally conducted every 5 years. Additionally, USDA ERS also provides classifications such as farm areas that are helpful to understand regional heterogeneity of the impact of climate on bank lending. Finally, I use the Summary of Deposit (SOD) dataset from FDIC to control for each county's banking characteristics such as number of bank branches.

Summary Statistics

The analysis in the chapter 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 (1.1). In the United States, large farms dominate the value of total market production (MacDonald (2021)). But as seen in Table (1.1), 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.[16] 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 1.1: 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"

[16]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.

Tables (1.2) 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 (1.2), due to the nature of CRA, the overall magnitudes of lending to small-medium farms are bigger than to large farms. Section 1.6 provides additional summary statistics grouped by the loan size thresholds.

To illustrate the geospatial distribution of CRA lending, I have mapped data through Figures (1.3) and (1.4) 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. Section 1.6 provides more maps of CRA lending to small-medium versus large farms (both in absolute values and normalized by county GDP). While Table (1.1) summarizes the size distribution of farms across years, Figure (1.5) 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.

1.4 Econometric Analysis

In this section I present econometric analysis testing the hypothesis that farms located in U.S. counties more exposed to climate change tend to receive less bank fi-

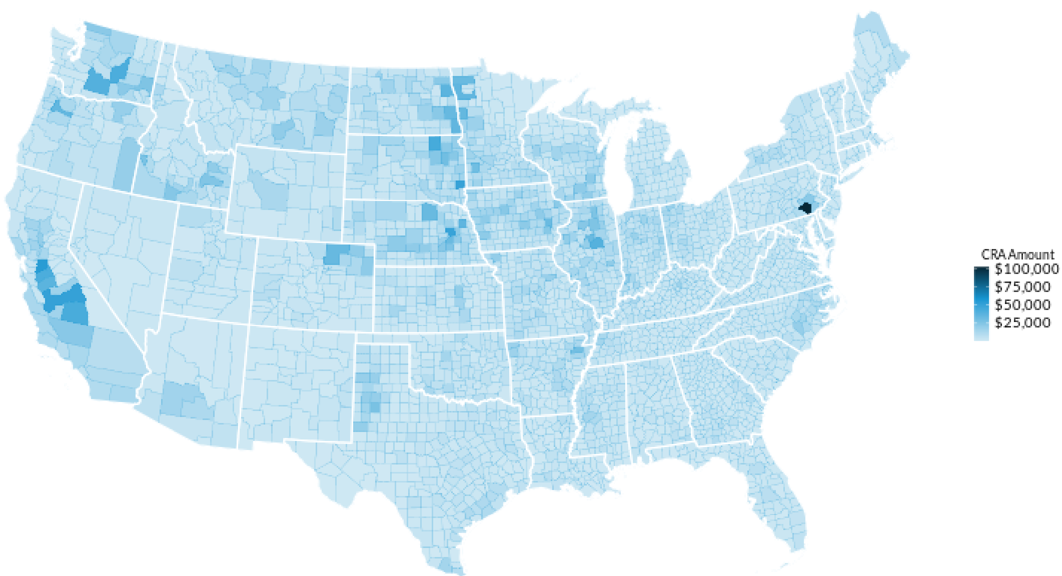


Figure 1.3: Yearly Average Total Amount of CRA Farm Loans, 1996-2019, in thousand 2015 USD

Source: FFIEC (2021)

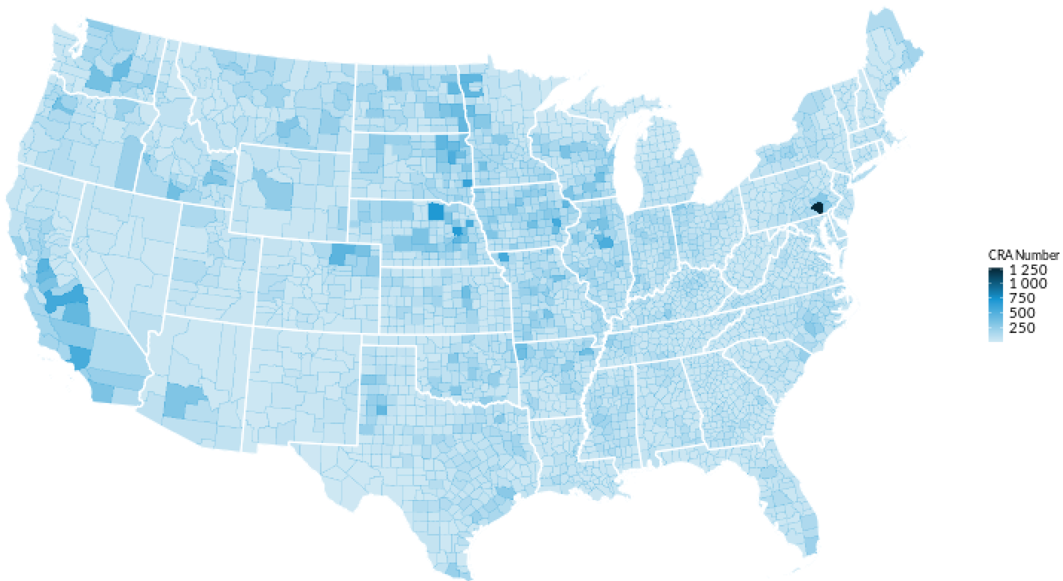


Figure 1.4: Yearly Average Number of CRA Farm Loans, 1996-2019
Source: FFIEC (2021)

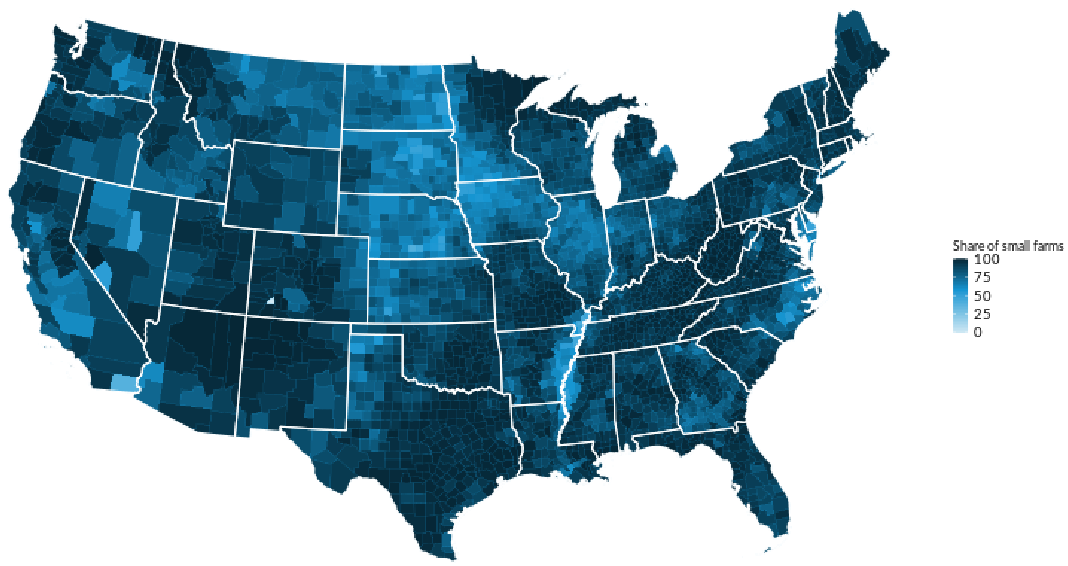


Figure 1.5: Share of Small Farms (gross sales < $250k), 2012-2017
Source: USDA Census

Table 1.2: 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

nancing. The analysis uses two measures of climate change: disasters; climate condition anomaly.[17] The econometric specifications in the chapter focus on the nonlinearity of temperature effect, following the standard approach in the literature such as Diffenbaugh *et al.* (2021) and Schlenker & Roberts (2009) on agriculture and climate change.

Empirical Framework

The framework follows closely that in Hsiang (2016) and Burke *et al.* (2015). Weather and climate are different, yet empirical measurements of climate change are largely derived from weather data such as temperature and precipitation. As in Hsiang (2016), one can define $\mathbf{c}(\mathbf{C})$ as the observable characteristics of weather $\mathbf{c}$ conditional on the underlying climate process $\mathbf{C}$. Suppose that vector $\mathbf{C}$ has length K, indexed by k. Additionally, define Y as an economic outcome, and in this case bank lending. Moreover, conditional on the climate process, agents' beliefs $\mathbf{b}$ may affect their decisions

[17] Additional empirical results forthcoming: constructing the Herfindahl index to measure bank's market power.

and relevant actions—for example, climate adaptation behavior. Suppose vector $\mathbf{b}$ has length N indexed by n. Thus the relationship between climate change and an economic outcome can be described as the following:

$$Y(\mathbf{C}) = Y[\mathbf{c}(\mathbf{C}), \mathbf{b}(\mathbf{C})] \tag{1.8}$$

Therefore, the total marginal effect of climate change is the following:

$$\begin{aligned} \frac{\mathrm{d}Y(\mathbf{C})}{\mathrm{d}\mathbf{C}} &= \nabla_{\mathbf{c}} Y(\mathbf{C}) \cdot \frac{\mathrm{d}\mathbf{c}}{\mathrm{d}\mathbf{C}} + \nabla_{\mathbf{b}} Y(\mathbf{C}) \cdot \frac{\mathrm{d}\mathbf{b}}{\mathrm{d}\mathbf{C}} \\ &= \underbrace{\sum_{k=1}^{K} \frac{\partial Y(\mathbf{C})}{\partial \mathbf{c}_k} \frac{\mathrm{d}\mathbf{c}_k}{\mathrm{d}\mathbf{C}}}_{\text{direct effects}} + \underbrace{\sum_{n=1}^{N} \frac{\partial Y(\mathbf{C})}{\partial \mathbf{b}_n} \frac{\mathrm{d}\mathbf{b}_n}{\mathrm{d}\mathbf{C}}}_{\text{belief / adaptation effects}} \quad , \end{aligned} \tag{1.9}$$

where $\nabla_{\mathbf{c}}$ and $\nabla_{\mathbf{b}}$ are the gradients of $\mathbf{c}$ and $\mathbf{b}$, and $\frac{\mathrm{dc}}{\mathrm{dC}}$ and $\frac{\mathrm{db}}{\mathrm{dC}}$ are $K \times K$ and $N \times K$ Jacobians.

In reality, it is difficult to observe beliefs, and thus challenging to disentangle the direct effects from belief effects. Thus, in this chapter I focus on estimating the overall effects.[18]

1.4.1 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

$$y_{it} = \beta_k \mathbf{disaster}_{it} + \gamma_i trend + \gamma_{i2} trend^2 + u_i + \eta_t + \lambda_{rt} + e_{it} \tag{1.10}$$

[18] I plan on using the data from Yale Climate Opinion Maps in future versions of the paper.

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 non-linear, 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 (1.3) reports the results from estimation of Equation (1.10). 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 1.6 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 1.6.

The results of Table (1.3) 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 (1.10) 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 chapter, I use temperature and precipitation data as more direct measures of climate change.

Table 1.3: 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	1.64**	-16.40	0.04	-169.21
	(0.73)	(48.44)	(1.89)	(103.11)
Flood	-0.82***	-7.06	-1.70**	-22.73
	(0.30)	(24.96)	(0.80)	(44.87)
Freezing (lagged)	10.68	225.97	7.39	340.29
	(8.47)	(241.82)	(8.48)	(211.47)
Hurricane	-0.91***	-44.37***	-0.57*	-105.77***
	(0.15)	(8.35)	(0.31)	(15.88)
Landslide	-8.10***	-519.86***	8.09**	-600.68***
	(1.77)	(112.00)	(3.21)	(104.77)
Ice storm (lagged)	-0.78***	-42.40***	1.49	-4.93
	(0.22)	(14.82)	(0.95)	(38.12)
Storm	-0.32**	-36.60***	-1.48***	-43.96**
	(0.12)	(9.59)	(0.44)	(19.45)
Snow (lagged)	-0.02	3.18	-5.61***	-11.76
	(0.24)	(20.74)	(0.95)	(46.84)
Tornado	-1.13*	11.23	3.39	206.95
	(0.67)	(62.78)	(2.78)	(130.59)
Observations	69,728	69,728	69,728	69,728
R-squared	0.203	0.138	0.140	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 (1.10) $y_{it} = \beta_k \textbf{disaster}_{it} + \gamma_i trend + \gamma_{i2} trend^2 + u_i + \eta_t + \lambda_{rt} + e_{it}$

1.4.2 Climate Change Measured by Temperature Anomaly: County Level

In this section, I use temperature and precipitation data from NOAA to measure climate change. Following the framework as in Burke *et al.* (2015), the baseline regression is the following:

$$y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it} \tag{1.11}$$

Here the variable T_{it} stands for anomaly of maximum temperature observed in a county in each year. To calculate this variable, I take the difference between each county's observation in a year and the same county's average maximum temperature in the past 30 years. There are two reasons for this choice of calculation. First, compared with mean value, temperature anomaly is a preferred metric for climate scientists to measure climate change.[19] Additionally, the process of calculating the anomaly is equivalent to "centering" the variable T_{it}, so that the issue of multicollinearity is minimized when including the quadratic term T_{it}^2. The inclusion of the quadratic term is similar to that in Burke *et al.* (2015), so that the nonlinear effect of temperature is accounted for. Everything else in Equation (1.11) is the same as in Equation (1.10).

Table (1.4) shows the results of the baseline regression. Columns (1)-(2) show the results of CRA lending to large farms, while Columns (3)-(4) showing lending to small-medium farms. The signs of coefficients are the opposite for these two groups in Table (1.4). More specifically, the linear effect of high temperature anomaly is negative for large farms, and it is positive for small-medium farms. In contrast, the quadratic effects for the two groups are the opposite.

The results are robust to excluding 2008 and 2009 observations, as shown in Section 1.6. Additionally, the results are robust to alternative year intervals of temperature anomaly, as seen in Section 1.6. More specifically, the current measure of anomaly is based on the deviation from the 30-year mean, but the results are consistent for the following year intervals as well: 50 years, 70 years, 100 years, and 1895 to 2019.

The shapes of the effects can be visualized in Figure (1.6), where Panels (a) and (b) illustrate small-medium and large farms respectively. The shape of temperature

[19]For example, see NOAA's description of its dataset Global Surface Temperature Anomalies

Table 1.4: 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
Temp. anomaly	-0.14*	-15.47***	1.49***	11.68
	(0.08)	(5.77)	(0.19)	(10.09)
Temp. anomaly (square)	0.01	4.22**	-0.85***	-11.01***
	(0.03)	(1.94)	(0.07)	(3.91)
Observations	72,834	72,834	72,834	72,834
R-squared	0.194	0.142	0.133	0.058
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

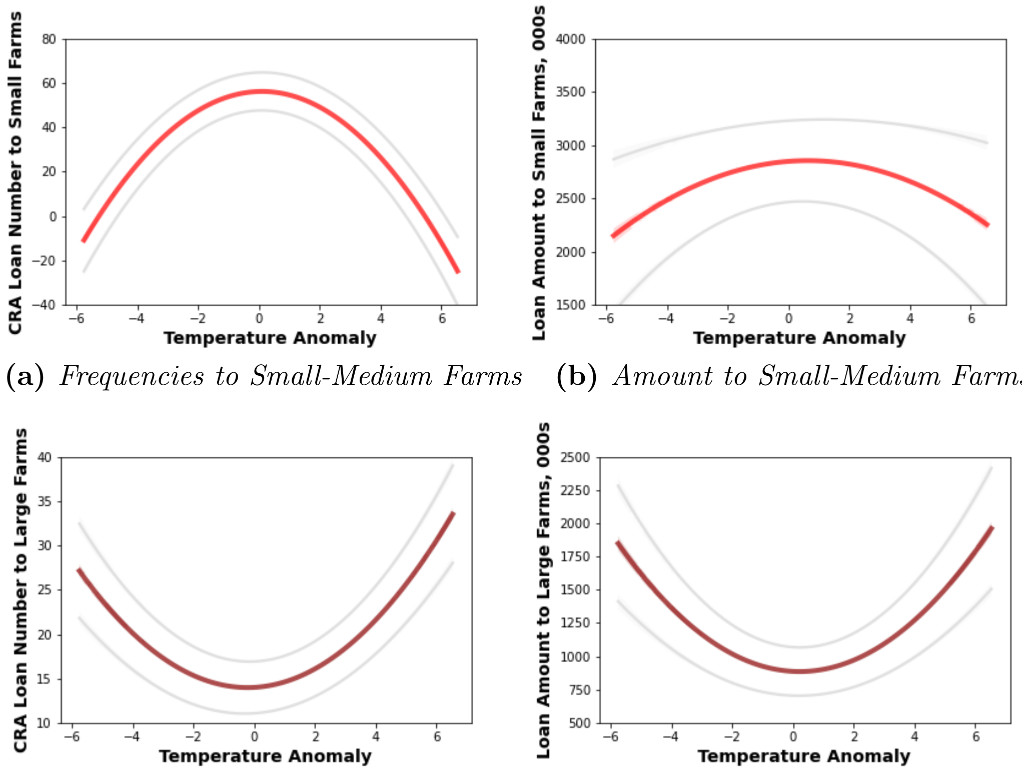
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification for this table is Equation (1.11), $y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$

anomaly effect for small-medium farms is concave. When temperature anomaly is negative (i.e., below normal), the level of CRA lending is increasing. But as the maximum temperature anomaly goes above normal, the level of lending goes down. This suggests that the overall effect of climate change, generally indicated by increasing temperature, is negative for lending to small-medium farms. In contrast, for large farms, the shape of the graph is convex. In particular, as temperature anomaly goes above normal, the CRA lending to this group actually rebounds.

One possible explanation for this contrast is that the estimation here includes both direct and adaptation effect. Large farms, due to more available resources, may be better able to adapt to increasing temperature. Hence banks are more willing to lend to such farms that are more adaptive to climate change. Another related explanation is that banks consider large farms to be less risky, and replace their lending to small-medium farms with loans to large farms—in other words, the overall lending to a county may stay relatively constant, but it simply shifts from small to large farms.

Figure 1.6: Nonlinear Effect of Temperature on CRA Lending



(a) *Frequencies to Small-Medium Farms* **(b)** *Amount to Small-Medium Farms*

(c) *Frequencies to Large Farms* **(d)** *Amount to Large Farms*

Note: Results based on regressions in Table (1.4); Gray lines indicate 95% confidence intervals

All the results so far focus on the level effect of temperature anomaly, and additional analysis is conducted on the growth effect: i.e., the dependent variable is the growth of CRA lending. The nonlinear effect still retains some significance, though the directions of impact are the same across farm groups. The results are reported in Tables (1.35) and (1.36) in Section 1.6 of Appendix.

Marginal Effects by Climate Scenarios

Since this chapter focuses on the impact of climate change, it is useful to estimate the how such impact could materialize in the near future. The United Nations (UN) Intergovernmental Panel on Climate Change (IPCC) conducts regular assessments of the state of climate change.[20] The IPCC assessments also provide projections for temperatures in different climate scenarios, known as the Shared Socioeconomic Pathways (SSPs), based on factors such as greenhouse gas emission, economic growth, and population growth.

For example, if assuming no effective climate policy, under the scenario of 'business as usual' (SSP5-8.5). the maximum temperature anomaly in continuous United States could be 2.8 Celsius (or 5.04 Fahrenheit). Using such projections,[21] I thus estimate the marginal effects of temperature anomaly on CRA lending. It is important to note that only the measure of *maximum* temperature anomaly, not *mean* temperature, is used. From Equation (1.11), the overall marginal effect can be derived as

$$\frac{\partial y}{\partial T} = \beta_1 + 2\beta_2 T^* \tag{1.12}$$

where T^* is a value of high temperature anomaly. For example, if the temperature anomaly is 1 degree Fahrenheit, the overall marginal effects on number of loans are negative for both the small-medium and large farms, which can be calculated using coefficient estimates from Table (1.4).

[20] For example, see a summary of the most recent IPCC assessment

[21] The projected numbers are retrieved from IPCC WGI Atlas: `https://interactive-atlas.ipcc.ch/`

Figure 1.7 shows[22] the estimated results under a range of climate scenarios. From left to right, the horizontal axes denote the climate scenarios, from the most optimistic to the most pessimistic. Within each graph, marginal effects are estimated for two different horizons: near term (now to 2040) and medium term (2041-2060). In general, the more pessimistic the scenario, the higher projected maximum temperature anomaly is. The longer the time horizon, the higher the projected temperature is.

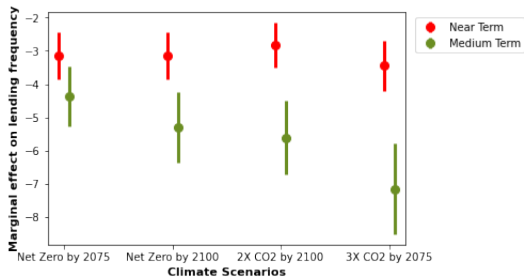
Three general patterns emerge from observing the figure. First, both small-medium and large farms suffer some loss of bank lending. Second, the marginal effects are large in magnitudes for small-medium farms. Third, the negative impact is minimal in terms of loan frequencies for large farms, and the impact is in fact positive in terms of loan amount. The figure here further suggests that farms fare differently, depending on their size, resulting in the lending approval region for large farms significantly wider.

Robustness Checks To assess robustness of the baseline results, I have conducted additional estimations: 1) inclusion of precipitation as an additional control; 2) distinguishing between growing and non-growing season. The results are shown in 1.6 and 1.6. In short, including precipitation does not significantly alter the baseline results. When focusing on growing season, the negative effects on small-medium farms become amplified. When focusing on non-growing season, the effects on large farms become

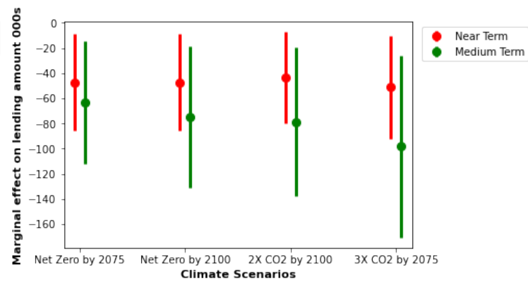
[22] Within the near term, i) 'net zero by 2075' (SSP1-2.6) is equivalent to 1.5 $^\circ C/$ 2.7$^\circ F$. 'Net zero by 2100' (SSP2-4.5) is equivalent to 1.5 $^\circ C/$ 2.7$^\circ F$. ii) '2X CO2 by 2100' (SSP5-8.5) is equivalent to 1.4 $^\circ C/$ 2.52$^\circ F$. iii) '3X CO2 by 2100' (SSP3-7.0) is equivalent to 1.6 $^\circ C/$ 2.88$^\circ F$.

Within the medium term, i) 'net zero by 2075' (SSP1-2.6) refers to 1.9 $^\circ C/$ 3.4$^\circ F$. 'net zero by 2100' (SSP2-4.5) is equivalent to 2.2 $^\circ C/$ 3.96$^\circ F$. ii) '2X CO2 by 2100' (SSP5-8.5) is equivalent to 2.3 $^\circ C/$ 4.14$^\circ F$. iii) '3X CO2 by 2100' (SSP5-8.5) is equivalent to 2.8 $^\circ C/$ 5.04$^\circ F$.

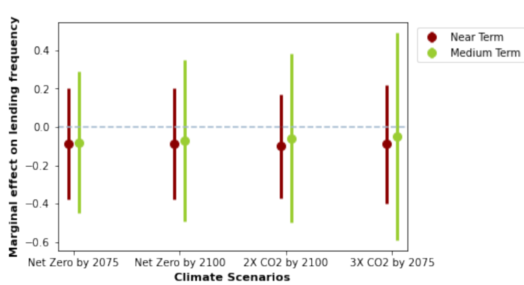
Figure 1.7: Marginal Effect of Temperature Anomaly on CRA Lending, Climate Scenarios



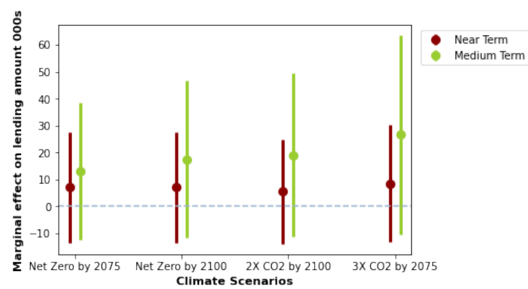
(a) Frequencies to Small-Medium Farms



(b) Amount to Small-Medium Farms



(c) Frequencies to Large Farms



(d) Amount to Large Farms

Note: Marginal effects with 95% confidence intervals, calculated based on Equation (1.12); 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 Coupled Model Intercomparison Project Phase 6 (CMIP6) Model, taking into account emission uncertainty, and use 1986- 2005 as baseline. Climate scenarios are categorized into near term (now to 2040) and medium term (2041-2060)

statistically insignificant.

Extension I: Census Tract Income Areas

So far the analysis has focused on county aggregates, with consideration of farm size. In this section, I expand the estimation by considering another dimension: the income areas where the farms are located. Such analysis is important as CRA-qualifying loans in theory should go to low-income or moderate-income (LMI) communities.[23] Therefore, whether farms are located in high- or low-income areas may matter for bank

[23] For example, see `https://www.federalreserve.gov/consumerscommunities/cra_about.htm`

lending decisions.

Using the definition of an income area from FFIEC, I conduct analysis at the level of county-income group pair. More specifically, a county may have one or more income groups (defined at Census tract level), hence resulting in multiple county-income group pairs within the same county. This dimension of analysis is possible due to the fact that CRA lending data is also available at the Census tract level. The unit of analysis is essentially the income group aggregate *within* each county, and there are 12,290 such county-income group pairs.[24]

Thus the regression adds the income group dimension, denoted by subscript c, and the specification is at the county-income group pair level, with income group fixed effect ξ_c added.

$$y_{ict} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ict} \tag{1.13}$$

Tables (1.5-1.9) show the estimation results. For the entire sample and controlling for income area fixed effects, Table (1.5) shows very similar results to Table (1.4), albeit with higher degrees of significance. Thus for all income areas, the impact of climate risks is significant for lending to large and smaller farms, and the signs of impact differ by the farm size. But this is not to say that income area has no relationship with the degrees of impact. To uncover this relationship, I repeat the analysis by four main income areas: low, moderate, middle, and high in Tables (1.6-1.9).

[24] FFIEC categorizes Census tracts into the following income groups based on what the Median Family Income (MFI) of a Census tract compared to that of the Metropolitan Statistical Areas (MSA): 1) Low Income, less than 50% of MFI of the MSA; 2) Moderate Income, 50% to 80% of MFI of the MSA; 3) Middle Income, 80% to 120% of MFI of the MSA; 4) Upper Income, greater than or equal to 120% of MFI of the MSA;

By comparing these four tables, it becomes clear that the impact of climate vulnerability is heterogeneous across income groups. In terms of the frequency of lending to small-medium farms, the impact is consistent across income areas. Moreover, as shown in Table (1.9), conditional on being located in high income area, farms generally experience limited or insignificant impact of climate vulnerability on lending, with the exception of lending frequency to smaller farms. This makes intuitive sense in that such high income areas may have more resources available that improve farms' financial resilience to adverse shocks.

When looking at the farms in low and moderate income areas, however, the results in Tables (1.6-1.7) are seemingly surprising. Conditional on being in these areas, large farms do not experience significant impact. Moreover, even for smaller farms, higher climate vulnerability largely do not contribute to lower amount of loans. One plausible explanation is that to meet CRA requirements, banks need to ensure that they provide funding to farms located in low- and moderate-income communities. Therefore, such lending activities are less sensitive to changing climate vulnerabilities.

In contrast, it seems that farms located in middle income areas are most affected by climate vulnerabilities. Compared with farms in high-income areas, they may not have as much financial resource to respond to climate change. Moreover, since banks are not mandated to maintain certain lending activities in middle income areas, they make lending decisions more purely based on their assessments of farms' terminal values in relation to climate vulnerabilities. In this case and consistent with Table (1.5), smaller farms are less likely to receive financing when climate risks increase. Put

Table 1.5: CRA Farm Loans and Climate Vulnerability, All 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	-0.20***	-13.99***	1.10***	18.43***
	(0.04)	(2.91)	(0.10)	(5.87)
Temp. anomaly (square)	0.08***	6.27***	-0.52***	-7.04***
	(0.02)	(1.12)	(0.04)	(2.43)
Observations	160,137	160,137	160,137	160,137
R-squared	0.111	0.045	0.075	0.027
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Income Area 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 (1.13), $y_{ict} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ict}$. Table (1.5) has greater number of observations than the sum of Tables (1.6)-(1.9), as there are Census tracts that are uncategorizable by income

Table 1.6: 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 (1.13), $y_{ict} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ict}$, but only for the sample of low income areas.

another way, the variations within the middle income areas are driving the results in Table (1.5).

Table 1.7: 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 1.8: 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 1.9: 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 1.7 to 1.9 is Equation (1.13), $y_{ict} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ict}$, and for the sample of moderate income area, middle income area, and high income area respectively.

Extension II: Including Bank Branches

One challenge of empirically estimating the impact of climate change is that it affects almost all activities in the economy. Thus it is difficult to justify using variables such as GDP growth and unemployment rate, often used as control variables, as they do not have exogenous variation in relation to climate change variables. At the same time, it could be problematic to completely ignore bank-related variables. The presence of bank branches may be able to explain variation in lending, and the opening and closing of branches could be a mechanism through which bank lending responds to climate change. I calculate the deviation of number of branches in each county from its mean (1996-2019), using the Summary of Deposits (SOD) dataset. This procedure of centering data also minimizes the issue of multicollinearity between climate and branch variables.

The econometric specification is the following:

$$\begin{aligned} y_{it} =& \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 branch_{it} + \theta_2 T_{it} \cdot branch_{it} + \theta_3 T_{it}^2 \cdot branch_{it} \\ &+ u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it} \end{aligned} \tag{1.14}$$

where $branch_{it}$ is the deviation of each county's bank presence from its historical mean. $T_{it} \cdot branch_{it}$ is the interaction term between high temperature anomaly and the bank branch variable, and $T_{it}^2 \cdot branch_{it}$ is the interaction of squared temperature anomaly and bank branch.

Table (1.10) presents the results. In terms of the coefficients for temperature, there are no noticeable differences between the estimation here and that in the baseline in Table (1.4). As shown by the row of "total number of bank branches," the more bank presence there is, the more CRA lending there is across all types of farms. This makes intuitive sense. What is interesting, however, is that the interaction effects between temperature anomaly and bank branches are largely negative. This means that given the same temperature anomaly, counties with more bank branches tend to have less CRA lending. This interaction effect is significant for the number of loans to both large and small-medium farms. This suggests bank presence, as measured by bank branches, may serve as an amplification mechanism of climate change risks into lending.

Table 1.10: CRA Farm Loans and Climate Vulnerability, Interaction with Bank Branch

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	-0.14*	-16.33***	1.54***	11.40
	(0.08)	(5.89)	(0.19)	(10.26)
Temp. anomaly (square)	0.02	4.54**	-0.85***	-10.81***
	(0.03)	(1.95)	(0.08)	(3.98)
Num. bank branches	0.21***	3.05***	0.22***	4.40***
	(0.02)	(1.16)	(0.04)	(1.58)
Temp. anomaly x Branches	-0.01	-0.61	-0.02	-0.80
	(0.01)	(0.45)	(0.03)	(0.55)
Temp. anomaly (square) x Branches	-0.01***	0.29	-0.03***	0.30
	(0.00)	(0.37)	(0.01)	(0.52)
Observations	72,447	72,447	72,447	72,447
R-squared	0.204	0.143	0.134	0.058
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 (1.14), $y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 branch_{it} + \theta_2 T_{it} \cdot branch_{it} + \theta_3 T_{it}^2 \cdot branch_{it} + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$

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 (1.11) 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 (1.12) 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 (1.11). 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

Table 1.11: CRA Farm Loan Amount and Climate Vulnerability, Loan Size Bracket

	(1)	(2)	(3)	(4)
VARIABLES	Total Amt.	Amount (less 100k)	Amount (100k to 250k)	Amount (250k to 500k)
Temp. anomaly	-4.93	18.48***	0.99	-24.40***
	(12.75)	(3.98)	(4.77)	(6.60)
Temp. anomaly (square)	-6.27	-13.56***	-1.58	8.87***
	(4.96)	(1.45)	(1.85)	(2.56)
Num. bank branches	7.45***	6.87***	0.34	0.24
	(2.46)	(1.28)	(0.66)	(1.41)
Temp. anomaly x Branches	-1.41	-0.15	-0.41	-0.85*
	(0.87)	(0.32)	(0.27)	(0.46)
Temp. anomaly (square) x Branches	0.58	-0.53***	0.43	0.68
	(0.85)	(0.10)	(0.28)	(0.60)
Observations	72,447	72,447	72,447	72,447
R-squared	0.090	0.054	0.072	0.125
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 (1.14), $y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 branch_{it} + \theta_2 T_{it} \cdot branch_{it} + \theta_3 T_{it}^2 \cdot branch_{it} + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$, where y_{it} is the loan variable based on loan size bracket.

in Column (1). In contrast to Table (1.11), in terms of number of loans, Table (1.12) shows that there does not seem to be substitution between different sizes of lending. Rather, climate change, measured in terms of increasing high temperature anomaly, has overall negative impact on the total number of loans.

Table 1.12: CRA Farm Loan Frequency and Climate Vulnerability, Loan Size Bracket

VARIABLES	(1) Total Num.	(2) Number (less 100k)	(3) Number (100k to 250k)	(4) Number (250k to 500k)
Temp. anomaly	1.40***	1.30***	0.13***	-0.02
	(0.21)	(0.18)	(0.03)	(0.02)
Temp. anomaly (square)	-0.83***	-0.78***	-0.06***	0.01
	(0.08)	(0.07)	(0.01)	(0.01)
Num. bank branches	0.43***	0.44***	-0.00	-0.01
	(0.04)	(0.04)	(0.01)	(0.01)
Temp. anomaly x Branches	-0.03	-0.03	-0.00	-0.00**
	(0.04)	(0.04)	(0.00)	(0.00)
Temp. anomaly (square) x 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 (1.14), $y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 branch_{it} + \theta_2 T_{it} \cdot branch_{it} + \theta_3 T_{it}^2 \cdot branch_{it} + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$, where y_{it} is the loan variable based on loan size bracket.

Extension III: Distributed Lag Model

In the chapter 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.

$$y_{it} = \sum_{l=0}^{2} (\beta_l T_{i,t-l}) + \sum_{m=0}^{2} \left(\theta_m T_{i,t-m}^2\right) + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it} \quad (1.15)$$

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

$$\sum_{l=0}^{2} \beta_l + \sum_{m=0}^{2} \theta_m = \beta_0 + 2\theta_0 T^* + \beta_1 + 2\theta_1 T^* + \beta_2 + 2\theta_2 T^* \tag{1.16}$$

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 (1.15) are shown is Table (1.13). 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 (1.16), 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 21.55 for the amount of loans. For small-medium farms, the effect is -0.92 for number of loans, and is -4.48 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 $4,480. 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 $118,160. 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

Table 1.13: 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
Temp. anomaly	-0.20**	-22.80***	1.93***	-30.97***
	(0.10)	(7.00)	(0.21)	(12.01)
Temp. anomaly (lag)	0.11	-20.48***	1.93***	22.41**
	(0.07)	(5.15)	(0.17)	(9.71)
Temp. anomaly (2 lags)	0.05	-6.65	1.88***	60.71***
	(0.07)	(5.08)	(0.19)	(9.65)
Temp. anomaly (square)	0.08**	12.83***	-1.31***	1.40
	(0.04)	(2.55)	(0.10)	(5.05)
Temp. anomaly (square, lag)	0.09**	12.69***	-1.29***	-18.04***
	(0.04)	(2.42)	(0.10)	(4.59)
Temp. anomaly (square, 2 lags)	0.03	10.14***	-0.74***	-11.78***
	(0.03)	(2.37)	(0.09)	(4.37)
Observations	66,622	66,622	66,622	66,622
R-squared	0.201	0.135	0.161	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

Note: Regression specification for this table is Equation (1.15), $y_{it} = \sum_{l=0}^{2}\left(\beta_l T_{i,t-l}\right) + \sum_{m=0}^{2}\left(\theta_m T_{i,t-m}^2\right) + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it}$

both number and amount of lending. As the results in Tables (1.11) and (1.12) 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 chapter 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.

Extension IV: 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 (1.8), 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 (1.12), 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 (1.9). Compare with Figure (1.7), 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).

By matching each county with its region category, I also run the regression

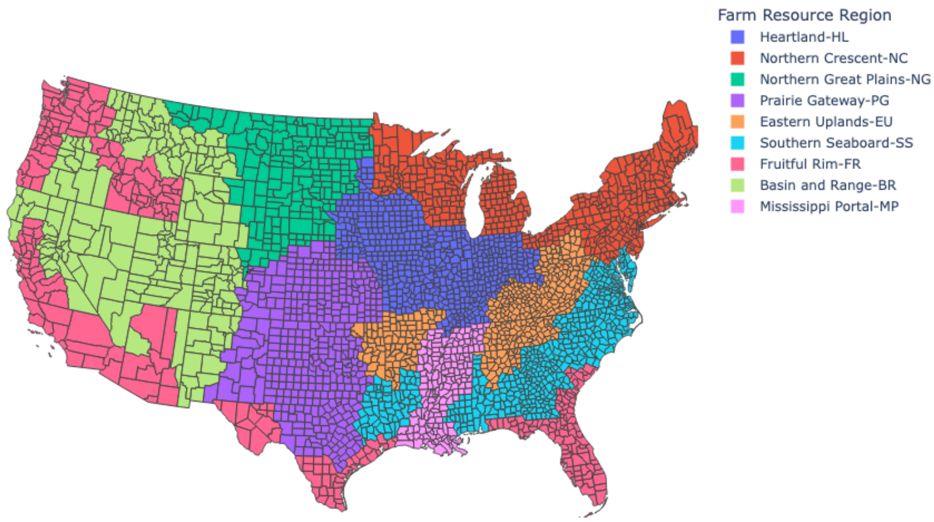


Figure 1.8: Farm Resource Regions
Source: USDA ERS

specified in Equation (1.15) 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.

The regression tables for individual regions are all reported in Appendix 1.6. Here I focus on discussing the cumulative effects, calculated using Equation (1.16). Table (1.14) 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 (1.13), 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.

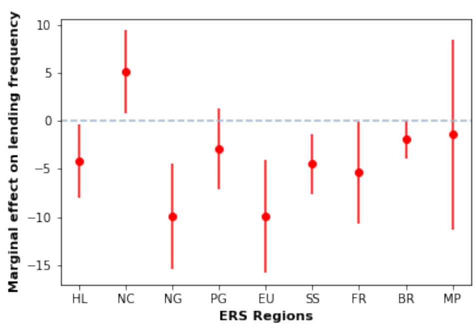
Table (1.14) illustrates the regional heterogeneity of bank lending, and is broadly consistent with the national results in Table (1.13): 1) The effect of climate change on lending to small-medium farms is generally negative; 2) In contrast, large farms seem to fare better; 3) There seems to be shift 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; 4) The overall magnitude is more pronounced in the Northern Great Plains and the whole Fruitful Rim.

Table 1.14: Cumulative Effects of 3 Fahrenheit Degrees of High Temp. Anomaly

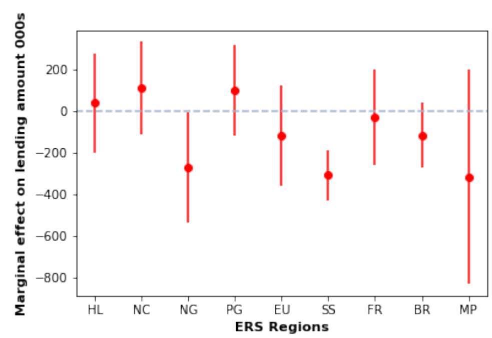
Region	(1) **Num. to large**	(2) **Amount to large**	(3) **Num. to small-mid**	(4) **Amount to small-mid**
Heartland	2.4	-41.41	-6.45	548.94
Northern Crescent	2.27	157.19	8.22	242.78
Northern Great Plains	4.24	452.63	-25.17	-481.88
Prairie Gateway	-4.5	-108.52	-10.46	4
Eastern Uplands	-0.53	125.15	-9.25	208.71
Southern Seaboard	-5.49	-215.23	-8.3	-603.25
Fruitful Rim (TX and FL)	-4.82	111.55	-17.48	-704.21
Fruitful Rim (remaining)	-13.96	-522.88	-12.78	-871.94
Basin and Range	-1.79	-145.69	-8.21	-579.41
Mississippi Portal	3.91	43.11	-2.54	-528.34

Note: Results calculated using Equation (1.16), $\sum_{l=0}^{2}\beta_l + \sum_{m=0}^{2}\theta_m = \beta_0 + 2\theta_0 T^* + \beta_1 + 2\theta_1 T^* + \beta_2 + 2\theta_2 T^*$

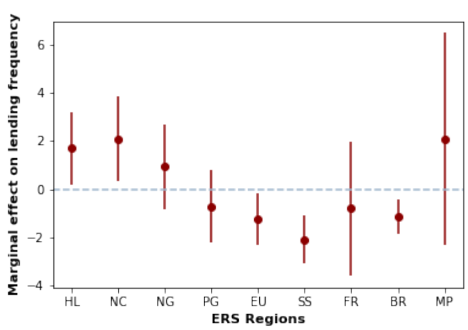
Figure 1.9: Marginal Effect of Temperature on CRA Lending, Regional Heterogeneity



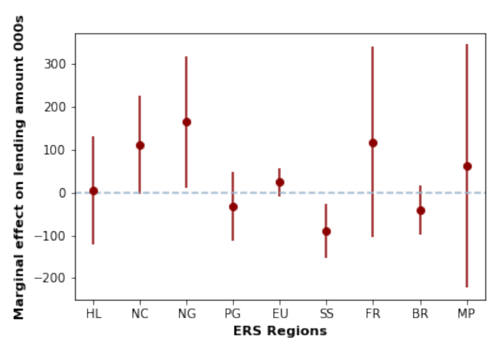
(a) Frequencies to Small-Medium Farms



(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 $^{\circ}C/$ 3.96$^{\circ}F$. Marginal effects with 95% confidence intervals, calculated based on Equation (1.12); 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.

1.4.3 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.[25] 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[26]: 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

[25] 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.

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

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.[27]

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.

Taking into account the interaction between bank size and temperature anomaly,

[27] 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 & 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

the econometric specification in this section is

$$\begin{aligned} y_{ibt} =& \beta_1 T_{it} + \beta_2 T_{it}^2 + (a_1 + a_2 T_{it} + a_2 T_{it}^2) small + (b_1 + b_2 T_{it} + b_3 T_{it}^2) medium \\ &+ (c_1 + c_2 T_{it} + c_3 T_{it}^2) large + u_i + \psi_b + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ibt} \end{aligned} \tag{1.17}$$

Compared with Equation (1.11), the main difference of Equation (1.17) 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 (1.17) is at the loan bracket level, and the results for the effects on loan origination frequencies are illustrated in Figure (1.10). Due to the interpretation challenge posed by the multitude of interaction terms, the full results of the regressions are reported in Table (1.52) in Appendix, where the vast majority of main and interaction terms are highly significant. To facilitate interpretation, I estimate the average marginal effects, reported in Figure (1.10).[28]

In response to climate risks, the contrast between how banks make 100k loans and the other two brackets is stark. As shown by the first row of graphs of Figure

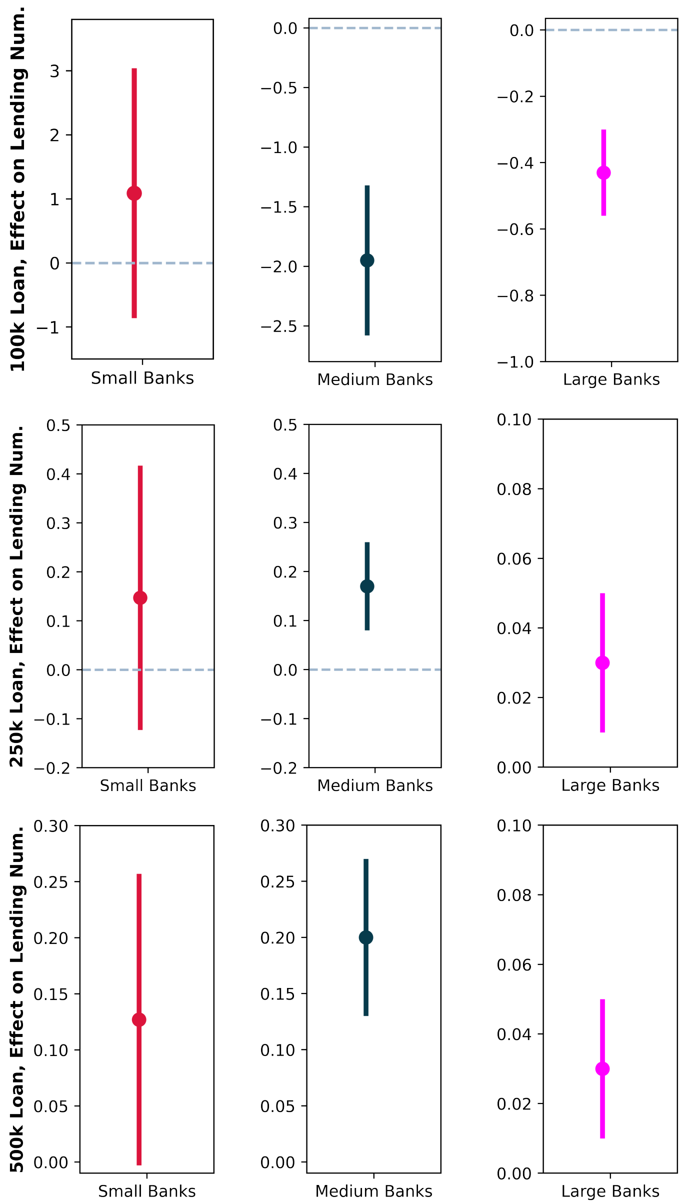
[28]The calculation procedure is similar to that in Equation (1.12). Note due to the peculiarity of how Stata calculates marginal effects, there may be slight differences between the results reported in the graph and those calculated by hand.

(1.10), 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 (1.10) 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 (1.54) in Appendix. Figure (1.11) illustrates the estimates of average marginal effects, and the results are consistent with Figure (1.10) in terms

Figure 1.10: Marginal Effect of Temperature Anomaly on CRA Lending Frequency, by Loan Size

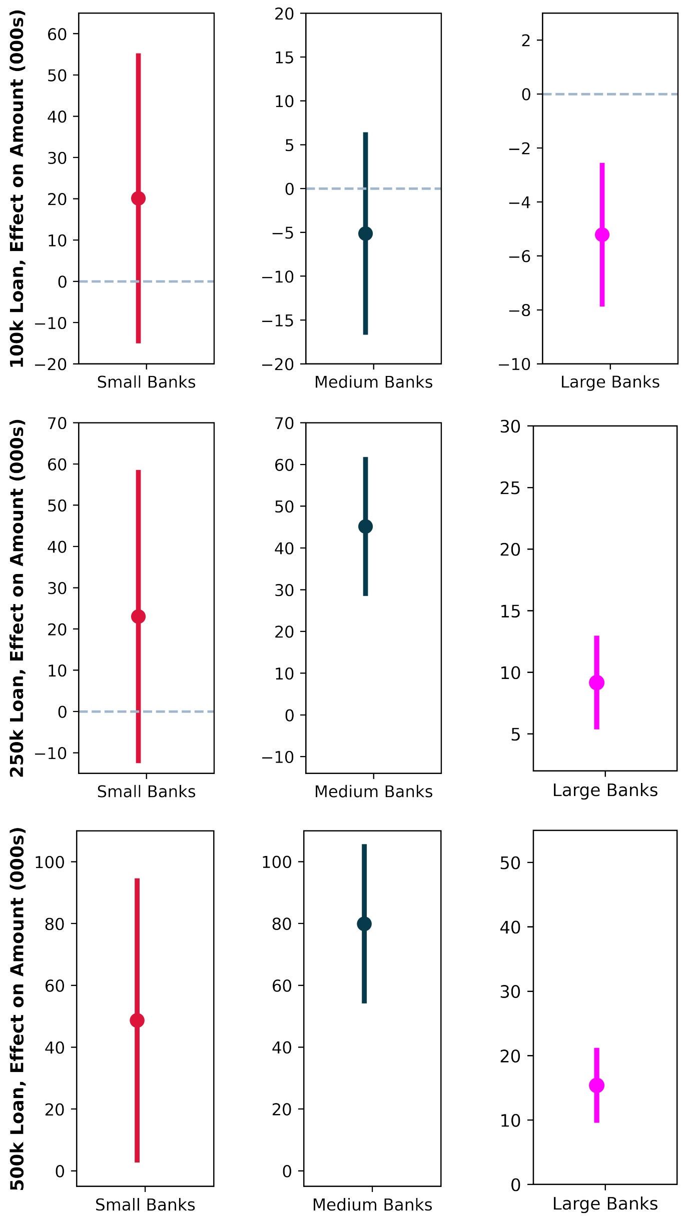


Note: Average marginal effects with 95% confidence intervals, assuming a temperature anomaly of 2.8 $^{\circ}C/$ 5.04$^{\circ}F$. This is consistent with an adverse climate scenario, or'3X CO2 by 2100' (SSP5-8.5). The regression results corresponding to this graph are in Table (1.52) in Appendix

of the directions of impact.

With the results of loan size providing contexts, I use Equation (1.17) to run

Figure 1.11: 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 (1.53) in Appendix regressions on the loans to small and large farms. The results of loan frequencies are illustrated in Figure (1.12), and those of loan magnitudes shown in Figure (1.13) (regression results shown in Table (1.54) in Appendix; most of the main and interaction coefficients are significant). Additionally, the results are estimated for two climate scenarios: moderate and severe.

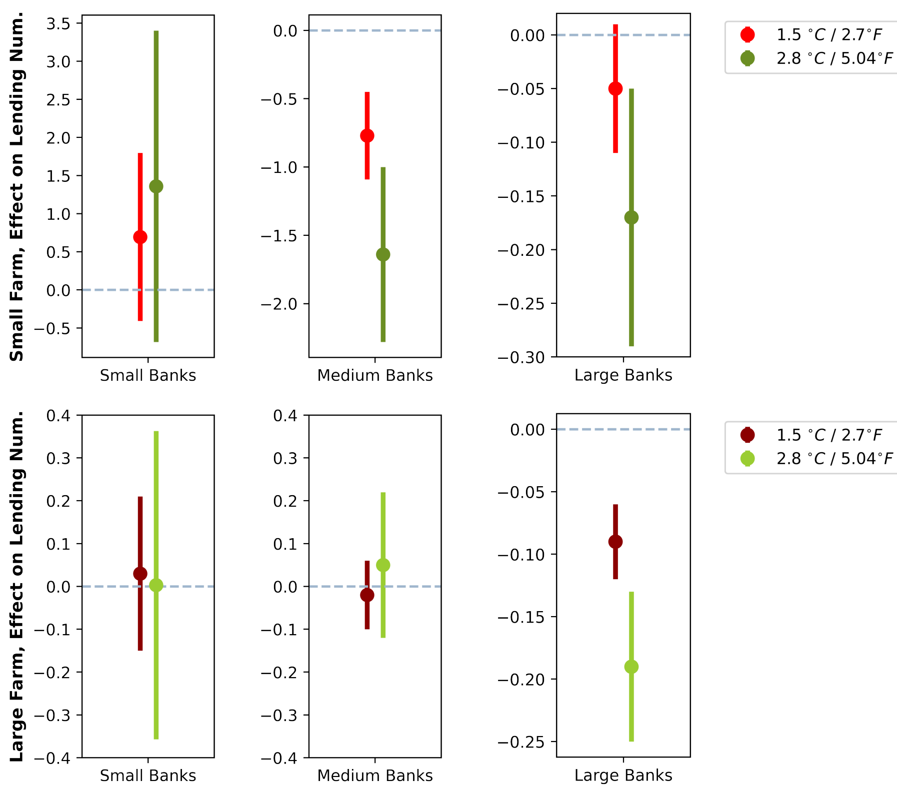
The first row of Figure (1.12) illustrates the results for small farms, while the second row shows the results for large farms. For small farms, the contraction of lending frequencies from medium and large banks are noticeable, and the magnitude of impact from medium banks is particularly large. Small 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.

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 (1.13) shows the results for the estimation of lending magnitudes. 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, 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. In comparison, the bank-county level estimation largely shows the effect *conditional on* the loans already being approved. The qualitative model of the chapter 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 (1.13). 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.

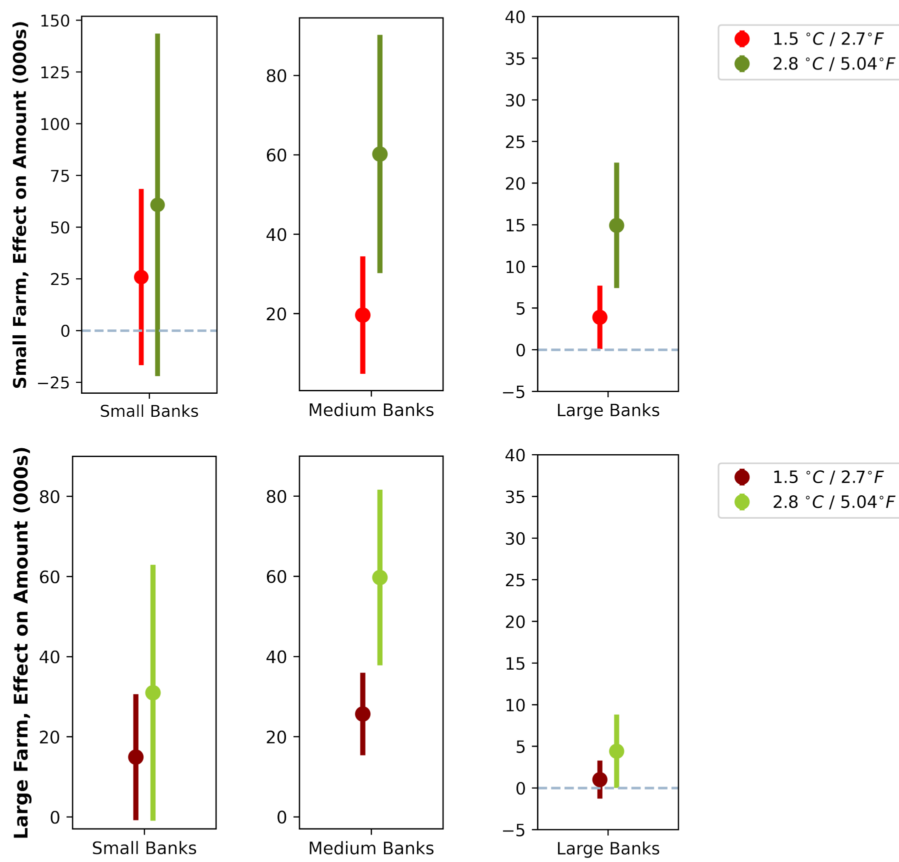
Besides the aforementioned results, I have estimated additional regressions separately for three groups of banks: very small, small-mid, and large. For the sake of brevity, Tables (1.55-1.57) appear in the Appendix. The results are largely the same as

Figure 1.12: 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 $^{\circ}C/$ 2.7$^{\circ}F$; ii). temperature anomaly of 2.8 $^{\circ}C/$ 5.04$^{\circ}F$; 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 (1.54) in Appendix.

Figure 1.13: 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 $^{\circ}C/$ 2.7$^{\circ}F$; ii). temperature anomaly of 2.8 $^{\circ}C/$ 5.04$^{\circ}F$; 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 (1.54) in Appendix.

in the estimations with bank dummies and interaction effects.[29]

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 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.

Extension: 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

$$y_{ibct} = \beta_1 T_{it} + \beta_2 T_{it}^2 + u_i + \psi_b + \xi_c + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{ibct} \quad (1.18)$$

[29]Tables (1.55-1.57) show results from the estimation, with bank-level fixed effects included. As seen in Table (1.55), 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 (1.56) 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.

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.

Tables (1.58-1.60) show the results for all income groups, estimated by bank sizes[30], which are mostly identical to the results in Tables (1.55-1.57). 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 1.4.2, 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 1.4.2 are at county level. This pattern continues to hold here at bank-county-income group level, as seen in Tables (1.61-1.63) for middle income areas, and additional tables in Appendix 1.6.

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.[31]

[30] 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)

[31] 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.

1.5 Conclusion and Discussions

In this chapter, I answer the question of how exposure to climate change risks affect farms' financial access. The causal effect exists because extreme temperature and disasters reduce farms' output and revenue, and therefore increase their likelihood of defaulting on bank loans. By designing a two-period model, I show that farm size matters in modulating such impact: it is more likely for smaller farms to lose financial access. Then using data from the Community Reinvestment Act (CRA), the empirical estimation shows that vulnerability to climate change indeed has negative and significant impact on bank lending to farms, and such effects are nonlinear. Moreover, the financial impact on large farms is negligible or at times positive. In contrast, small to medium farms generally suffer from loss of credit access.

In addition to the overall patterns by farm size, I also present additional granular results based on bank type, region, and income area. Banks' own size also acts as a mechanism in determining the frequencies and amount of lending. Large banks tend to lend less frequently altogether in risky counties, and likely move their operations elsewhere. Medium banks are less willing to lend to small farms, and are in fact more wiling to lend to large farms as climate risks increase. Due to their highly localized operations, very small banks maintain and even increase lending to small farms. There is a range of regional heterogeneity as well. In particular, the magnitudes of effect are large in parts of the Midwest, southwestern, and southeastern states. Moreover, the income areas where farms are located also matter, and the impact is more pronounced in middle income areas.

While it is difficult to directly test whether there is diversion of lending from smaller farms to large farms, the results suggest there is such evidence, particularly observed by the lending behavior of medium banks. In short, it is not necessarily the case that all banks reduce lending completely as climate risks increase. Rather, banks reassess and readjust their lending strategies to minimize potential loss and maximize profits. Consequently, with the advantages of size and higher productivity, large farms are less vulnerable to the adverse financial impact, while smaller farms are not. Though focusing on farm lending, the results of the chapter suggest the financial impact of climate change may hit smaller stakeholders the hardest. This calls for further research not only in bank lending but in other financial issues such as insurance premium. Deeper understandings of such inequity are necessary to broaden communities' financial access to improve their climate resilience.

1.6 Appendix

Additional Figure

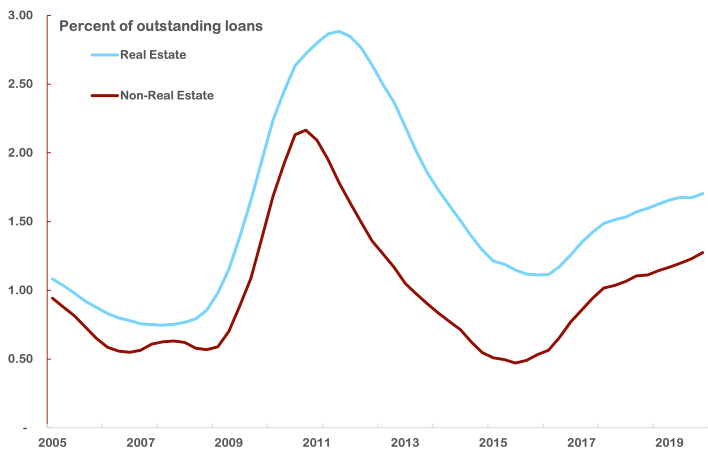


Figure 1.14: Non-Performing Farm Loans at U.S. Commercial Banks

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

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

Appendix: Summary Statistics

Table 1.15: 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 1.16: 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

Appendix: Robustness Check: Including Precipitation

Besides temperature anomaly, precipitation anomaly is another measurement of climate change. In Burke & 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.

$$y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \theta_1 P_{it} + \theta_2 P_{it}^2 + u_i + \eta_t + \lambda_{rt} + \gamma_i trend + \gamma_{i2} trend^2 + e_{it} \quad (1.19)$$

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 (1.11).

Table (1.17) 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 Column (1) 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 chapter, I focus on using high temperature anomaly to measure climate change.

Table 1.17: 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
Temp. anomaly	-0.09	-13.38**	1.34***	15.21
	(0.09)	(5.93)	(0.20)	(11.08)
Temp. anomaly (square)	0.02	4.21**	-0.85***	-11.43***
	(0.03)	(1.94)	(0.08)	(3.88)
Precip. anomaly	0.24**	10.53	-0.75**	18.88
	(0.12)	(8.32)	(0.34)	(16.14)
Precip. anomaly (square)	-0.11	8.08	-0.63***	32.15***
	(0.08)	(5.47)	(0.22)	(10.17)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.141	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

Appendix: 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 1.11. Tables (1.18) and (1.19) show the results. For small-medium farms, a temperature anomaly shock seems more costly during the growing season, as the coefficients for the amount of loans are both negative, indicating that both the first and second effects are negative. 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 1.18: 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
Temp. anomaly (season)	-0.33***	-20.91***	1.13***	-25.45***
	(0.07)	(5.00)	(0.17)	(9.42)
Temp. anomaly (square, season)	-0.01	3.97***	-0.67***	-8.96***
	(0.02)	(1.50)	(0.06)	(3.10)
Observations	72,834	72,834	72,834	72,834
R-squared	0.195	0.142	0.133	0.058
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 1.19: 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
Temp. anomaly (non-season)	0.11**	-1.70	0.66***	28.40***
	(0.04)	(3.06)	(0.12)	(5.20)
Temp. anomaly (square, non-season)	0.01	-0.20	-0.22***	-5.11***
	(0.01)	(0.83)	(0.03)	(1.72)
Observations	72,834	72,834	72,834	72,834
R-squared	0.194	0.142	0.132	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

Appendix: Estimations by Loan Size Brackets

Table 1.20: Amount of CRA Farm Loans and Climate Disasters, County Total

VARIABLES	(1) Total Amount	(2) Amount of loan (less 100k)	(3) Amount of loan (100k to 250k)	(4) Amount of loan (250k to 500k)
Coastal Storm	-185.61	-18.55	-43.76	-123.31**
	(123.55)	(38.53)	(50.51)	(62.10)
Flood	-29.79	-32.62*	-31.16	33.99
	(60.51)	(17.46)	(22.20)	(29.04)
Freezing (lagged)	566.26*	206.57	195.28**	164.41
	(339.66)	(196.23)	(86.55)	(153.15)
Hurricane	-150.14***	-42.95***	-43.88***	-63.31***
	(19.86)	(7.30)	(7.52)	(9.37)
Landslide	-1,120.54***	-86.12**	-309.04***	-725.38***
	(184.29)	(42.23)	(52.82)	(122.79)
Ice storm (lagged)	-47.33	-6.48	-13.26	-27.58
	(42.53)	(16.04)	(16.09)	(19.53)
Storm	-80.56***	-16.93**	-19.73**	-43.90***
	(23.86)	(8.02)	(8.97)	(11.50)
Snow (lagged)	-8.58	-75.37***	14.23	52.55*
	(58.34)	(17.23)	(23.07)	(28.61)
Tornado	218.18	79.14	90.52	48.52
	(164.14)	(54.23)	(59.34)	(83.63)
Observations	69,728	69,728	69,728	69,728
R-squared	0.082	0.049	0.063	0.118
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 1.21: Number of CRA Farm Loans and Climate Disasters, County Total

VARIABLES	(1) Total Number	(2) Number of loan (less 100k)	(3) Number of loan (100k to 250k)	(4) Number of loan (250k to 500k)
Coastal Storm	1.68	1.96	-0.12	-0.16
	(2.17)	(1.93)	(0.34)	(0.18)
Flood	-2.52***	-2.17***	-0.36***	0.00
	(0.89)	(0.76)	(0.14)	(0.08)
Freezing (lagged)	18.07	15.38	1.81**	0.88*
	(16.33)	(16.05)	(0.78)	(0.48)
Hurricane	-1.48***	-1.15***	-0.19***	-0.14***
	(0.37)	(0.34)	(0.05)	(0.03)
Landslide	-0.01	2.01	-0.58	-1.44***
	(1.94)	(1.43)	(0.60)	(0.38)
Ice storm (lagged)	0.71	0.67	0.06	-0.02
	(0.96)	(0.89)	(0.11)	(0.06)
Storm	-1.79***	-1.58***	-0.11*	-0.10***
	(0.47)	(0.42)	(0.06)	(0.03)
Snow (lagged)	-5.63***	-5.51***	-0.15	0.03
	(0.99)	(0.88)	(0.16)	(0.08)
Tornado	2.26	1.35	0.77*	0.13
	(2.82)	(2.51)	(0.40)	(0.24)
Observations	69,728	69,728	69,728	69,728
R-squared	0.080	0.086	0.045	0.067
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

Appendix: Dropping Years 2008 and 2009

Table 1.22: Number of CRA Farm Loans and Climate Disasters, County Total

	(1)	(2)	(3)	(4)
VARIABLES	Num. of loans to large farms	Amount of loans to large farms	Num. of loans to small-medium farms	Amount of loans to small-medium farms
Coastal Storm	1.81**	-14.46	0.28	-168.37
	(0.74)	(49.11)	(1.96)	(106.49)
Flood	-0.79***	0.70	-1.97**	-17.29
	(0.30)	(25.44)	(0.81)	(44.87)
Freezing (lagged)	-9.08**	-434.70*	-15.59***	-163.66
	(3.70)	(248.16)	(5.70)	(295.25)
Hurricane	-0.95***	-47.45***	0.04	-87.70***
	(0.16)	(8.71)	(0.30)	(15.71)
Landslide	-7.93***	-521.70***	8.94***	-597.17***
	(1.79)	(110.49)	(3.31)	(105.82)
Ice storm (lagged)	-0.81***	-51.25***	3.75***	19.78
	(0.27)	(18.65)	(1.17)	(48.01)
Storm	-0.34**	-52.27***	-0.81	-24.00
	(0.14)	(10.41)	(0.50)	(21.76)
Snow (lagged)	0.31	11.43	-4.31***	61.26
	(0.24)	(20.69)	(1.02)	(49.51)
Tornado	-1.38**	-0.24	3.48	211.89
	(0.69)	(63.11)	(2.79)	(132.12)
Observations	63,642	63,642	63,642	63,642
R-squared	0.214	0.146	0.142	0.054
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 1.23: Number of CRA Farm Loans and Climate Disasters, County Total

VARIABLES	(1) Total Amount	(2) Amount of loan (less 100k)	(3) Amount of loan (100k to 250k)	(4) Amount of loan (250k to 500k)
Coastal Storm	-182.83	-17.29	-43.00	-122.54*
	(127.15)	(40.40)	(51.53)	(62.95)
Flood	-16.59	-31.83*	-25.19	40.43
	(60.56)	(17.40)	(22.16)	(29.48)
Freezing (lagged)	-598.36	-370.74**	84.46	-312.09
	(446.00)	(160.95)	(131.94)	(234.00)
Hurricane	-135.15***	-39.14***	-41.40***	-54.62***
	(19.99)	(7.39)	(7.67)	(9.53)
Landslide	-1,118.86***	-80.25*	-310.12***	-728.49***
	(185.08)	(41.38)	(51.63)	(122.75)
Ice storm (lagged)	-31.47	8.26	-10.50	-29.23
	(55.10)	(19.20)	(20.67)	(25.84)
Storm	-76.27***	-7.40	-19.63*	-49.23***
	(26.52)	(9.10)	(10.06)	(12.60)
Snow (lagged)	72.68	-46.08***	39.94*	78.83***
	(60.19)	(17.82)	(23.97)	(29.40)
Tornado	211.64	73.64	92.09	45.91
	(165.72)	(54.87)	(60.62)	(83.91)
Observations	63,642	63,642	63,642	63,642
R-squared	0.086	0.050	0.066	0.124
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 1.24: Number of CRA Farm Loans and Climate Disasters, County Total

VARIABLES	(1) Total Number	(2) Number of loan (less 100k)	(3) Number of loan (100k to 250k)	(4) Number of loan (250k to 500k)
Coastal Storm	2.09	2.36	-0.11	-0.16
	(2.25)	(2.00)	(0.35)	(0.18)
Flood	-2.77***	-2.47***	-0.32**	0.03
	(0.90)	(0.77)	(0.14)	(0.08)
Freezing (lagged)	-24.67***	-26.43***	1.70	0.06
	(8.18)	(7.69)	(1.15)	(0.46)
Hurricane	-0.91**	-0.64*	-0.16***	-0.10***
	(0.36)	(0.33)	(0.05)	(0.03)
Landslide	1.01	3.01**	-0.56	-1.44***
	(1.98)	(1.45)	(0.59)	(0.39)
Ice storm (lagged)	2.94**	2.86***	0.10	-0.02
	(1.20)	(1.10)	(0.15)	(0.08)
Storm	-1.15**	-0.95**	-0.09	-0.11***
	(0.53)	(0.48)	(0.07)	(0.04)
Snow (lagged)	-4.00***	-4.12***	0.02	0.10
	(1.04)	(0.93)	(0.17)	(0.08)
Tornado	2.09	1.17	0.79*	0.14
	(2.84)	(2.53)	(0.40)	(0.24)
Observations	63,642	63,642	63,642	63,642
R-squared	0.078	0.084	0.046	0.071
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 1.25: Number of CRA Farm Loans 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	-0.18**	-11.39*	1.18***	11.81
	(0.08)	(6.39)	(0.20)	(10.75)
High temperature anomaly (square)	0.00	3.46*	-0.84***	-11.40***
	(0.03)	(1.94)	(0.08)	(3.83)
Observations	66,748	66,748	66,748	66,748
R-squared	0.203	0.149	0.134	0.060
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 1.26: Number of CRA Farm Loans 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	-0.15*	-10.85*	1.05***	14.48
	(0.09)	(6.44)	(0.21)	(11.42)
High temperature anomaly (square)	0.01	3.41*	-0.84***	-11.78***
	(0.03)	(1.94)	(0.08)	(3.79)
Precipitation anomaly	0.13	3.58	-0.76**	18.93
	(0.12)	(8.67)	(0.35)	(17.02)
Precipitation anomaly (square)	-0.12	5.32	-0.69***	33.12***
	(0.08)	(5.56)	(0.22)	(10.58)
Observations	66,748	66,748	66,748	66,748
R-squared	0.203	0.149	0.134	0.060
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

Appendix: Using Min Temperature and Seasonal Effect

Table 1.27: CRA Farm Loans 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
Low temperature anomaly	-0.34***	-29.12***	1.30***	-15.83
	(0.11)	(7.10)	(0.25)	(15.61)
Low temperature anomaly (square)	-0.24***	-10.93***	-0.13	-43.81***
	(0.05)	(2.75)	(0.12)	(5.29)
Observations	72,834	72,834	72,834	72,834
R-squared	0.195	0.143	0.132	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 1.28: CRA Farm Loans 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
Temperature anomaly (max and min combined)	-0.15**	-18.23***	1.35***	4.22
	(0.07)	(4.94)	(0.18)	(10.81)
Temperature anomaly, square (max and min combined)	-0.01	11.25***	-1.06***	-13.73***
	(0.03)	(2.15)	(0.09)	(4.42)
Observations	72,834	72,834	72,834	72,834
R-squared	0.194	0.142	0.134	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

Note: The temperature measure here uses maximum temperature for spring and summer, and minimum temperature for fall and winter

Table 1.29: CRA Farm Loans 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
Temperature anomaly (min and max combined)	-0.34***	-29.90***	1.79***	-6.12
	(0.08)	(5.93)	(0.21)	(12.37)
Temperature anomaly, square (min and max combined)	-0.17***	-10.44***	-0.60***	-41.20***
	(0.04)	(2.86)	(0.10)	(5.82)
Observations	72,834	72,834	72,834	72,834
R-squared	0.194	0.143	0.133	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

Note: The temperature measure here uses minimum temperature for spring and summer, and maximum temperature for fall and winter

Table 1.30: CRA Farm Loans 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
Max temp. anomaly (winter)	0.01	-6.56***	0.93***	1.97
	(0.03)	(2.21)	(0.09)	(4.54)
Max temp. anomaly (square, winter)	-0.05***	-3.92***	0.03	-6.43***
	(0.01)	(0.72)	(0.02)	(1.37)
Observations	72,834	72,834	72,834	72,834
R-squared	0.195	0.143	0.132	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 1.31: CRA Farm Loans 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
Max temp. anomaly (spring)	-0.09**	-2.62	0.05	28.05***
	(0.04)	(2.90)	(0.09)	(4.92)
Max temp. anomaly (square, spring)	0.06***	2.39***	-0.24***	-3.97***
	(0.01)	(0.72)	(0.02)	(1.10)
Observations	72,834	72,834	72,834	72,834
R-squared	0.195	0.142	0.132	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 1.32: CRA Farm Loans 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
Max temp. anomaly (summer)	-0.09	-10.76***	0.24*	-17.84**
	(0.06)	(3.75)	(0.13)	(6.96)
Max temp. anomaly (square, summer)	0.03**	3.34***	-0.05	3.20**
	(0.01)	(0.83)	(0.03)	(1.57)
Observations	72,834	72,834	72,834	72,834
R-squared	0.194	0.142	0.131	0.058
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 1.33: CRA Farm Loans 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
Max temp. anomaly (fall)	-0.21***	-12.55***	0.43***	-22.92***
	(0.06)	(3.87)	(0.13)	(7.04)
Max temp. anomaly (square, fall)	-0.04***	-0.84	-0.27***	-11.05***
	(0.01)	(1.03)	(0.04)	(1.98)
Observations	72,834	72,834	72,834	72,834
R-squared	0.195	0.142	0.132	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

Appendix: Lagged and Growth Effect

Table 1.34: CRA Farm Loans and Climate Vulnerability (Lagged), 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***	-4.55	1.65***	54.43***
	(0.07)	(5.30)	(0.18)	(9.43)
High temperature anomaly (square, lag)	-0.00	2.19	-0.94***	-28.14***
	(0.03)	(1.84)	(0.08)	(3.66)
Observations	69,728	69,728	69,728	69,728
R-squared	0.202	0.138	0.142	0.053
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 1.35: 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***	2.57	-0.54***	-5.60
	(0.06)	(4.14)	(0.13)	(7.91)
High temperature anomaly (square)	0.07**	-2.90*	0.01	-1.28
	(0.03)	(1.73)	(0.04)	(2.75)
Observations	69,728	69,728	69,728	69,728
R-squared	0.053	0.029	0.049	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 1.36: 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***	4.10	0.13	2.13
	(0.07)	(4.59)	(0.13)	(8.10)
High temperature anomaly (square, lag)	-0.04	-3.10*	-0.03	-7.29**
	(0.03)	(1.70)	(0.05)	(2.91)
Observations	69,728	69,728	69,728	69,728
R-squared	0.053	0.029	0.049	0.042
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

Appendix: Alternative Measures of Temperature Anomaly

Table 1.37: CRA Farm Loans 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 (50 years)	-0.14	-18.91***	2.08***	20.83*
	(0.09)	(6.44)	(0.22)	(11.55)
High temperature anomaly (square, 50 years)	0.00	4.37**	-0.80***	-11.39***
	(0.03)	(1.97)	(0.08)	(3.82)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.141	0.132	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

Table 1.38: CRA Farm Loans 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 (70 years)	-0.16*	-20.79***	2.20***	23.26*
	(0.09)	(6.59)	(0.23)	(11.94)
High temperature aneromaly (square, 70 years)	0.01	5.12**	-0.76***	-11.48***
	(0.03)	(2.01)	(0.07)	(3.76)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.141	0.132	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

Table 1.39: CRA Farm Loans 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 (100 years)	-0.15	-19.84***	2.01***	21.78*
	(0.09)	(6.48)	(0.22)	(11.50)
High temperature anomaly (square, 100 years)	0.01	4.73**	-0.66***	-11.14***
	(0.03)	(1.96)	(0.07)	(3.51)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.141	0.132	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

Table 1.40: CRA Farm Loans 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 (since 1895)	-0.17*	-21.44***	2.12***	24.70**
	(0.10)	(6.76)	(0.23)	(12.03)
High temperature anomaly (square, since 1895)	0.02	4.82**	-0.61***	-10.79***
	(0.03)	(1.92)	(0.07)	(3.38)
Observations	72,834	72,834	72,834	72,834
R-squared	0.193	0.141	0.132	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

Table 1.41: CRA Farm Loans 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 (1981-2010)	-0.10	-16.61***	1.89***	18.93*
	(0.09)	(6.21)	(0.21)	(11.08)
High temperature anomaly (square, 1981-2010)	-0.03	3.01	-0.76***	-12.00***
	(0.03)	(1.88)	(0.07)	(3.67)
Observations	72,834	72,834	72,834	72,834
R-squared	0.194	0.142	0.133	0.058
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

Appendix: Regression Tables of Regional Heterogeneity

Table 1.42: Heartland, Amount of CRA Farm Loans and Extreme Temperature, 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	0.38	3.64	2.88***	-34.19
	(0.53)	(43.99)	(0.92)	(60.00)
High temperature anomaly (lag)	-0.52*	-23.14	3.78***	113.20**
	(0.29)	(22.72)	(0.91)	(50.76)
High temperature anomaly (two lags)	0.38	70.09***	1.34	258.09***
	(0.31)	(25.55)	(1.06)	(67.93)
High temperature anomaly (square)	0.25**	1.90	-0.92***	25.14
	(0.13)	(10.87)	(0.32)	(19.73)
High temperature anomaly (square, lag)	0.09	-5.26	-1.10***	-1.31
	(0.10)	(8.40)	(0.32)	(17.58)
High temperature anomaly (square, two lags)	0.01	-11.93	-0.39	12.00
	(0.11)	(12.18)	(0.36)	(20.91)
Observations	11,954	11,954	11,954	11,954
R-squared	0.314	0.235	0.249	0.110
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 1.43: Northern Crescent, Amount of CRA Farm Loans and Extreme Temperature, 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	-1.44***	-129.56***	5.20***	151.62**
	(0.29)	(24.72)	(1.20)	(64.46)
High temperature anomaly (lag)	-0.82***	-21.42	3.56***	119.82***
	(0.22)	(19.43)	(0.87)	(42.05)
High temperature anomaly (two lags)	-0.93***	-40.74***	1.72**	99.28***
	(0.17)	(13.43)	(0.68)	(36.28)
High temperature anomaly (square)	0.64***	42.28***	0.01	2.54
	(0.13)	(8.99)	(0.30)	(16.30)
High temperature anomaly (square, lag)	0.24***	14.91	-0.31	-6.94
	(0.09)	(9.19)	(0.28)	(17.84)
High temperature anomaly (square, two lags)	0.03	0.93	-0.09	-17.15
	(0.06)	(6.13)	(0.21)	(13.97)
Observations	9,052	9,052	9,052	9,052
R-squared	0.334	0.157	0.173	0.044
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 1.44: Northern Great Plains, Amount of CRA Farm Loans and Extreme Temperature, 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	0.03	29.14	-0.34	29.67
	(0.78)	(43.26)	(1.52)	(70.19)
High temperature anomaly (lag)	0.64	22.56	-2.07	-118.05*
	(0.48)	(42.15)	(1.39)	(65.76)
High temperature anomaly (two lags)	2.05**	138.14**	-0.27	98.92
	(0.82)	(60.66)	(1.41)	(72.22)
High temperature anomaly (square)	0.08	17.24*	-1.19***	-24.35
	(0.15)	(9.96)	(0.42)	(22.59)
High temperature anomaly (square, lag)	0.40*	21.99**	-1.04*	-3.54
	(0.21)	(10.90)	(0.53)	(23.45)
High temperature anomaly (square, two lags)	-0.23*	4.68	-1.50***	-54.90**
	(0.12)	(8.78)	(0.48)	(21.34)
Observations	3,915	3,915	3,915	3,915
R-squared	0.323	0.303	0.284	0.140
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 1.45: Prairie Gateway, Amount of CRA Farm Loans and Extreme Temperature, 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	-0.84**	-16.94	1.47*	-28.09
	(0.40)	(20.45)	(0.78)	(43.23)
High temperature anomaly (lag)	0.49	4.32	1.65**	18.22
	(0.35)	(15.39)	(0.65)	(36.98)
High temperature anomaly (two lags)	-1.15***	-28.36**	0.38	-1.85
	(0.28)	(13.20)	(0.68)	(37.03)
High temperature anomaly (square)	-0.02	-3.58	-1.07***	7.89
	(0.12)	(6.31)	(0.32)	(17.56)
High temperature anomaly (square, lag)	-0.11	-0.75	-0.90***	-11.45
	(0.15)	(5.85)	(0.29)	(17.04)
High temperature anomaly (square, two lags)	-0.37*	-7.13	-0.37	5.96
	(0.20)	(8.08)	(0.25)	(15.02)
Observations	8,602	8,602	8,602	8,602
R-squared	0.212	0.152	0.153	0.095
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 1.46: Eastern Uplands, Amount of CRA Farm Loans and Extreme Temperature, 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	0.02	-32.03**	-0.50	-170.66***
	(0.30)	(15.53)	(0.95)	(38.96)
High temperature anomaly (lag)	0.09	-1.93	1.85***	21.65
	(0.12)	(7.65)	(0.54)	(23.63)
High temperature anomaly (two lags)	0.25*	-6.05	2.90***	33.56*
	(0.14)	(5.28)	(0.57)	(18.51)
High temperature anomaly (square)	-0.11	10.20***	-0.98**	2.86
	(0.10)	(3.87)	(0.43)	(13.12)
High temperature anomaly (square, lag)	-0.02	7.51**	-1.04***	2.69
	(0.11)	(3.43)	(0.40)	(11.06)
High temperature anomaly (square, two lags)	-0.02	9.86***	-0.23	48.22***
	(0.06)	(2.96)	(0.35)	(11.94)
Observations	8,671	8,671	8,671	8,671
R-squared	0.190	0.064	0.159	0.091
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 1.47: Southern Seaboard, Amount of CRA Farm Loans and Extreme Temperature, 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	-1.19***	-32.30**	-2.55***	-103.19***
	(0.31)	(13.05)	(0.79)	(34.38)
High temperature anomaly (lag)	0.44**	3.08	0.83*	50.15***
	(0.20)	(11.06)	(0.46)	(17.07)
High temperature anomaly (two lags)	-0.30	-9.24	-0.22	6.93
	(0.28)	(9.91)	(0.53)	(19.00)
High temperature anomaly (square)	-0.09	-5.09	-0.47*	-37.06***
	(0.09)	(5.40)	(0.26)	(10.80)
High temperature anomaly (square, lag)	-0.25**	-8.43*	-0.51**	-30.69***
	(0.11)	(4.87)	(0.22)	(10.14)
High temperature anomaly (square, two lags)	-0.39***	-16.00***	-0.08	-24.72***
	(0.08)	(4.51)	(0.20)	(9.08)
Observations	10,679	10,679	10,679	10,679
R-squared	0.252	0.136	0.159	0.068
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 1.48: Fruitful Rim (TX and FL), Amount of CRA Farm Loans and Extreme Temperature, 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	0.47	87.62***	2.06***	105.84***
	(0.52)	(23.77)	(0.77)	(37.51)
High temperature anomaly (lag)	0.13	38.35**	-0.12	54.74*
	(0.50)	(18.57)	(0.59)	(29.83)
High temperature anomaly (two lags)	-0.40	22.48	0.56	44.78
	(0.47)	(21.44)	(0.70)	(28.14)
High temperature anomaly (square)	-0.73*	-32.00**	-1.13**	-60.68**
	(0.37)	(13.09)	(0.57)	(27.87)
High temperature anomaly (square, lag)	-0.73*	-32.93***	-0.46	-55.70**
	(0.38)	(11.79)	(0.50)	(25.33)
High temperature anomaly (square, two lags)	-0.88**	-45.32***	-0.84**	-62.17***
	(0.37)	(12.67)	(0.37)	(20.43)
Observations	2,461	2,461	2,461	2,461
R-squared	0.109	0.073	0.293	0.094
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 1.49: Fruitful Rim (western states), Amount of CRA Farm Loans and Extreme Temperature, 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	1.85***	146.82***	1.89**	87.14*
	(0.66)	(48.35)	(0.82)	(46.77)
High temperature anomaly (lag)	0.85	-11.95	0.15	83.92
	(0.53)	(32.57)	(0.81)	(53.76)
High temperature anomaly (two lags)	1.80***	107.55**	0.27	22.84
	(0.61)	(51.41)	(1.37)	(51.04)
High temperature anomaly (square)	-0.67	9.02	-1.37*	-48.11
	(0.41)	(27.42)	(0.82)	(34.85)
High temperature anomaly (square, lag)	-0.35	-12.17	-0.67	-15.94
	(0.36)	(27.43)	(0.63)	(27.49)
High temperature anomaly (square, two lags)	-0.54	-19.48	-1.29*	-83.80**
	(0.34)	(26.82)	(0.70)	(33.98)
Observations	3,525	3,525	3,525	3,525
R-squared	0.310	0.168	0.290	0.156
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 1.50: Basin and Range, Amount of CRA Farm Loans and Extreme Temperature, 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	-0.13	-24.14	0.07	-120.23
	(0.17)	(17.47)	(0.79)	(73.85)
High temperature anomaly (lag)	-0.19	-29.33**	-0.31	-99.70**
	(0.14)	(12.16)	(0.51)	(47.12)
High temperature anomaly (two lags)	0.15	-3.19	0.56	-23.90
	(0.12)	(11.00)	(0.54)	(36.64)
High temperature anomaly (square)	-0.11**	0.40	-0.36**	4.87
	(0.05)	(4.01)	(0.17)	(14.78)
High temperature anomaly (square, lag)	-0.07	-9.23**	-0.36**	-16.07
	(0.05)	(4.40)	(0.16)	(11.24)
High temperature anomaly (square, two lags)	-0.09	-5.69	-0.73***	-47.07**
	(0.06)	(5.10)	(0.20)	(19.67)
Observations	4,151	4,151	4,151	4,151
R-squared	0.307	0.131	0.127	0.074
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 1.51: Mississippi Portal, Amount of CRA Farm Loans and Extreme Temperature, 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	-2.21***	-157.92**	4.61*	96.18
	(0.67)	(63.79)	(2.40)	(104.12)
High temperature anomaly (lag)	-2.01***	-152.71**	1.05	-81.89
	(0.63)	(66.69)	(1.85)	(84.95)
High temperature anomaly (two lags)	-0.03	-85.78*	3.86*	78.07
	(0.54)	(51.10)	(2.23)	(106.65)
High temperature anomaly (square)	0.84***	44.89*	-1.46*	-64.34
	(0.24)	(26.01)	(0.87)	(42.16)
High temperature anomaly (square, lag)	0.55***	34.82*	-0.04	0.20
	(0.18)	(18.54)	(0.70)	(37.37)
High temperature anomaly (square, two lags)	-0.02	-6.02	-0.50	-39.33
	(0.19)	(15.41)	(0.69)	(37.17)
Observations	3,596	3,596	3,596	3,596
R-squared	0.350	0.103	0.373	0.203
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

Appendix: Tables of Bank Level Estimates

Table 1.52: Number of CRA Farm Loans and Climate Vulnerability, Bank-County Level by Loan Size

	(1)	(2)	(3)	(4)
VARIABLES	Total Num. of Loans	Number of loan (less 100k)	Number of loan (100k to 250k)	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 1.53: Amount of CRA Farm Loans and Climate Vulnerability, Bank-County Level by Loan Size

	(1)	(2)	(3)	(4)
VARIABLES	Total Amt. of Loans	Amount of loan (less 100k)	Amount of loan (100k to 250k)	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 1.54: 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 1.55: 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 1.56: 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 1.57: 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

Table 1.58: CRA Farm Loans and Climate Vulnerability, Very Small Banks x All Income Areas

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	-1.96	0.02	2.58
	(0.03)	(1.31)	(0.09)	(3.95)
High temperature anomaly (square)	0.01	0.59	-0.02	-0.37
	(0.01)	(0.87)	(0.03)	(1.64)
Observations	77,026	77,026	77,026	77,026
R-squared	0.004	0.004	0.004	0.005
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Income Area FE	Yes	Yes	Yes	Yes
Bank Size 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 1.59: CRA Farm Loans and Climate Vulnerability, Small-Mid Banks x All Income Areas

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	0.01	1.24*	-0.04	-2.62**
	(0.01)	(0.72)	(0.02)	(1.32)
High temperature anomaly (square)	0.00	-0.01	-0.02***	-0.44
	(0.00)	(0.24)	(0.01)	(0.44)
Observations	376,490	376,490	376,490	376,490
R-squared	0.003	0.009	0.006	0.003
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Income Area FE	Yes	Yes	Yes	Yes
Bank Size 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 1.60: CRA Farm Loans and Climate Vulnerability, Large Banks x All Income Areas

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	0.01***	-0.13	0.01***	-0.16
	(0.00)	(0.16)	(0.00)	(0.28)
High temperature anomaly (square)	-0.00***	0.01	-0.01***	-0.07
	(0.00)	(0.05)	(0.00)	(0.08)
Observations	2,351,067	2,351,067	2,351,067	2,351,067
R-squared	0.002	0.001	0.006	0.003
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Income Area FE	Yes	Yes	Yes	Yes
Bank Size 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 1.61: CRA Farm Loans and Climate Vulnerability, Very Small Banks × Middle Income Areas

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	-0.05	-7.32	0.19	12.71
	(0.14)	(7.19)	(0.39)	(17.90)
High temperature anomaly (square)	0.03	1.59	-0.08	-5.19
	(0.03)	(3.30)	(0.16)	(7.38)
Observations	14,678	14,678	14,678	14,678
R-squared	0.027	0.048	0.034	0.040
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.62: CRA Farm Loans and Climate Vulnerability, Small-Mid Banks × Middle Income Areas

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	0.01	5.03	-0.15	-12.70*
	(0.04)	(3.37)	(0.11)	(6.67)
High temperature anomaly (square)	0.00	0.50	-0.12***	-2.77
	(0.01)	(1.21)	(0.05)	(2.44)
Observations	68,736	68,736	68,736	68,736
R-squared	0.014	0.048	0.029	0.017
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.63: CRA Farm Loans and Climate Vulnerability, Large Banks × Middle Income Areas

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*	-0.62	0.07***	0.16
	(0.01)	(0.77)	(0.02)	(1.52)
High temperature anomaly (square)	-0.02***	0.18	-0.02***	-0.20
	(0.00)	(0.25)	(0.01)	(0.46)
Observations	402,543	402,543	402,543	402,543
R-squared	0.005	0.007	0.029	0.015
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.64: CRA Farm Loans and Climate Vulnerability, Very Small Banks × Low Income Areas

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	-0.00	-0.02	-0.00	-0.82
	(0.00)	(0.03)	(0.00)	(0.54)
High temperature anomaly (square)	0.00	0.02	-0.00	-0.20
	(0.00)	(0.01)	(0.00)	(0.16)
Observations	14,673	14,673	14,673	14,673
R-squared	0.020	0.016	0.018	0.015
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.65: CRA Farm Loans and Climate Vulnerability, Small-Mid Banks × Low Income Areas

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	-0.00	-0.15	0.01	0.03
	(0.00)	(0.25)	(0.00)	(0.30)
High temperature anomaly (square)	0.00	-0.02	0.00	0.04
	(0.00)	(0.06)	(0.00)	(0.15)
Observations	68,746	68,746	68,746	68,746
R-squared	0.004	0.005	0.004	0.003
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.66: CRA Farm Loans and Climate Vulnerability, Large Banks × Low Income Areas

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	0.00	0.03	0.00	0.05
	(0.00)	(0.06)	(0.00)	(0.09)
High temperature anomaly (square)	-0.00	-0.00	-0.00**	-0.05**
	(0.00)	(0.02)	(0.00)	(0.02)
Observations	402,538	402,538	402,538	402,538
R-squared	0.003	0.003	0.002	0.002
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.67: CRA Farm Loans and Climate Vulnerability, Very Small Banks × Moderate Income Areas

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*	2.60	0.07	7.43
	(0.02)	(1.83)	(0.18)	(6.46)
High temperature anomaly (square)	-0.00	0.71	-0.08*	-0.11
	(0.01)	(0.58)	(0.05)	(1.54)
Observations	14,674	14,674	14,674	14,674
R-squared	0.027	0.044	0.016	0.021
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.68: CRA Farm Loans and Climate Vulnerability, Small-Mid Banks × Moderate Income Areas

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	0.03	2.57**	0.00	1.63
	(0.02)	(1.22)	(0.04)	(2.80)
High temperature anomaly (square)	-0.00	-0.39	0.00	-0.02
	(0.01)	(0.31)	(0.01)	(0.73)
Observations	68,746	68,746	68,746	68,746
R-squared	0.004	0.011	0.009	0.007
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.69: CRA Farm Loans and Climate Vulnerability, Large Banks × Moderate Income Areas

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	0.00	-0.12	0.01	0.02
	(0.00)	(0.31)	(0.01)	(0.51)
High temperature anomaly (square)	-0.00***	-0.13*	-0.00**	-0.36*
	(0.00)	(0.08)	(0.00)	(0.19)
Observations	402,537	402,537	402,537	402,537
R-squared	0.003	0.002	0.008	0.005
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.70: CRA Farm Loans and Climate Vulnerability, Very Small Banks × High Income Areas

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	-0.05	-3.73	-0.32**	-13.31
	(0.07)	(4.45)	(0.16)	(9.06)
High temperature anomaly (square)	0.02	1.57	0.07	5.38
	(0.01)	(1.63)	(0.04)	(3.44)
Observations	14,678	14,678	14,678	14,678
R-squared	0.016	0.019	0.025	0.031
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.71: CRA Farm Loans and Climate Vulnerability, Small-Mid Banks × High Income Areas

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	-0.00	-1.06	-0.06*	-4.64*
	(0.01)	(1.00)	(0.04)	(2.68)
High temperature anomaly (square)	-0.00	-0.18	-0.01	-0.04
	(0.00)	(0.41)	(0.02)	(1.14)
Observations	68,745	68,745	68,745	68,745
R-squared	0.007	0.013	0.009	0.011
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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 1.72: CRA Farm Loans and Climate Vulnerability, Large Banks $\times$ High Income Areas

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	0.01*	-0.04	-0.00	-1.08*
	(0.00)	(0.50)	(0.01)	(0.56)
High temperature anomaly (square)	-0.01***	0.02	-0.00	0.24
	(0.00)	(0.11)	(0.00)	(0.19)
Observations	402,534	402,534	402,534	402,534
R-squared	0.008	0.004	0.007	0.004
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Size 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

Appendix: Additional Choropleths

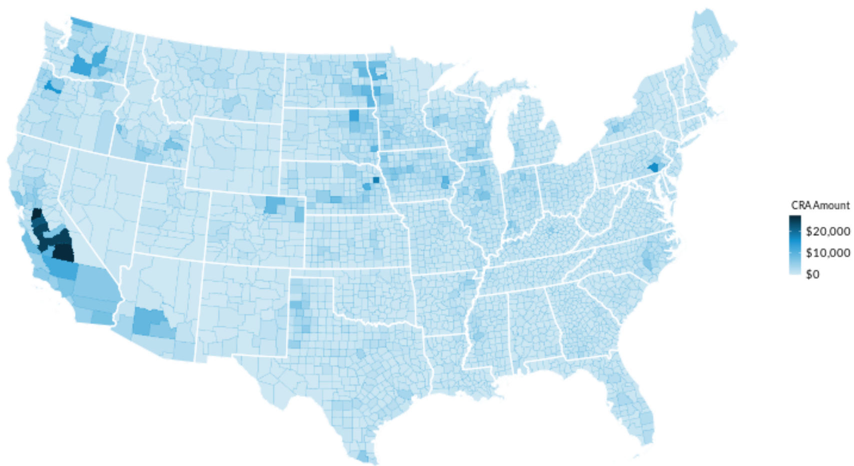


Figure 1.15: Yearly Average Total Amount of CRA Loans to Large Farms, 1996-2019, in thousand 2015 $

Source: FFIEC (2021)

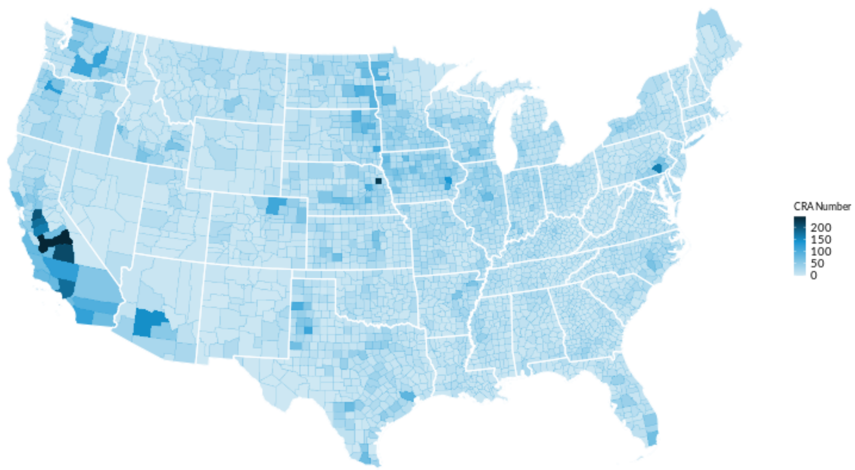


Figure 1.16: Yearly Average Number of CRA Loans to Large Farms, 1996-2019

Source: FFIEC (2021)

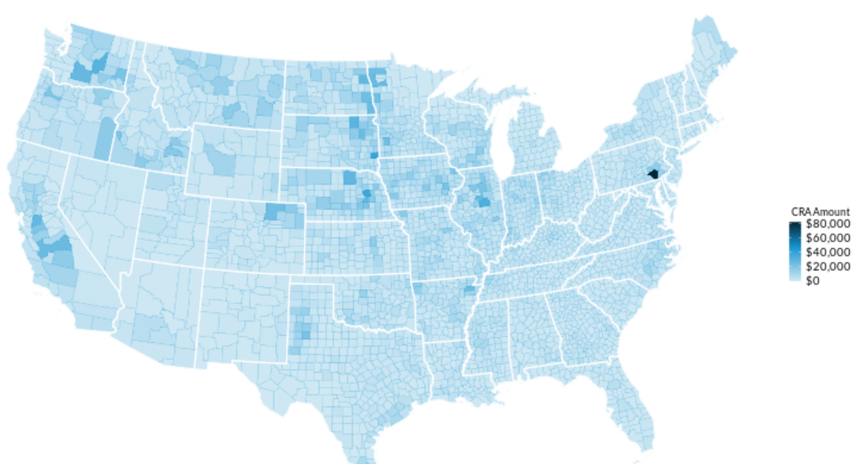


Figure 1.17: Yearly Average Total Amount of CRA Loans to Small-Med Farms, 1996-2019, in thousand 2015 $

Source: FFIEC (2021)

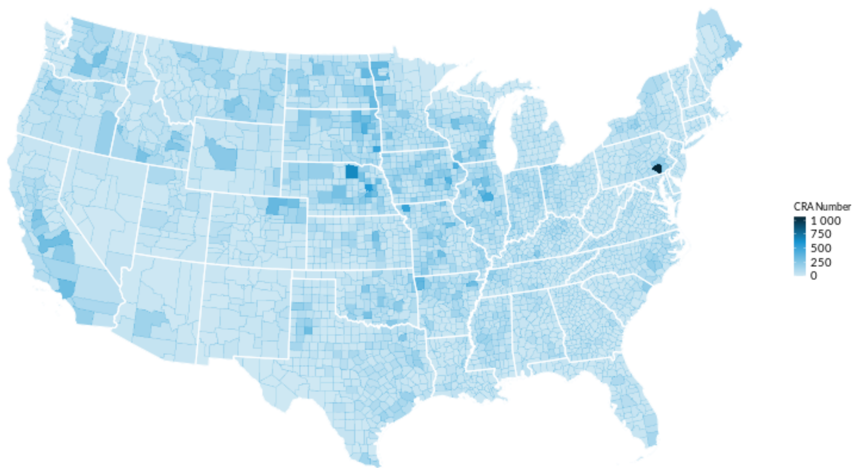


Figure 1.18: Yearly Average Number of CRA Loans to Small-Med Farms, 1996-2019
Source: FFIEC (2021)

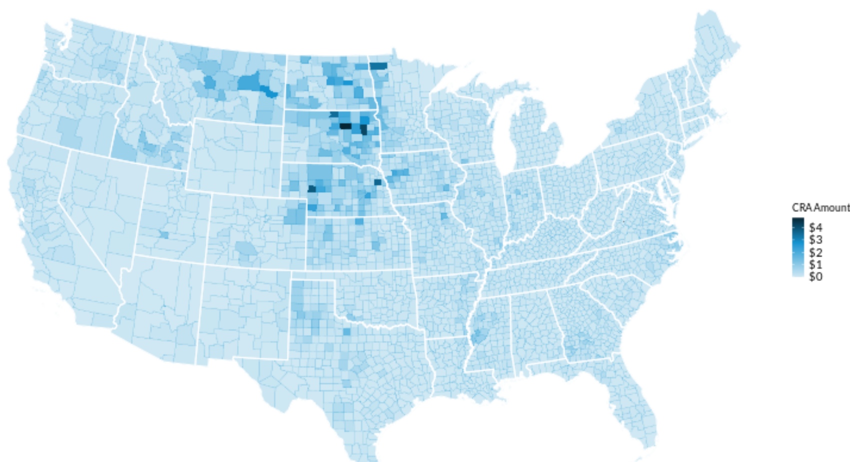


Figure 1.19: Yearly Average Total Amount of CRA Loans to Large Farms (share of county GDP), 1996-2019, in thousand 2015 $
Source: FFIEC (2021)

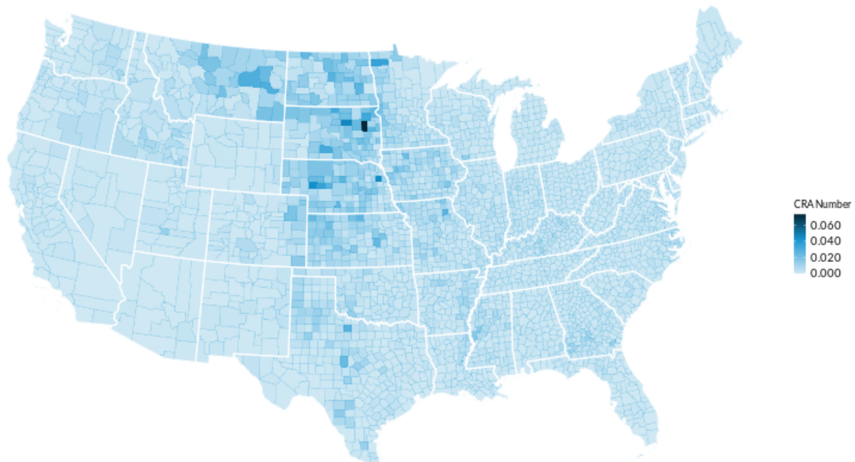


Figure 1.20: Yearly Average Number of CRA Loans to Large Farms (share of county GDP), 1996-2019

Source: FFIEC (2021)

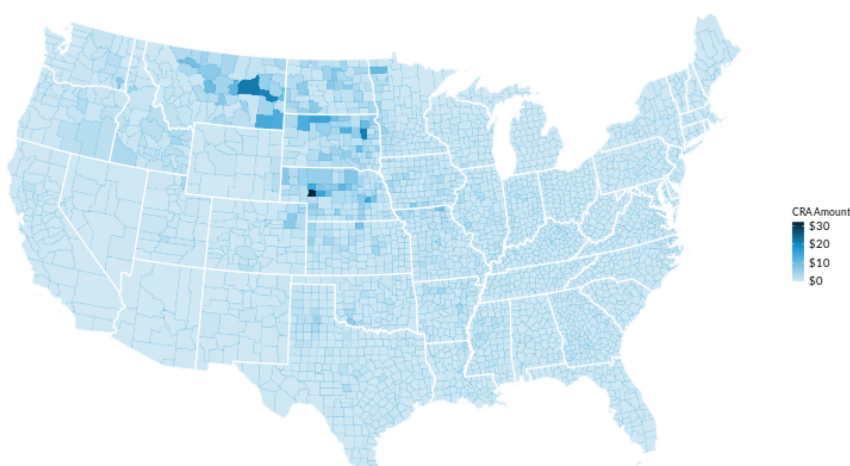


Figure 1.21: Yearly Average Total Amount of CRA Loans to Small-Med Farms (share of county GDP), 1996-2019, in thousand 2015 $

Source: FFIEC (2021)

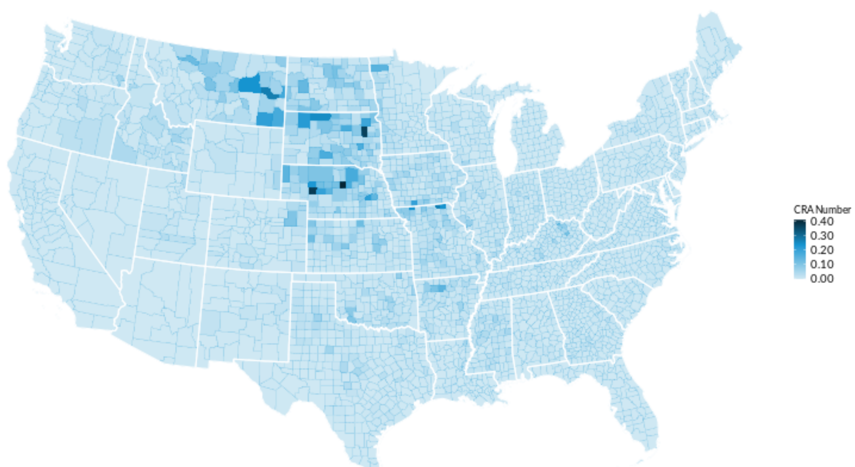


Figure 1.22: Yearly Average Number of CRA Loans to Small-Med Farms (share of county GDP), 1996-2019

Source: FFIEC (2021)

Chapter 2

Sovereign Default Risk and Household Consumption

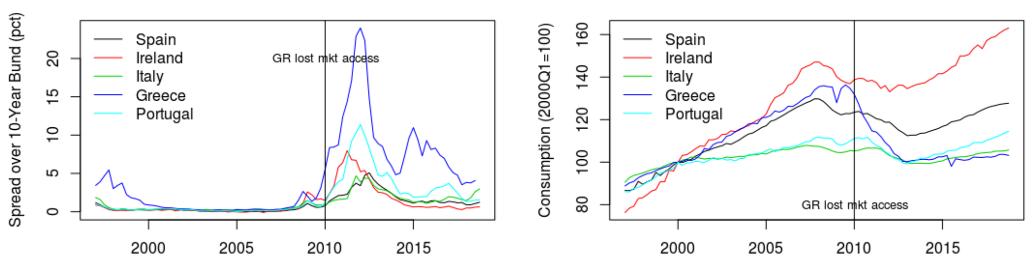
2.1 Introduction

Governments borrow to facilitate consumption smoothing and to provide public services, as described in canonical models such as Eaton & Gersovitz (1981) and Arellano (2008). A key question of sovereign debt default studies is why nations service external liabilities in the first place. Studies on default costs including Arteta & Hale (2008), Borensztein & Panizza (2009), and Zymek (2012) suggest the loss of access to the capital and trade markets as an explanation of why countries fulfill their debt commitments. When the government has difficulty repaying the debt, it often needs to implement fiscal adjustment through tax increase or expenditure reduction. But during the sovereign debt distress, how such fiscal adjustment spills over into household consumption behavior is poorly understood. While some recent studies such as Balke (2023) analyze consumption costs of sovereign risks, few have quantified such costs from micro data. In this chapter, I intend to fill this gap by providing estimates of this relationship.

The linkage between sovereign debt default risks (and default) and household consumption may not seem immediately obvious. A commonly accepted assumption in existing literature is that a default loosens the government budget constraint, thus freeing up money to provide for public and private consumption. But this may not necessarily be the case. First, there is an aggregate output loss associated with default, thus suggesting a reduction of aggregate income as a possible outcome. Moreover, sovereign debt returns can correlate with broader asset returns, leading to household consumption response through the wealth channel. Most importantly, sovereign debt is closely related to public taxation and revenue decisions, and government transfers often play a role in household consumption. Thus fiscal policy serves as crucial channel transmitting sovereign default risks to households. At the same time, there may be heterogeneous effects on households across the income distribution.

The eurozone crisis provides an example of this link. Figure (2.1) is a comparison of sovereign bond spread and household real consumption in the euro-periphery countries: Spain, Ireland, Italy, Greece, and Portugal. All these countries experienced sovereign default distress after Greece lost capital market access and sought IMF bailout in 2010. Their default risks—measured by the spread over German bond—all rose drastically between 2010 and 2012. Almost around the same time, all countries except for Ireland also observed sharp decline in real household consumption. After the risk receded, consumption also seemed to increase. Anecdotal evidence suggests that fiscal adjustment may have served as a propagation mechanism of sovereign risk into households' reduced consumption: these countries especially Greece imposed austerity policies that included drastic expenditure cut of items such as pension and public sector wage. In short, it is worth investigating the precise sovereign-household consumption linkage.

Figure 2.1: Sovereign Risk and Household Consumption (Quarterly)



(a) 10-Year Sovereign Bond Spread **(b)** Household Real Consumption Index

Source: OECD

In this chapter, I answer the following question: what is the relationship between sovereign debt default risks and the heterogeneity of household consumption; the role of public expenditure and its rigidity in this relationship. Fiscal rigidity refers to constraints that limit the ability to adjust budget in the short term. Put another way, the question is two-fold: 1) how household consumption responds to sovereign default risk;[1] 2) how to measure public expenditure rigidity using micro data, which helps answer a broader question of what fiscal rigidity is.

[1]Moreover, how such response is disaggregated by groups: for instance, those who receive high share of government transfers and those who do not

Measuring fiscal rigidity is important because fiscal policy may either act as a buffer against or propagation mechanism of sovereign default risk. A country experiencing government debt distress typically conducts fiscal consolidation, whether by choice or required by bailout agencies, to avoid default. But with high degree of fiscal rigidity, a government's expenditure may not be able to adjust much—fiscal transfer thus can act as a buffer if they are significant enough for household consumption. Besides, understanding fiscal rigidity is important in its own right for the sovereign default literature. Despite much debate about fiscal consolidation, there is no consensus on whether front-loaded (adjust more today than later) or back-loaded adjustment is optimal. The aforementioned discussion and the current sovereign default literature have largely missed considering a government's ability to adjust, namely the effectiveness to raise revenue or cut expenditure. For some governments, the rigidity of budget due to institutional and legal factors constrains such an ability.

To help answer the research question, I focus on using Mexico's data, in particular the National Survey of Household Income and Expenditure (ENIGH) of Mexico. Emerging markets (EMs) are of particular interest for sovereign default studies, and Mexico is a widely studied case.[2] My research hypothesis is that there is a negative relationship between sovereign default risk and household consumption, and the government takes this relation into account when deciding whether or not to default.

[2]To provide initial understandings, Figure (2.6) in the Appendix presents a set of scatter plots that illustrate the relationships of pension expenditure (as measured in the government's budget), private consumption, and default risk for Mexico, using quarterly aggregate data in 1993-2019. The spread here is defined as the difference between Mexico's and United States' 3-month treasury yields. According to Figure (2.6) (b), there seems be a strong positive correlation between pension and household consumption. The relationship between pension and spread is slightly less clear.

However, aggregate data are not always informative for mapping the linkage. For one, not all households have the same portfolios of financial assets (or hold significant assets at all), thus the wealth channel affects some households more or than others. In other words, understanding the sovereign-household consumption linkage calls for more granular data.[3]

Allowing for household heterogeneity will make both empirical and theoretical contribution to the literature. To the best of my knowledge, there are few studies that link sovereign debt distress and household well-being at a micro level.[4] Additionally, a typical sovereign default model assumes a representative household, and a decision to default is often motivated by freeing up resources to provide public goods. Yet in reality fiscal adjustment such as austerity measures rarely affects everyone equally. It is possible that sovereign default theory needs to consider the differential impact of default, thus rendering the sovereign's decision more nuanced and realistic.

Using the ENIGH data, my results show at both the state and household levels, there is a significant and negative relationship between sovereign default risk and household consumption, which is linked by fiscal transfers such as pension. Additionally, measuring fiscal rigidity through micro data makes methodological contributions. These results warrant a modification to standard sovereign default models by considering heterogeneous household consumption and the friction of expenditure rigidity.

[3]In the simplest structural model, there are two types of households: higher income with wealth, and lower income living hand-to-mouth with government transfers. There is no mobility between these two groups, and I assume that government transfer perfectly targets the hand-to-mouth households. In the more realist version of the model, there exists a continuum of households that vary by their initial draw of productivity or income. Thus, these households' income growth path is an AR process with idiosyncratic shock.

[4]One exception is Garbinti et al (2020)

The chapter is structured as the followings. Section 2.2 provides a review of relevant literature, which includes both structural models and empirical papers. In Section 2.3, I focus on describing the ENIGH dataset, its advantages as well as shortcomings, and some summary statistics. Additionally, a subsection is devoted to the institutional background pertaining to Mexico's fiscal transfers. Section 2.4 describes the main methods used to measure fiscal rigidity, and to map the relationship between sovereign default risk and household consumption. Section 2.5 presents the empirical results, and the following section concludes.

2.2 Literature Review

This chapter contributes to two related, but largely separate strands of literature: one on strategic sovereign default; and the second on financial crises and household consumption. In the first type of studies, the sovereign default model in Arellano (2008) generally serves the conceptual basis. Studies in this literature can be organized into three subsets, depending on their incorporation of the mechanisms of bailout, fiscal adjustment, and international trade. In the second type of literature, many studies examine household consumption responses, such as marginal propensity to consume, in the context of an aggregate financial shock.

The first subset of sovereign debt studies connect fiscal policy with default (and risks). Fiscal adjustment often goes hand in hand with policy conditionality imposed by the international financial institutions (IFIs). For example, Boz (2011) models fiscal adjustment as a higher discount factor (i.e., more prudent government) imposed by the IFI. In Fink & Scholl (2016), fiscal adjustment means that government expenditure in each period cannot be higher than a fixed parameter; fiscal adjustment enters into the model as part of the government budget constraint. In a similar paper, Kirsch & Rühmkorf (2017) examine the effect of financial assistance on default probability. But in this case, the policy conditionality that official creditors impose is a debt limit instead of primary balance target.[5] In a theory paper, Hatchondo *et al.* (2022) test the the effects of fiscal rules on sovereign default premium.[6] There are two other studies that are specifically on austerity and debt: Arellano & Bai (2017) and Anzoategui (2022). In the model of Arellano & Bai (2017), their model allows for the scenario in which the government defaults to free up resources to accommodate public and private consumption. Anzoategui (2022) examines the effects of fiscal austerity on sovereign spreads.[7] The aforementioned studies are generally concerned with explaining endogenous default behavior or what accounts for sovereign default risk, and household consumption is rarely a focus.

Within the sovereign default literature, there exists a second subset of studies that examine the interaction between default incentives and redistributive implications. A paper by Ferriere (2015) is one such example that links sovereign default

[5]One limitation of this paper is that it does not explicitly model the behavior of expenditure, tax, or production.

[6]They define fiscal rule as debt ceiling chosen by the country government, instead of being required by an external lender. Their main result is that the sovereign prioritizes a procyclical debt ceiling, leading to larger reduction of default probability. Higher debt level, however, limits the government's ability to implement a less procyclical fiscal policy to reduce consumption volatility. While private consumption is discussed, the paper does not go beyond simulating its volatility.

[7]In the model, the government starts with a fixed value of fiscal target, and if austerity is implemented, cuts the spending monotonically.

models with heterogeneous households, through income inequality and the redistribution costs of taxes. The author finds that taking tax progressivity as given, the more regressive the tax system is, the higher default incentive is.[8] Similarly, the paper by Jeon & Kabukcuoglu (2018) also examines how income inequality affects sovereign default, where they model heterogeneous households that are subject to income inequality shock.[9] In another study, Dovis *et al.* (2016) develops a political economy model, where the inter-temporal trade-off between paying external debt and addressing household wealth inequality gives rise to an optimal policy in which populist fiscal policy (i.e. increased transfers) is followed by austerity.[10] In short, such studies point out that sovereign default has tangible welfare implications for households. Yet they do not focus on the consumption implications of default risks, nor do they discuss the role of fiscal rigidity.

While my chapter does not account for international trade, it is related to a third subset of sovereign debt studies, in which the trade costs of default has received increased attention. In an empirical paper, Zymek (2012) argues that sovereign default reduces exporters' access to credit, especially sectors that are more reliant on external finance. Asonuma *et al.* (2016) examine the differential impact of debt restructuring

[8]This relationship is explained by income inequality: contemporaneously, the default gains increase with a higher share of low-income households that value tax reduction more than their higher-income counterparts. But the welfare costs of volatile taxes (due to capital market exclusion) are also higher for low-income households, thus increasing the future default costs—but overall the contemporaneous effects tend to dominate.

[9]They argue that a default actually helps redistribute household welfare by reducing the high- and low-income households' difference in marginal utilities of consumption. With both negative productivity and inequality shocks, the government has a higher incentive to default so that the tax burden on the poor can decrease.

[10]While the theoretical predictions are appealing, this paper does not offer evidence of the model's quantitative performance, therefore is less convincing in explaining the endogenous default behavior of the government.

(preemptive versus delayed) on external trade, and find that delayed restructuring (or outright default) leads to more severe and protracted decline in both import and export. A paper by Gu (2021) rationalizes the trade costs of default using a two country model with endogenous default risks, penalty, and consumption home bias.[11] By examining the default-consumption linkage, my chapter may enrich the understandings of the trade costs of default.[12]

In short, very few studies in the sovereign default literature explicitly examine default as an aggregate shock with implications for household consumption. A commonly accepted assumption in such papers is that a default loosens the government budget constraint, thus freeing up money to provide for public and private consumption. But it is uncommon to see a paper that takes a step back, and rigorously and empirically tests if a default, or rising default risks necessarily lead to an increase of private consumption. Empirical understanding of the consumption ramification of default is important because existing studies generally only account for the loss of capital or trade access. It is possible that direct household consumption cost is a factor of endogenous sovereign default decision making.

In the following paragraphs, I focus on reviewing the second strand of literature—relevant empirical studies that link financial crises and household consumption: 1) it is

[11] In the model, the defaulting country experiences income reduction due to adverse productivity shock and wage decline. The defaulting country's income loss is further amplified due to home bias leading to deteriorating real exchange rate and terms of trade. The model also captures important trade dynamics during default episodes: the volume of final goods export is less than that of import—leading to more decline of total goods import than of goods export. This decline in income, coupled with reduced import, has important implications for total consumption.

[12] In such studies, firms typically play a more prominent role than households—for instance, import dynamics are driven by demand for intermediate goods for production. However, at a fundamental level, trade and firm production eventually materialize as final goods for household consumption.

important to point out that my chapter has three key differences with such studies: not many papers explicitly account for sovereign default and risks as macroeconomic shocks; 2) very few studies in this strand of literature specifically model fiscal or sovereign debt behavior in their frameworks; 3) consequently such papers pay limited attention to the possibility that default risks can be linked to households through fiscal policy. Therefore, my chapter makes a contribution by connecting this literature and the sovereign default papers.

Representing the more conventional strand of the literature, Barrell *et al.* (2006) uses aggregate data of advanced economies to examine the impact of banking and currency crises on consumption.[13] More recent empirical studies, increasingly employing micro data in advanced economies such as France and Italy, point to heterogeneity of consumption responses to income shocks or an economic crisis. Some focus specifically on the wealth channel, while others such as Bunn *et al.* (2018) examine both positive and negative income shocks by also considering British households' balance sheet characteristics. Households' interest rate exposure is a commonly used mechanism through which macro shocks (for instance monetary policy shocks) transmit into household consumption in such studies.[14]

For example, in Banks *et al.* (2013), the authors survey British households' expectations of financial resource adequacy, and uncover the effects of the 2008-09 crisis

[13]A major shortcoming of this type of study is the lack of clean identification that pins down the transmission mechanism of crises into household consumption.

[14]There are three approaches in modeling income (and wealth) shocks in relation to marginal propensity to consume (MPC): 1) identifying episodes of unexpected changes in incomes (quasi-experimental approach), 2) statistical decomposition of the income process into permanent and transitory components, as seen in Blundell et al (2008), 3) newly designed survey questions eliciting responses to hypothetical income changes.

by simulating wealth changes based on asset price changes—therefore measuring the wealth shock due to a crisis. A paper by Jappelli & Pistaferri (2014), closely related to studies on fiscal stimulus and consumption, draws on an Italian survey of consumers' anticipated consumption due to an unexpected transitory income change.[15] One study closely related to my research is by Garbinti *et al.* (2020). Using a cross-country harmonized household level panel, Garbinti *et al.* (2020) examine the heterogeneity of MPC out of wealth in five euro countries[16] during the region's financial crises in 2010-14, though the impact of sovereign default impact is not the focus.[17]

Two papers most similar to my study are McKenzie (2003) and McKenzie (2006), where the author uses ENIGH to examine the differential impact of the 1995 Mexican peso crisis across household types.[18] In McKenzie (2003), the dependent variables are mainly social outcomes such as fertility, education, and household structure. In McKenzie (2006), the author focuses on the changes in consumption composition (durable versus nondurable) following the crisis. Since the peso crisis is an exogenous shock, its impact on consumption are identified as mean effects by difference-in-differences using data in 1994-96. The main finding is that the peso crisis decreased in-

[15]While high-quality direct survey data of consumer expectations would be ideal, it is uncommon that such data are widely available for EMs. Mexico's National Institute of Statistics and Geography (INEGI) does house a National Survey on Consumer Confidence (ENCO), but the main data are not about specific consumption values. Instead, the survey focuses on the consumer's subjective view of the general economic situations of the household and the country—there is one question about whether the consumer expects to buy more or less durables

[16]Belgium, Cyprus, Germany, Spain, and Italy

[17]Their main estimation approach is an instrumented panel regression, and they use sovereign default risk (aggregate asset prices changes) as an *instrument* to simulate household wealth changes and to minimize endogeneity bias (household precautionary saving and portfolio reallocation behavior). While sovereign default is not the direct focus, the results of the chapter are consistent with other studies that a macroeconomic crisis can change household consumption through the wealth channel.

[18]The author employs an empirical approach that isolates the long-term trends (cohort effects) to identify the effects of the crisis on the variables on interest.

come and consumption across household types; in particular households reduce durable and nonessential consumption to cope with the crisis.

My chapter differs from Mckenzie's works in three main ways, though we both employ ENIGH to understand the consumption implications of a financial crisis. First, Mckenzie solely examines one near-default episode of Mexico, whereas the macroeconomic shock—sovereign default risk—in my framework is broader and longer-term. Further, Mckenzie's papers refrain from explicitly modeling macroeconomic variables or government behavior—the peso crisis is simply an exogenous (and abstract) shock in the paper. In contrast, the underlying structure in my study allows for modeling government's endogenous fiscal and debt policies as well as their interactions with household consumption. Finally and most importantly, my research question is different from Mckenzie's. His studies intend to understand the shift of household expenditure compositions during a crisis in light of Engel's Law. In my chapter, I intend to identify the *channels* and *mechanisms* through which sovereign default risks transmit into household consumption. In particular, I pay attention to the role of fiscal transfer and public expenditure rigidity in modulating the shock.[19]

Fiscal Rigidity Moreover, few of the current studies pay attention to the issue of fiscal rigidity, as they tend to focus on *how* a government can adjust, instead of *whether* it can. Measuring fiscal rigidity is a relatively new endeavor. Munoz & Olaberria (2019) measure rigid expenditures as inflexible budget components such as pension expenditure,

[19]Though the results so far are empirical, my ultimate goal is using the parameters and results from the micro data to enrich a structural sovereign default model.

public wage bill, debt service, and national-local revenue sharing. They argue that the structural components of the rigid expenditure, due to institutional and legal factors, are beyond fiscal policymakers' control, at least in the short term. For example, in countries like Brazil, job stability of public employees is protected by the country's constitution.[20] It is generally difficult for a democratically accountable government to drastically cut rigid spending such as public wage bill, unless required by bailout agencies.

Existing studies employ two methods: a simple ratio of rigid budget item (e.g., pension payment) to total expenditure; an econometric estimation of the structural and nonstructural components. More specifically, based on cross-country aggregate data, Herrera & Olaberria (2020) estimate structural rigidity using a fixed effect model. The structural component is determined by variables such as GDP and population. The nonstructural component is simply the residual from the regression—the difference between the actual and predicted expenditure, and is affected by short-term variables such as election and business cycles.

However, this approach neglects the fact that nominal rigidity is also an intertemporal issue: tomorrow's public expenditure partly depends on today's, due to the aforementioned institutional and legal factors that are resistant to change. Additionally, the aggregate data in Herrera & Olaberria (2020) relies on exploiting cross-country variation and country time-invariant fixed effects. The structural rigidity coefficient being estimated is just an average across countries sampled. It cannot inform us precisely of a sovereign's default decision that can be tied to its idiosyncratic consumption or

[20] Soto & Karpowicz (2018) "Rightsizing Brazil's Public-Sector Wage Bill"

rigidity conditions. Thus, using household level data ENIGH in Mexico can exploit within-country variation. If this parameter and related micro moments are properly identified, they yield strong external validity for the rigidity friction to be incorporated in a structural model.

In summary, most of the current macroeconomic studies have yet to establish a direct link between sovereign debt default and the heterogeneity of household consumption; nor do they pay attention to the role that public expenditure and its rigidity play in this relationship. The wealth channel of a crisis or shock into household consumption is corroborated by current literature. But it is unclear whether public expenditure acts either as a buffer or a propagation mechanism of sovereign default risk. In my chapter, I pay attention to the wealth channel but also propose *fiscal transfer (and its rigidity)* as another mechanism (part of my assumption is that for poorer households, the wealth channel will not be very important, but the fiscal transfer mechanism may be significant).

2.3 Data Description and Institutional Background

To estimate public expenditure rigidity, measure household consumption, and understand their relationships with sovereign default, I primarily use the National Survey of Household Income and Expenditure (ENIGH) of Mexico. The survey is conducted by Mexico's National Institute of Statistics and Geography (INEGI) dating back to 1984. Since 1992, ENIGH has occurred, using multi-stage random sampling, every two years with the most recent data available as of 2018. In essence, ENIGH is a representative database of the income and expenditure behavior of Mexican households in urban and rural areas, complemented by information of their socio-demographic and occupational characteristics. Not all the households are surveyed every time, thus the entire database is pooled cross-sectional rather than panel-type.

ENIGH contains three main components: income (monetary and nonmonetary) and its sources, expenditure and its goals, and household member characteristics (e.g. age, occupation, education, health). The section most relevant to my research is called "income and financial and capital payments of each of the members of the household." In the 2014 survey, for example, 21,427 housing units with a total of 89,131 observations are in the income section of the survey. Each individual member of the household is asked about their incomes and sources over the past 6 months. There is an extensive list of codes (*clave*) that categorize the income sources: wages and salaries, sales from self-employment, and government transfers. The variable most useful for my analysis will be quarterly income (*ing_tri*) organized by each income source, especially various types of government transfers. Additionally, there is one aggregate variable measuring households' cash flows/income (*percep_tot*) generated by their assets.

While my chapter currently focuses on Mexico, the approach is applicable to other countries with comparable data. In fact, World Bank's Socio-Economic Database for Latin America and the Caribbean (SEDLAC), a meta-database, shows that household income surveys similar to ENIGH exist in most of the 25 countries in the region. The vast majority of such surveys also include information of pension and government transfers.

2.3.1 Summary Statistics

2.3.1.1 Aggregate Data

In order to gain more comprehensive understandings of Mexico's public expenditures, I have analyzed all major items in the government's quarterly balance sheets from 1993 through 2019. These balance sheets reveal the main types of programs provided by the Mexican government. Table (2.1) illustrates the top 10 types of spending (as a share of total government expenditure), in terms of 5-year average.

From this table, it seems that there are four key types of fiscal spending that are also related to household consumption: federal transfer, pension, wage, and welfare. Funding allocated to state and municipal governments is the most significant item, generally accounting for around a quarter of the total government spending. Since 2000, pension consistently ranks as the second biggest government spending, and seems to be on an upward trend in its importance. The increased relative importance is also seen in public wage and welfare (social programs). In comparison, items such as defense and agricultural development seem to have diminishing relative importance. In short, when examining the sovereign-consumption linkage, these summary statistics suggest it is sufficient to focus on federal transfer, pension, wage, and welfare.[21]

[21] Unemployment insurance is not among the top expenditure items. Mexico does not have a national unemployment insurance program. The country's unemployment insurance system is too fragmented to account for a big portion of the "social welfare" category. For example, in response to COVID19, the national housing fund Infonavit has provided temporary unemployment benefits to formal sector workers. However, Infonavit is actually part of the pension system (formal workers make mandatory housing contributions, which then would become housing savings or when they retire, pension). Unemployment

Table 2.1: 5-Year Average of Top 10 Expenditure as Share of Total Gov. Spending

	1995-99	2000-04	2005-09	2010-14	2015-19
Federal Transfer to States and Municipalities	14.0	32.4	26.9	23.5	22.4
Pension	10.2	14.1	15.4	19.1	21.8
Public Education	16.3	13.5	12.3	12.6	10.6
Public Wage	2.1	2.5	7.2	5.0	8.0
Health	4.1	2.6	3.8	4.9	4.2
Energy	3.4	3.8	5.5	1.2	4.1
Communication & Transportation	5.6	2.8	3.5	4.1	3.9
Welfare (social programs)	2.2	2.1	3.0	3.9	3.8
Defense	4.1	3.0	2.5	2.8	2.7
Agricultural & Rural Development	6.4	4.5	4.2	3.4	2.4

Source: Mexico's Ministry of Finance and Public Credit

2.3.1.2 ENIGH

Using the 2014 data, the summary statistics below provide some preliminary insights into the role of public expenditure in household incomes. Table (2.2) illustrates the income sources of households at an individual level. For Mexican households, wages and salaries are the most important way to make a living. Nearly a quarter of all households rely on employment. By comparison, pension income constitutes a much smaller share of income source measured by frequency. At the same time, around 16 percent of individuals receive some kind of social program assistance from the government.

Table 2.2: Household Income by Sources in 2014 (Individual Level)

Income source	**Frequency**	**Percent**
Wages and/or salaries	22,114	24.81
Pension	2,869	3.21
Social programs	14,291	16.03

More specifically, such government transfer includes food and farming support, education scholarship, benefits for the elderly, unemployment benefits, and other assis-

data may confound the pension data, but they are unlikely to be significant enough to alter results in the chapter.

tance. These government transfers come from both the federal and/or state level. Table 2.3 provides summary statistics of income at a household level. There are 19,104 unique household-level observations for total quarterly income. On average, a Mexican household earns 11,021 pesos per month in 2014. However, there is significant variability in household income, suggesting the existence of high income inequality.

For the pensioners, each household earns only 6,044 pesos per month, which is over 82 percent less than the average income. While more information is needed, it is possible that there is an upward nominal pension rigidity: the pension income here is already so low compared with the mean household income, it is politically difficult for the government to cut pension. The magnitudes of government social programs are small, as evident in Table (2.2). However, this does not mean that they play no role in households' incomes and well-being. For instance, it seems nearly over 18% of households receive some type of cash or food assistance.

As discussed in Section 2.1, my research hypothesis is that there is a negative relationship between sovereign default risk and household consumption, both of which linked by fiscal transfer such as pension. Based on the aggregate data, it seems that there is a strong positive relationship between pension and household consumption. Figure (2.2) is a scatter plot of this relationship using the ENIGH data in 2014 for households that receive pension. The micro data in 2014 are largely consistent with the macro data.

There are two key benefits in using this micro dataset: the heterogeneity and distribution implications of the sovereign-consumption link; the external validity and

Table 2.3: Summary of Income by Sources in 2014 (Unique Household Level & in Mexican pesos)

Income source	Obs	Mean	Std. Dev.	Min	Max
Household Income (quarterly)	19,104	33,064.4	54,551.2	96.8	4,101,295
Pension	2,468	18,132.8	22,959.1	88	246,521.7
Education Support	895	2,326.1	5,050.7	58.69	71,539.7
Oportunidades and Food Assistance	3,992	2,433.8	1542.7	129.28	12,013
Agricultural Subsidy	749	2,854.7	7,341.1	146.7	166,304.3
Other Benefits for Elders	2,318	2,055.2	930.6	129.28	10,330.4
Unemployment and Other Benefits	388	1,283.1	1,529.5	48.91	14,673.9

Figure 2.2: Household Pension and Consumption in 2014

Note: only households with pension income are shown here

portability of the moments generated from empirical analysis to structural modeling. It is possible to use only aggregate statistics to measure the relationship between sovereign risk and consumption, but the estimated coefficient, averaged across all types of households, would weed out the diversity of consumption responses. We can think of this in terms of the distribution of household consumption. Figure (2.3) shows histograms of the natural log of consumption using household-level data for years 1994-2018,[22] disaggregated by those who receive pension and those who do not. Within each category, the distribution is relatively wide-ranging. There are also noticeable differences between these two groups. These differences are important because pension is a possible channel that transmits or prevents sovereign default risk. In other words, sovereign risk has tangible distributional consequences for households. Figures (2.4) and (2.5) show the yearly averages by municipality for consumption and other income. The distinction between the pension and no pension groups are less obvious but still noticeable.

The second benefit of using micro data for research identification is the wide applicability (or external validity) of the estimated moments, which is difficult to achieve by using aggregate data. While international statistics standards exist, there remain differences in how countries measure and implement aggregate data. While micro data do not automatically eliminate this issue, it is possible to minimize it by controlling for essential individual and household characteristics (e.g., education, income, health). Put another way, identification based on micro moments can generate the "portable statistics" discussed by Nakamura and Steinsson (2018). Relating this specifically to sovereign default literature, if properly identified in my chapter, the consumption cost parameter and rigidity friction can be incorporated in a structural model (as opposed to macro moments that depend heavily on the model structure and assumptions).

[22] It may be problematic to graph pooled cross-sectional data as histograms. Figure (2.3) is purely for illustrative purpose

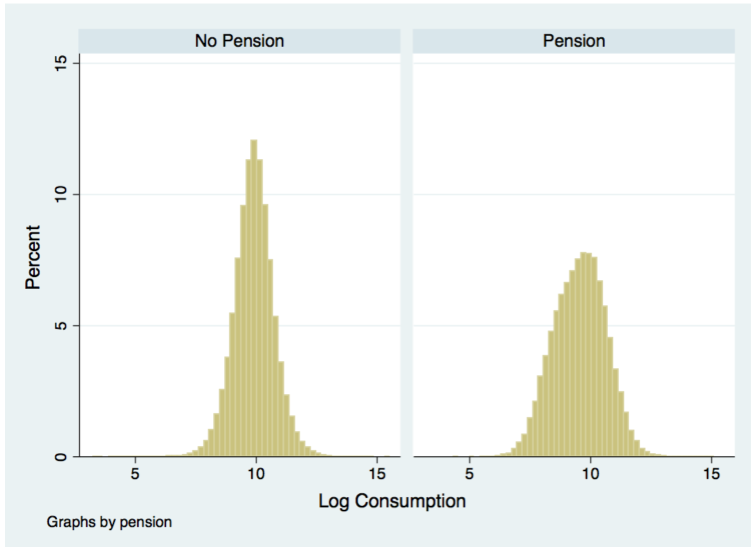


Figure 2.3: Household Consumption in 1994-2018

2.3.2 Background on Pension and Other Government Transfers

Using the ENIGH data we can observe a notable structural break that is difficult to discern in the aggregate data. At a household level and averaged by state, there is a drastic decline of pension income in the mid-to-late 1990s. In fact, the Mexican government conducted a structural reform of the pension system during 1996-97: some of the pension schemes switched from pay-as-you-go to defined-contribution, and the funds are managed by private administrators that are regulated by the National Commission for the Retirement Savings System (CONSAR).[23] While there are multiple reasons for the reform, one important factor is the high fiscal cost of the pre-reform regime: for instance, the lifetime benefits and contributions of the worker have almost no correlation.[24]

[23] Alonso *et al.* (2015)
[24] Sales-Sarrapy *et al.* (1998)

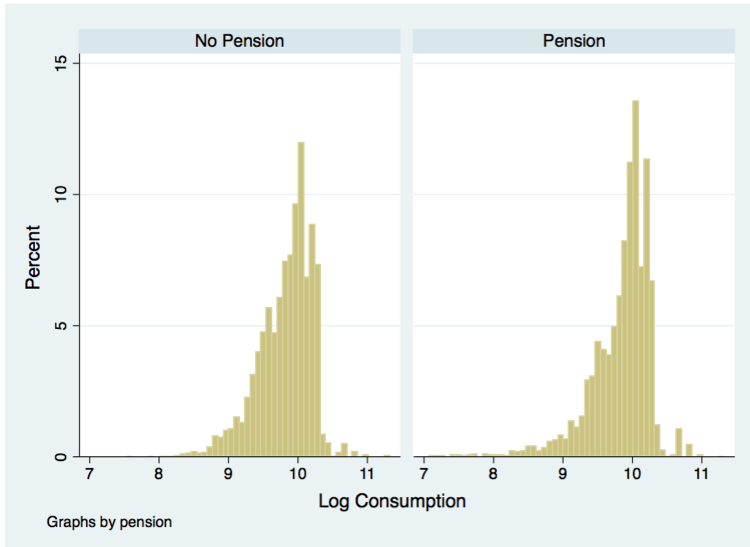


Figure 2.4: Yearly Average of Household Consumption by Municipality

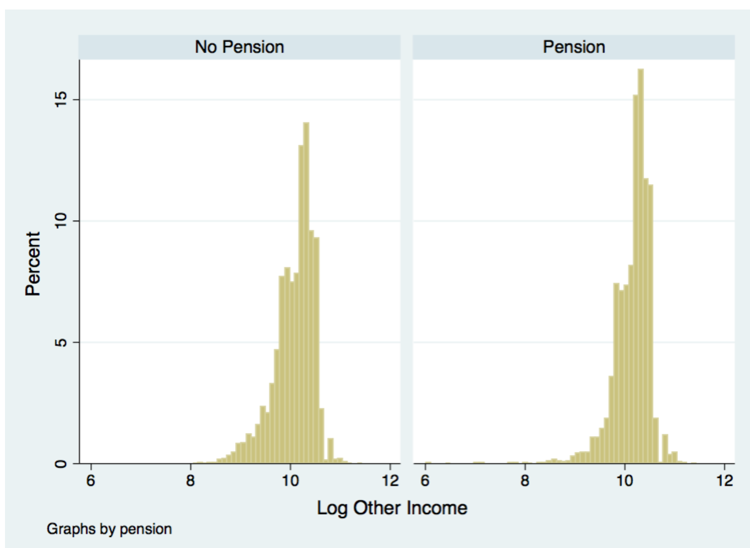


Figure 2.5: Yearly Average of Household Non-Pension Income by Municipality

The two most important pension systems are the Mexican Social Security Institute (IMSS) and the Social Security Institute for Public-Sector Workers (ISSSTE), both public entities under direct budgetary control of the Mexican government. Private sector workers contribute to IMSS, while public employees contribute to ISSSTE—

together these two systems account for around 40% of the economically active population of Mexico.[25] In other words, the pension coverage is low, which is consistent with the high level of informality in the country's labor force.

Additionally, it is important to note that despite the structural reform in the 1990s, Mexico's pension architecture is still in a transition period. The country maintains two pension regimes: the pre-1997 regime (L73) and the reformed regime (L97). The L73 regime only requires 500 weeks (less than 10 years) of contribution,[26] while the L97 requires a minimum of 1,250 weeks (24 years) of contributions.[27] At the time of the reform, workers that were already contributing could choose between the L73 and L97 schemes to receive their benefits upon retirement.[28] However, L73 was more generous than L97 because it is based on a defined benefits (DB) formula instead of DC[29]—workers who entered the system after 1997 likely receive far less retirement benefits. In both regimes, the minimum age to receive pension is 65 years, while the minimum early retirement age is 60. Additionally, while pension relies on individual contributions, under L97, the Mexico government also makes a contribution (*Cuota Social*) to the system for low-income workers.[30] Besides the federal pension systems, there are some state-level programs (13 states as of 2015), but both their coverage and benefits are very low.[31] Though the management of pension funds is privatized, social security is still an important item in Mexico government's balance sheet. But it is

[25] Alonso *et al.* (2015)
[26] https://www.gob.mx/consar/articulos/pension-por-regimen-73
[27] https://www.gob.mx/consar/articulos/por-regimen-de-97
[28] Alonso *et al.* (2015)
[29] OECD (2016)
[30] Alonso *et al.* (2015)
[31] Alonso *et al.* (2015)

important to acknowledge the limitation of my chapter: the assets dynamics of pension funds management is not measured.

2.4 Research Methods

This section describes the method through which to answer the main research question: how household consumption responds to sovereign default risk. ENIGH surveys generally include residency information such as state, municipality, and Basic Geostatistical Area (AGEB),[32] which allows for panel data estimation at the state level. The household-level estimation is conducted using pooled cross-section data. All the data are in real terms (2015 peso).

2.4.1 Specification at State Level

By converting ENIGH into a residency-level panel dataset, I can use a fixed effect model with a measure of sovereign risk on the right-hand side. The first step is to estimate the response of government transfers to sovereign default risk.[33] Then I use the predicted change of transfers as the independent variable in the second regression, where household consumption (disaggregated by wealth or fiscal transfer) is the dependent variable.

Stage 1. Examine the relationship between government expenditure and

[32]However, while AGEB is a variable, it is generally coded as "000-0" in the publicly available data. In other words, I will rely on state-level and municipality-level variation.

[33]The relationship between sovereign risk and fiscal expenditure likely exists primarily at the national/federal level—states rely on federal transfers, and state-level expenditures such as pension are relatively insignificant.

sovereign risk. More specifically,

$$g_t = \beta_0 + \beta_1 d_t + \gamma Z_t + trend + \epsilon_t \tag{2.1}$$

where t refers to time. g_t is a type of federal government expenditure such as pension and public wage. d_t is a measurement of default risk. $Z_{s,t}$ is a list of control variables. ϵ_t is the error term. From this regression, we can generate predicted government transfer changes $\Delta\hat{g}_{s,t}$ using the coefficient β_1. In other words, the aggregate spending change can be observed at the state level in the second stage.

Stage 2. Regress household consumption against $\Delta\hat{g}_{s,t}$ and control variables.

$$\Delta c_{s,t} = \alpha_0 + \alpha_1 \Delta\hat{g}_{s,t} + \phi\Delta\xi_{s,t} + e_s + \delta_t + \mu_{s,t} \tag{2.2}$$

where $c_{s,t}$ is household consumption observed at state level s, $\xi_{s,t}$ is the list of control variables, δ_t is time fixed effect, and $\mu_{s,t}$ is the error term. Through the coefficient α_1, we can interpret the direction as well as the magnitude of consumption response due to government transfer changes that are induced by sovereign default risk changes.

2.4.2 Specification at Household Level

We can also analyze the data at a household level. The first stage is identical to that of the state level. The key difference lies in the second stage, where it is possible to also control for household demographic characteristics such as size and age profile, as well as income group fixed effects. In particular, households are categorized into deciles based on their total income. It is likely that households in the same income distribution share certain unobserved characteristics that affect their consumption choices. Controlling for such unobserved characteristics minimizes the potential omitted variables bias.

Stage 2. The specification at the household level is

$$\Delta c_{i,s,t,g} = \alpha_0 + \alpha_1 \Delta \hat{g}_{i,s,t,g} + \phi \Delta \xi_{i,s,t,g} + e_s + \delta_t + \omega_g + \mu_{i,s,t,g} \tag{2.3}$$

where the the subscript g refers to the income group that a household belongs to, and ω_g stands for time-invariant and state-invariant income group fixed effect. The data employed in the estimation are pooled cross-section.

2.5 Results

2.5.1 Household Consumption

This section presents results using primarily the ENIGH data at household level and at state level. The analyses are conducted at two stages: first stage at the macro level (quarterly), and second stage stage at the disaggregated level (state and household level). The first stage estimation is conducted at the aggregate level (using data in per capita and in real terms), namely the specification shown in Equation (2.1). Such aggregate data are from Mexico's Ministry of Finance and Public Credit (SHCP). For ENIGH, the sample considers data for years 1994 through 2018 (the survey is generally conducted every two years).

2.5.1.1 Stage 1

Using aggregate data, it is important to first flesh out which fiscal spending correlates significantly with sovereign default risk. Following Equation (2.1) (but without control variables), I have conducted univariate regressions of expenditure items against measures of sovereign default risks. There are two types of risk measures: Mexico-U.S. 3-month Treasury spread; JPMorgan Emerging Market Bond Index (EMBI) for Mexico. All the expenditure variables are de-seasonalized, real, and in per capita terms.

As shown in Table 2.1, there are 10 types of expenditure of interest due to their large shares in Mexican government's budget. These items, in order of importance, are: 1) federal transfer to states and municipal governments, 2) pension, 3)public education, 4)public wage, 5)health, 6)energy, 7) communication and transportation, 8) social welfare programs, 9) defense, and 10) agricultural development. Therefore the univariate regressions focus on these 10 variables.

Table 2.4 presents results using two types of explanatory variables: 3-month spread and EMBI index. Among the 10 important expenditure items, six are statistically significant: federal transfer, pension, education, energy, defense, and agricultural development. For all such variables except defense, when sovereign default risk rises, there is reduction in expenditure. Notably, public wage bill has no significant correlation with either 3-month spread or EMBI. Table 2.23 in Appendix shows the specifications in which the sovereign risk measures are lagged by one quarter. The results are broadly consistent with the previous table, with transportation expenditure now significantly

Table 2.4: First Stage OLS Regression by Expenditure Type (Aggregate, Real, Per Capita)

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
3-month spread (log)	-0.119***	-0.185***	-0.097***	-0.044	-0.038	-0.445**	0.028	-0.013	0.047*	-0.162***
	(0.027)	(0.035)	(0.020)	(0.276)	(0.051)	(0.216)	(0.073)	(0.046)	(0.027)	(0.042)
Observations	88	108	108	107	108	108	108	108	108	108
R-squared	0.423	0.932	0.674	0.282	0.673	0.040	0.214	0.871	0.493	0.184

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
EMBI (log)	-0.096***	-0.204***	-0.046**	-0.090	0.021	-0.334	0.115	0.031	0.085***	-0.134***
	(0.034)	(0.043)	(0.022)	(0.340)	(0.061)	(0.252)	(0.081)	(0.049)	(0.031)	(0.049)
Observations	82	99	99	98	99	99	99	99	99	99
R-squared	0.363	0.924	0.720	0.305	0.690	0.019	0.294	0.881	0.475	0.086

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification is Equation (2.1) without the control variables, $g_t = \beta_0 + \beta_1 d_t + trend + \epsilon_t$, where d_t is a measurement of default risk. Spread (in percentage) is the difference between Mexico 3-month and U.S. 3-month yields. All dependent variables are seasonally adjusted, and are in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, FRED, JPMorgan EMBI

correlated with EMBI.

To check the robustness of the above results, the data are adjusted through first differencing (log) and Christiano-Fitzgerald (CF) filter to better account for time trend. Table 2.24 shows that now only three types of expenditure are significant: pension, energy, and agricultural development. Though smaller in magnitude, the results for pension are consistent with those in Tables 2.4 & 2.23. Table 2.25 illustrates the case for CF-filtered data. Due to data availability and log transformation, the number of observations is much smaller. However, at least for the EMBI measure, when sovereign risk rises, pension experiences a reduction. Across all the tables, there is no case in which public wage significantly responds to rising sovereign risk. This suggests that public wage could be among the most rigid expenditure.

Besides the above results, I have also conducted similar regressions for granular variables of public wage. Mexico's Ministry of Finance and Public Credit provides public wage data disaggregated by government sector: for example, wage for public employees working in the health sector. The vast majority of such wage variables have no significant correlation with sovereign risk measures.[34]

In short, though there is much diversity in Mexico government's expenditure, Table 2.1 establishes that only 10 items matter due to their magnitude. However, not all them matter directly for household consumption. Moreover, not all of them correlate with the fluctuation of sovereign default risk. In other words, some of them are rigid expenditure. Based on the regression results, it seems that pension is likely the primary fiscal channel through which sovereign risk transmits into household consumption.[35]

The following regressions focuses on pension, but now with inclusion of control variables. Tables 2.5 through 2.7 report the first stage results: pension expenditure is the dependent variable and spread is the independent variable. In Table 2.5, it seems that in all cases, there is a significant negative relationship between spread and pension—when sovereign default risk rises, pension expenditure decreases. The relationship remains significant, when we take into account pension revenue, which in theory should be the most important predictor for pension expenditure. Overall, with default risk rising by 1 basis point, the pension expenditure decreases by around 0.18%. In Table 2.6, the sovereign debt shock is lagged by one period, and the magnitudes of the spread coefficients become much bigger. In Table 2.7, all the variables except GDP growth

[34] the results are available upon request

[35] Federal transfer to local governments and public wage bill are not as important as pension, but may be worth further examination.

Table 2.5: First Stage OLS Regression (Aggregate Data, Real, Per Capita)

VARIABLES	(1) Pension (log)	(2) Pension (log)	(3) Pension (log)	(4) Pension (log)
Spread (log)	-0.183***	-0.189***	-0.180***	-0.190***
	(0.0349)	(0.0357)	(0.0367)	(0.0357)
Real GDP growth		-0.010	-0.008	-0.012
		(0.014)	(0.014)	(0.014)
Labor force part. rate (log)			-1.485	
			(1.466)	
Pension rev. growth rate (log)				1.313
				(1.802)
Observations	108	108	108	107
R-squared	0.933	0.933	0.934	0.932

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification is Equation (2.1), $g_t = \beta_0 + \beta_1 d_t + \gamma Z_t + trend + \epsilon_t$, where d_t is a measurement of default risk. Z_t is a list of control variables. Spread (in basis points) is the difference between Mexico 3-month and U.S. 3-month yields. Pension, revenue, and labor force participate rate are seasonally adjusted. All in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, OECD, FRED, ILO, National Institute of Statistics and Geography

have been first differenced. The magnitudes and significance of the coefficients become a lot smaller, though the directions of change are still consistent with the previous table. For example, in Column (1) the coefficient is -0.045.

2.5.1.2 Stage 2

In the remainder of the analysis, for the second stage regression, I use two coefficients: -1.172 from Table 2.6 and -0.045 from Table 2.7. There are two types of regressions conducted: state-level panel based on the ENIGH data; household-level pooled cross-section. There are 32 states in Mexico, and state-level observations are obtained by taking unweighted averages of household-level observations by residency/location. Then the average household pension at the state level is multiplied to obtain the pre-

Table 2.6: First Stage OLS Regression with Lag Spread (Aggregate, Real, Per Capita)

VARIABLES	(1) Pension (log)	(2) Pension (log)	(3) Pension (log)	(4) Pension (log)
Lag Spread (log)	-1.172***	-1.201***	-1.141***	-1.207***
	(0.238)	(0.243)	(0.249)	(0.244)
Real GDP growth		-0.009	-0.006	-0.010
		(0.014)	(0.014)	(0.014)
Labor force part. rate (log)			-1.695	
			(1.476)	
Pension rev. growth rate (log)				1.446
				(1.830)
Observations	107	107	107	107
R-squared	0.929	0.930	0.931	0.930

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification is a variant of Equation (2.1), $g_t = \beta_0 + \beta_1 d_{t-1} + \gamma Z_t + trend + \epsilon_t$, where d_{t-t} is the lagged measure of default risk. Z_t is a list of control variables. Spread (in basis points) is the difference between Mexico 3-month and U.S. 3-month yields. Pension, revenue, and labor force participate rate are seasonally adjusted. All in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, OECD, FRED, ILO, National Institute of Statistics and Geography

Table 2.7: First Stage OLS Regression with First Differencing (Aggregate Data, Real, Per Capita)

VARIABLES	(1) Δ Pension	(2) Δ Pension	(3) Δ Pension	(4) Δ Pension	(5) Δ Pension	(6) Δ Pension
Δ Spread	-0.045*	-0.025	-0.022	-0.025	-0.046*	
	(0.023)	(0.024)	(0.024)	(0.024)	(0.023)	
Real GDP growth		0.010**	0.010**	0.010**		
		(0.004)	(0.004)	(0.004)		
Δ Labor Force rate			0.998			
			(0.674)			
Δ Pension revenue				-0.089	-0.067	-0.059
				(0.080)	(0.081)	(0.082)
Observations	107	107	107	107	107	107
R-squared	0.035	0.080	0.099	0.091	0.041	0.005

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification is a variant of Equation (2.1), $\Delta g_t = \beta_0 + \beta_1 \Delta d_t + \gamma \Delta Z_t + trend + \epsilon_t$ with first differencing of logs, where Δd_t is measure of default risk. ΔZ_t is a list of control variables. Spread (in basis points) is the difference between Mexico 3-month and U.S. 3-month yields. Pension, revenue, and labor force participate rate are seasonally adjusted. All in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, OECD, FRED, ILO, National Institute of Statistics and Geography

dicted pension change (the data are multiplied by -1.172 or -0.045). To establish some baselines, the second stage include regressions without the sovereign debt shock, namely without using the first stage results. Moreover, thanks to the micro nature of the ENIGH data, three types of consumption are considered: total consumption, food consumption, and non-food discretionary consumption. Finally, all the analyses include the mid-1990s years in which pension reform occurred. In the actual data, the structural break appears to occur during 1998-2000. Thus a dummy variable for year 2000 is included in the following regressions.

State-Level Results Tables 2.8 and 2.9 present the results for total consumption at the state level. In the baseline, all columns show a positive and significant relationship between pension income and total consumption. The "other income" variable measures not only wage but also earnings from self-employment and informal sector earnings as well. Table 2.9 presents the second stage results using log-diff values and the estimate from the first stage. It is important to note that the predicted pension change is lagged by one period (namely, pension is multiplied by -1.172 and then lagged).

For columns (1) through (5) of Table 2.9, the coefficients are positive—this means that when Δ *Pension* increases, say from -2 to -1 (reduced risk and less pension reduction), consumption actually increases as a response [36]. In other words, a positive coefficient in Table 2.9 actually means that the lower the pension, the lower the consumption is. In the case of a debt crisis, wealth channel may be at work—therefore the

[36] for example, $\hat{y}_1 = -1 * b > -2 * b = \hat{y}_2$, increasing from -2 to -1 results in an increase of y

results in Column (4) may be the most robust.

Tables 2.10 and 2.11 repeat the exercise, but with food consumption as the dependent variable. In the baseline, the signs of pension coefficients are consistent with the baseline for total consumption. More importantly, as shown by Table 2.11, when we incorporate sovereign debt shock, all the pension coefficients remain positive. In short, lower pension income due to higher default risk leads to lower food spending.

Tables 2.12 and 2.13 present the results for discretionary consumption. It is important to note that the measure of "discretionary" spending used here is broad: it only excludes food, but includes other life necessities such as housing and medical spending. At the baseline, as shown by Table 2.12, the pension coefficients are largely consistent with the estimates for total and food consumption. In Table 2.13, all the coefficients are positive—lower pension income due to higher default risk leads to lower discretionary spending. However, as shown by Columns (3) through (5), when controlling for wage, wealth, or labor, the relationships become insignificant.

Based on the results from the state-level regressions, it is plausible to derive the following statements: when sovereign default risk rises, pension expenditure experiences downward pressure contemporaneously, which materializes as lower household pension income in the next period. As a result, lower pension income also leads to lower consumption, especially total and food consumption items. It is important to emphasizes that this negative default-consumption link is more likely to be lagged than contemporaneous. This reinforces the idea that certain government transfers such as pension are rigid expenditures in the inter-temporal sense.

Table 2.8: State-Level Baseline Fixed Effect Regression—No Sovereign Default Shock (Total Consumption)

VARIABLES	(1) Consumption (log)	(2) Consumption (log)	(3) Consumption (log)	(4) Consumption (log)	(5) Consumption (log)
Pension (log)	0.185***	0.574***	0.148***	0.151***	0.173***
	(0.0251)	(0.0355)	(0.0289)	(0.0260)	(0.0212)
Other Income (log)		0.495***			
		(0.0344)			
Wage (log)			0.202**		
			(0.0754)		
Wealth (log)				0.099***	
				(0.0154)	
Work Hours (log)					0.129***
					(0.0249)
Reform	0.626***	-0.593***	0.378***	0.592***	0.569***
	(0.0895)	(0.0965)	(0.116)	(0.0890)	(0.0759)
Observations	448	448	448	448	448
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
R-squared	0.746	0.853	0.757	0.777	0.784
Number of state	32	32	32	32	32

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

Note: Regression specification follows a variant of Equation (2.2) without sovereign default risks, $c_{s,t} = \alpha_0 + \alpha_1 \hat{g}_{s,t} + \phi\xi_{s,t} + e_s + \delta_t + \mu_{s,t}$ where $c_{s,t}$ is household consumption observed at state level s, $\xi_{s,t}$ is the list of control variables, δ_t is time fixed effect. Unweighted averages at household level by state. All in real terms. For robustness check, the regression is also done using first differenced values—the results (shown in the Appendix) are not significantly different from the level observations
Sources: ENEGI and other data from Mexico's National Institute of Statistics and Geography

Table 2.9: State-Level Second-Stage Fixed Effect Regression—With Lagged Sovereign Default Shock (Δ Consumption)

VARIABLES	(1) Δ Consumption	(2) Δ Consumption	(3) Δ Consumption	(4) Δ Consumption	(5) Δ Consumption
Δ Pension (predicted, lag)	0.116***	0.150***	0.078***	0.106***	0.101***
	(0.0196)	(0.0279)	(0.0218)	(0.0206)	(0.0192)
Δ Other Income (log-diff)		0.055			
		(0.0329)			
Δ Wage (log-diff)			0.481***		
			(0.0576)		
Δ Wealth (log-diff)				0.087***	
				(0.0164)	
Δ Work Hours (log-diff)					0.120***
					(0.0266)
Reform	0.263***	-0.027	-0.096	-0.017	0.272***
	(0.057)	(0.199)	(0.065)	(0.083)	(0.050)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	416	416	416	416	416
R-squared	0.537	0.543	0.628	0.585	0.598
Number of state	32	32	32	32	32

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

Note: Regression specification of Equation (2.2) considering sovereign default risks, using coefficient -1.172 from Table 2.6: $\Delta c_{s,t} = \alpha_0 + \alpha_1 \Delta \hat{g}_{s,t-1} + \phi \Delta \xi_{s,t} + e_s + \delta_t + \mu_{s,t}$ where $c_{s,t}$ is household consumption observed at state level s, $\xi_{s,t}$ is the list of control variables, δ_t is time fixed effect. Unweighted averages at household level by state. All in real terms
Sources: ENEGI and other data from Mexico's National Institute of Statistics and Geography

Table 2.10: State-Level Baseline Fixed Effect Regression—No Sovereign Default Shock (Food Consumption)

VARIABLES	(1) Food Consum. (log)	(2) Food Consum. (log)	(3) Food Consum. (log)	(4) Food Consum. (log)	(5) Food Consum. (log)
Pension (log)	0.103***	0.187**	0.042	0.083***	0.103***
	(0.0344)	(0.0802)	(0.0325)	(0.0295)	(0.0352)
Other Income (log)		0.107			
		(0.0876)			
Wage (log)			0.332***		
			(0.0752)		
Wealth (log)				0.061***	
				(0.016)	
Work Hours (log)					0.003
					(0.043)
Reform	3.293***	3.031***	2.890***	3.272***	3.291***
	(0.120)	(0.238)	(0.138)	(0.110)	(0.125)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	446	446	446	446	446
R-squared	0.987	0.987	0.988	0.988	0.987
Number of state	32	32	32	32	32

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

Note: Regression specification follows a variant of Equation (2.2) without sovereign default risks, $c_{s,t} = \alpha_0 + \alpha_1 \hat{g}_{s,t} + \phi \xi_{s,t} + e_s + \delta_t + \mu_{s,t}$ where $c_{s,t}$ is household consumption observed at state level s, $\xi_{s,t}$ is the list of control variables, δ_t is time fixed effect. Unweighted averages at household level by state. All in real terms. For robustness check, the regression is also done using first differenced values—most of the results (shown in the Appendix) have different signs from the level observations here
Sources: Mexico's National Institute of Statistics and Geography

Table 2.11: State-Level Second-Stage Fixed Effect Regression—With Lagged Sovereign Default Shock (Δ Food Consumption)

VARIABLES	(1) Δ Food Consump.	(2) Δ Food Consump.	(3) Δ Food Consump.	(4) Δ Food Consump.	(5) Δ Food Consump.
Δ Pension (predicted, lag)	0.068***	0.008	0.045***	0.064***	0.066***
	(0.015)	(0.036)	(0.010)	(0.015)	(0.014)
Δ Other Income (log-diff)		-0.097*			
		(0.053)			
Δ Wage (log-diff)			0.293***		
			(0.097)		
Δ Wealth (log-diff)				0.035**	
				(0.013)	
Δ Work Hours (log-diff)					0.018
					(0.059)
Reform	4.609***	5.122***	4.395***	4.497***	4.610***
	(0.110)	(0.288)	(0.140)	(0.107)	(0.109)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	412	412	412	412	412
R-squared	0.954	0.954	0.955	0.954	0.954
Number of state	32	32	32	32	32

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

Note: Regression specification of Equation (2.2) considering sovereign default risks, using coefficient -1.172 from Table 2.6: $\Delta c_{s,t} = \alpha_0 + \alpha_1 \Delta \hat{g}_{s,t-1} + \phi \Delta \xi_{s,t} + e_s + \delta_t + \mu_{s,t}$ where $c_{s,t}$ is household consumption observed at state level s, $\xi_{s,t}$ is the list of control variables, δ_t is time fixed effect. Unweighted averages at a household level by state. All in real terms
Sources: Mexico's National Institute of Statistics and Geography

Table 2.12: State-Level Baseline Fixed Effect Regression—No Sovereign Default Shock (Discretionary Consumption)

VARIABLES	(1) Nonfood Consum. (log)	(2) Nonfood Consum. (log)	(3) Nonfood Consum. (log)	(4) Nonfood Consum. (log)	(5) Nonfood Consum. (log)
Pension (log)	0.082**	0.389***	0.105***	0.069*	0.069*
	(0.038)	(0.086)	(0.033)	(0.038)	(0.038)
Other Income (log)		0.391***			
		(0.094)			
Wage (log)			-0.129		
			(0.096)		
Wealth (log)				0.038	
				(0.024)	
Work Hours (log)					0.127***
					(0.038)
Reform	-2.668***	-3.628***	-2.512***	-2.681***	-2.725***
	(0.131)	(0.247)	(0.116)	(0.135)	(0.136)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	446	446	446	446	446
R-squared	0.984	0.986	0.984	0.984	0.985
Number of state	32	32	32	32	32

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

Note: Regression specification follows a variant of Equation (2.2) without sovereign default risks, $c_{s,t} = \alpha_0 + \alpha_1 \hat{g}_{s,t} + \phi\xi_{s,t} + e_s + \delta_t + \mu_{s,t}$ where $c_{s,t}$ is household consumption observed at state level s, $\xi_{s,t}$ is the list of control variables, δ_t is time fixed effect. Unweighted averages at household level by state. All in real terms. For robustness check, the regression is also done using first differenced values—the results (shown in the Appendix) are not significantly different from the level observations
Sources: Mexico's National Institute of Statistics and Geography

Table 2.13: State-Level Second-Stage Fixed Effect Regression—With Lagged Sovereign Default Shock (Δ Discretionary Consumption)

VARIABLES	(1) Δ Nonfood Consum.	(2) Δ Nonfood Consum.	(3) Δ Nonfood Consum.	(4) Δ Nonfood Consum.	(5) Δ Nonfood Consum.
Δ Pension (predicted, lag)	0.045*	0.138***	0.031	0.039	0.033
	(0.024)	(0.049)	(0.024)	(0.025)	(0.024)
Δ Other Income (log-diff)		0.150**			
		(0.061)			
Δ Wage (log-diff)			0.183		
			(0.111)		
Δ Wealth (log-diff)				0.052**	
				(0.021)	
Δ Work Hours (log-diff)					0.010
					(0.062)
Reform	-4.358***	-5.156***	-4.491***	-4.525***	-4.348***
	(0.128)	(0.354)	(0.147)	(0.148)	(0.121)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	412	412	412	412	412
R-squared	0.941	0.943	0.941	0.942	0.942
Number of state	32	32	32	32	32

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

Note: Regression specification of Equation (2.2) considering sovereign default risks, using coefficient -1.172 from Table 2.6: $\Delta c_{s,t} = \alpha_0 + \alpha_1 \Delta\hat{g}_{s,t-1} + \phi\Delta\xi_{s,t} + e_s + \delta_t + \mu_{s,t}$ where $c_{s,t}$ is household consumption observed at state level s, $\xi_{s,t}$ is the list of control variables, δ_t is time fixed effect. Unweighted averages at household level by state. All in real terms.
Sources: Mexico's National Institute of Statistics and Geography

Household-Level Results Having examined the data at the state level, I further examine the default-consumption relationship using household-level data. By combining ENIGH surveys from 1994 through 2018, I obtain a pooled cross-section dataset, where each household unit is randomly selected and not repeated. In other words, it is difficult to analyze the default effect that is lagged by time. Therefore, all the following results illustrate contemporaneous relationships. Here predicted pension is calculated by multiplying the observations by -0.045. Similar to the state-level regressions, the analyses here are organized by total, food, and discretionary consumption. The results are overall consistent with the state-level but with notable differences.

Table 2.14 and Table 2.15 illustrate results of total consumption. The baseline result is consistent with the state-level estimates, though at a much smaller magnitude. Table 2.15 is the estimation by taking into account sovereign default risk shock. Column (1) shows the specification in which predicted pension is the only financial explanatory variable. The coefficient is positive and significant—the lower the pension, the lower total consumption. When taking into account wealth, the coefficient remains positive and significant. The result becomes insignificant when considering wage. However, when controlling for other income and work hours, the pension coefficient becomes negative. It seems the results for total consumption could be driven by composition effects of what households consume.

To further understand the results here, I continue the analysis for food consumption and discretionary consumption. Table 2.17 shows that for food consumption, the pension coefficients are all negative and significant. This makes sense since food is a relatively inflexible expense—it is difficult to cut down such spending even with reduced pension income. Table 2.19 shows the estimation for discretionary spending: the signs of the coefficients are the same as in Table 2.15. If focusing on the results in Columns (1) and (4), it is likely that when pension income is reduced due to rising sovereign risk, contemporaneously households respond by cutting discretionary spending, while maintaining or increasing their food consumption. It requires further investigation why including non-pension income flips the coefficient sign (as seen in Column 2), while taking into account wealth does not.

The results presented here suggest three insights. First, the relationship between sovereign default risk and pension is significant, as is the relationship between pension and consumption. Second, in the majority of the cases at both the state and household levels, we observe a negative correlation between sovereign default risk and consumption. Third, this default-consumption linkage is more likely to be negative when lagged by one period. In fact, it is possible that contemporaneously this linkage is positive, but becomes negative in the next period as the changes of rigid public expenditures actually materialize. In other words, households' consumption decisions respond to changes in rigid government transfers inter-temporally.

2.5.1.3 Robustness Tests

Tables 2.29, 2.30, and 2.31 examine the changes in total, food, and discretionary consumption in response to pension fluctuation within the same period. These are state-level results and show that the coefficients are negative and significant. Tables

Table 2.14: Household Level, Baseline Fixed Effect Regression—No Sovereign Default Shock (Total Consumption, Log)

VARIABLES	(1) Consumption	(2) Consumption	(3) Consumption	(4) Consumption	(5) Consumption
Pension (log)	0.002***	0.024***	0.047***	0.042***	0.052***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Other Income (log)		0.366***			
		(0.003)			
Wage (log)			0.039***		
			(0.000)		
Wealth (log)				0.034***	
				(0.000)	
Work Hours (log)					0.115***
					(0.001)
Household Size	0.015***	0.012***	0.111***	0.141***	0.097***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of Minors	0.000	0.005***	-0.133***	-0.160***	-0.119***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
Number of Elders (65+)	-0.103***	-0.107***	-0.218***	-0.284***	-0.232***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Reform	-0.011*	-0.046*	-0.182***	-0.073***	-0.086***
	(0.006)	(0.023)	(0.010)	(0.010)	(0.010)
Fixed Effects	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income
Observations	340,638	314,455	340,638	340,638	340,638
R-squared	0.703	0.706	0.274	0.260	0.262

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows a variant of Equation (2.3) without sovereign default risks, $c_{i,s,t,g} = \alpha_0 + \alpha_1 g_{i,s,t,g} + \phi\xi_{i,s,t,g} + e_s + \delta_t + \omega_g + \mu_{i,s,t,g}$ where the the subscript g refers to the income group that a household belongs to, and ω_g stands for income group fixed effect. All in real terms. Income fixed effect refers to unobserved household characteristics due to their position in the income distribution (deciles). *Sources*: Mexico's National Institute of Statistics and Geography

Table 2.15: Household Level, Second Stage Fixed Effect Regression—With Sovereign Default Shock (Δ Consumption)

VARIABLES	(1) Δ Consumption	(2) Δ Consumption	(3) Δ Consumption	(4) Δ Consumption	(5) Δ Consumption
Δ Pension (predicted)	0.095***	-0.778***	-0.014	0.089***	-0.137***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.011)
Δ Other Income (log-diff)		0.644***			
		(0.001)			
Δ Wage (log-diff) (log-diff)			0.025***		
			(0.000)		
Δ Wealth (log-diff)				0.023***	
				(0.000)	
Δ Work Hours (log-diff)					0.111***
					(0.000)
Household Size	0.067***	0.029***	0.054***	0.068***	0.033***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of Minors	-0.013***	0.002	-0.005***	-0.016***	0.017***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Number of Elders (65+)	-0.099***	-0.101***	-0.071***	-0.098***	-0.059***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Reform	0.065***	0.170	0.056***	0.064***	0.048***
	(0.011)	(0.115)	(0.011)	(0.011)	(0.011)
Fixed Effects	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income
Observations	340,637	313,566	340,637	340,637	340,637
R-squared	0.214	0.528	0.236	0.227	0.254

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows Equation (2.3) considering sovereign default risks, using coefficient -0.045 from Table 2.7: $\Delta c_{i,s,t,g} = \alpha_0 + \alpha_1 \Delta \hat{g}_{i,s,t,g} + \phi \Delta \xi_{i,s,t,g} + e_s + \delta_t + \omega_g + \mu_{i,s,t,g}$ where the the subscript g refers to the income group that a household belongs to, and ω_g stands for income group fixed effect. All in real terms. Income fixed effect refers to unobserved household characteristics due to their position in the income distribution (deciles). *Sources*: Mexico's National Institute of Statistics and Geography

2.32, 2.33, and 2.34 repeat the state-level baseline by first-differencing the variables. The results reinforce the significant relationship between pension income and consumption.

Table 2.16: Household Level, Baseline Fixed Effect Regression—No Sovereign Default Shock (Food Consumption, Log)

VARIABLES	(1) Food Consum.	(2) Food Consum.	(3) Food Consum.	(4) Food Consum.	(5) Food Consum.
Pension (log)	0.009***	0.017***	0.039***	0.034***	0.046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Other Income (log)		0.138***			
		(0.007)			
Wage (log)			0.047***		
			(0.005)		
Wealth (log)				0.015***	
				(0.001)	
Work Hours (log)					0.144***
					(0.002)
Household Size	0.010***	0.096***	0.142***	0.177***	0.122***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of Minors	-0.032***	-0.031***	-0.097***	-0.128***	-0.079***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of Elders (65+)	-0.181***	-0.178***	-0.214***	-0.298***	-0.228***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Reform	0.067***	0.023	-0.010***	0.030**	0.015
	(0.014)	(0.050)	(0.014)	(0.014)	(0.014)
Fixed Effects	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income
Observations	340,638	314,455	340,638	340,638	340,638
R-squared	0.207	0.211	0.141	0.116	0.133

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows a variant of Equation (2.3) without sovereign default risks, $c_{i,s,t,g} = \alpha_0 + \alpha_1 g_{i,s,t,g} + \phi\xi_{i,s,t,g} + e_s + \delta_t + \omega_g + \mu_{i,s,t,g}$ where the the subscript g refers to the income group that a household belongs to, and ω_g stands for income group fixed effect. All in real terms. Income fixed effect refers to unobserved household characteristics due to their position in the income distribution (deciles). *Sources*: Mexico's National Institute of Statistics and Geography

Table 2.17: Household Level, Second Stage Fixed Effect Regression—With Sovereign Default Shock (Δ Food Consumption)

VARIABLES	(1) Δ Food Consump.	(2) Δ Food Consump.	(3) Δ Food Consump.	(4) Δ Food Consump.	(5) Δ Food Consump.
Δ Pension (predicted)	-0.097***	-0.641***	-0.272***	-0.010***	-0.457***
	(0.019)	(0.018)	(0.019)	(0.019)	(0.017)
Δ Other Income (log-diff)		0.408***			
		(0.003)			
Δ Wage (log-diff) (log-diff)			0.040***		
			(0.000)		
Δ Wealth (log-diff)				0.010***	
				(0.000)	
Δ Work Hours (log-diff)					0.172***
					(0.001)
Household Size	0.130***	0.102***	0.109***	0.130***	0.077***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of Minors	-0.036***	-0.027***	-0.024***	-0.038***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of Elders (65+)	-0.164***	-0.161***	-0.119***	-0.164***	-0.103***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Reform	0.069***	0.182	0.054***	0.069***	0.042**
	(0.019)	(0.241)	(0.018)	(0.019)	(0.018)
Fixed Effects	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income
Observations	340,637	313,566	340,637	340,637	340,637
R-squared	0.063	0.119	0.086	0.064	0.102

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows Equation (2.3) considering sovereign default risks, using coefficient -0.045 from Table 2.7: $\Delta c_{i,s,t,g} = \alpha_0 + \alpha_1 \Delta \hat{g}_{i,s,t,g} + \phi \Delta \xi_{i,s,t,g} + e_s + \delta_t + \omega_g + \mu_{i,s,t,g}$ where the the subscript g refers to the income group that a household belongs to, and ω_g stands for income group fixed effect. All in real terms. Income fixed effect refers to unobserved household characteristics due to their position in the income distribution (deciles). *Sources*: Mexico's National Institute of Statistics and Geography

Table 2.18: Household Level, Baseline Fixed Effect Regression—No Sovereign Default Shock (Discretionary Consumption, Log)

VARIABLES	(1) Nonfood Consum.	(2) Nonfood Consum.	(3) Nonfood Consum.	(4) Nonfood Consum.	(5) Nonfood Consum.
Pension (log)	0.002***	0.028***	0.056***	0.050***	0.062***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Other Income (log)		0.427***			
		(0.004)			
Wage (log)			0.044***		
			(0.000)		
Wealth (log)				0.043***	
				(0.000)	
Work Hours (log)					0.129***
					(0.001)
Household Size	-0.001	-0.005***	0.116***	0.149***	0.099***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of Minors	0.007***	0.012***	-0.154***	-0.184***	-0.138***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Number of Elders (65+)	-0.110***	-0.116***	-0.253***	-0.326***	-0.269***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Reform	-0.017**	-0.050*	-0.212***	-0.091***	-0.105***
	(0.008)	(0.029)	(0.012)	(0.012)	(0.012)
Fixed Effects	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income
Observations	340,638	314,455	340,638	340,638	340,638
R-squared	0.695	0.697	0.287	0.280	0.277

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows a variant of Equation (2.3) without sovereign default risks, $c_{i,s,t,g} = \alpha_0 + \alpha_1 g_{i,s,t,g} + \phi\xi_{i,s,t,g} + e_s + \delta_t + \omega_g + \mu_{i,s,t,g}$ where the the subscript g refers to the income group that a household belongs to, and ω_g stands for income group fixed effect. All in real terms. Income fixed effect refers to unobserved household characteristics due to their position in the income distribution (deciles). *Sources*: Mexico's National Institute of Statistics and Geography

Table 2.19: Household Level, Second Stage Fixed Effect Regression—With Sovereign Default Shock (Δ Discretionary Consumption)

VARIABLES	(1) Δ Nonfood Consum.	(2) Δ Nonfood Consum.	(3) Δ Nonfood Consum.	(4) Δ Nonfood Consum.	(5) Δ Nonfood Consum.
Δ Pension (predicted)	0.112***	-0.918***	-0.003	0.104***	-0.133***
	(0.013)	(0.011)	(0.013)	(0.013)	(0.013)
Δ Other Income (log-diff)		0.758***			
		(0.002)			
Δ Wage (log-diff) (log-diff)			0.026***		
			(0.000)		
Δ Wealth (log-diff)				0.030***	
				(0.000)	
Δ Work Hours (log-diff)					0.117***
					(0.001)
Household Size	0.061***	0.017***	0.047***	0.062***	0.025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of Minors	-0.010***	0.008***	-0.001	-0.014***	0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of Elders (65+)	-0.106***	-0.110***	-0.077***	-0.105***	-0.064***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Reform	0.070***	0.227	0.061***	0.069***	0.052***
	(0.013)	(0.143)	(0.013)	(0.013)	(0.013)
Fixed Effects	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income	State & Year & Income
Observations	340,637	313,566	340,637	340,637	340,637
R-squared	0.197	0.498	0.214	0.212	0.228

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows a variant of Equation (2.3) without sovereign default risks, $c_{i,s,t,g} = \alpha_0 + \alpha_1 g_{i,s,t,g} + \phi\xi_{i,s,t,g} + e_s + \delta_t + \omega_g + \mu_{i,s,t,g}$ where the the subscript g refers to the income group that a household belongs to, and ω_g stands for income group fixed effect. All in real terms. Income fixed effect refers to unobserved household characteristics due to their position in the income distribution (deciles). *Sources*: Mexico's National Institute of Statistics and Geography

2.5.2 Measuring Rigidity

The previous results suggest that the degree to which government expenditure is rigid matters for how sovereign default risks transmit into household consumption behavior. Therefore it is useful to better understand fiscal rigidity, and it serves predictors of which types of government expenditures are more likely to affect household consumption in times of sovereign distress. In this section I present results of measuring fiscal rigidity.

2.5.2.1 Specification 1—Panel with Fixed Effects

The first approach is to construct a new panel dataset by year and household residency. One section of ENIGH identifies household's residency information by Mexico's states and municipality. Assuming such information exists for all the years surveyed, I can construct new variables illustrating public transfer to households at a state level. Then I can use a specification similar to Herrera and Olaberria (2020), but just at the residency level. More specifically,

$$ln(g_{i,t}) = Ax_{i,t} + u_i + \epsilon_{i,t} \tag{2.4}$$

where $g_{i,t}$ is a rigid expenditure, $x_{i,t}$ is the set of independent structural variables including GDP and population, and $\epsilon_{i,t}$ represents the nonstructural component. To facilitate preliminary analysis, ENIGH is converted into a panel dataset at state level for years 1998 through 2018, with a gap of 2 years in between. Basically I calculated state-level averages (unweighted) for variables of interest based on household level data.

In other words, $g_{i,t}$ in Equation (2.4) refers to the pension income per household by state. Currently there are four control variables: real GDP index by state, state age index (ratio of elderly to youth) by state, population by state, and elderly population by state.

Following Herrera and Olaberria (2020), I also employ the corrected ordinary least square (COLS) method, but with state and year fixed effects. The main benefit of this approach is to ensure that the estimated residuals, the nonstructural component of the rigid expenditure, are always positive to facilitate interpretation. Additionally, as discussed later, this approach essentially measures the minimum spending implied by structural factors, which dovetails with the question of rigid spending. COLS is a method described in Greene (2008) to estimate deterministic production or cost frontier models [37]. More specifically, COLS involves subtracting the largest estimated residual:

$$\epsilon_{i,t}^{\text{COLS}} = \epsilon_{i,t} - \max_{i} \epsilon_{i,t} \tag{2.5}$$

This is equivalent to shifting the intercept in the OLS equation "upward" (and simultaneously shifting the predicted values "downward") so that all observations lie above or on the regression line. By shifting the line "downward" to the frontier, I ensure that the residuals are always positive. "Frontier" in this context refers to the minimum level of rigid expenditure predicted by Mexico's structural characteristics in each state [38]. Since the residuals also represent the nonstructural component of a rigid

[37] William H. Greene (2008) "The Econometric Approach to Efficiency Analysis" *The Measurement of Productive Efficiency and Productivity Change*: Oxford University Press

[38] Page 48 of Herrera and Olaberria (2020) provides illustration of this idea

expenditure, it is possible to infer the structural component.

Consequently, the main results of interest are the estimated residuals, rather than the individual coefficients of the regression. Table 2.20 summarizes the mean residuals by state through COLS. The structural variables used include GDP growth, elderly population, population, and age index. It is important to note that all these variables are at the state level: for example, the GDP growth data are for each of the 32 states. For all these specifications, state-level pension data (per household) of ENIGH serve as the dependent variable. The main difference between specifications 1-3 and specifications 4-6 is that the latter group are first differenced, including for the dependent variable (Table 2.26 in the Appendix shows the OLS results and provides further details on the specifications).

For Table 2.20, the estimated residuals are averaged by state, and the table summarizes such average values depending on regression specification. For specifications 1-3, the mean residual is generally 0.32, measuring the nonstructural component of the pension expenditure. In other words, for every 1 peso of pension, 0.32 of the unit is nonstructural, implying that the structural component is around 68%. This figure is in fact consistent with the number of 70% for the regional average of rigid spending (including pension and public wage bill) in Latin America, based on cross-country regression in Herrera and Olaberria (2020). Specifications 4-6, however, suggest that the structural component of a rigid expenditure like pension may be much higher—between 82% and 90%.

Table 2.20: Summary of Nonstructural Component of Pension by State

	Mean	Std. Dev.	Min	Max
Spec 1: GDP & elderly pop.	0.3225	0.0110	0.3125	0.3701
Spec 2: GDP & population	0.3255	0.0111	0.3155	0.3734
Spec 3: GDP & age index	0.3277	0.0112	0.3175	0.3757
Spec 4: GDP & elderly pop. (1st diff)	0.0977	0.0139	0.0903	0.1731
Spec 5: GDP & population (1st diff)	0.0999	0.0141	0.0924	0.1764
Spec 6: GDP, pop., & age index (1st diff)	0.0999	0.0141	0.0924	0.1763

Note: Results follow from first estimating Equation (2.4), $ln(g_{i,t}) = Ax_{i,t} + u_i + \epsilon_{i,t}$ and then calculations using Equation (2.5), $\epsilon_{i,t}^{\text{COLS}} = \epsilon_{i,t} - \max_i \epsilon_{i,t}$

Specification 2—Time Series and Inter-temporal

Another approach is to use an AR(1) type model to estimate fiscal rigidity in the inter-temporal sense. Studies such as Blanchard and Perotti (2002) and Fernández-Villaverde et al (2015) have established that we can empirically identify fiscal rules and policy shocks in a reduced form. More specifically, there is an inter-temporal relationship between today's and yesterday's fiscal policies. Similar to Fernández-Villaverde et al (2015), we can estimate the law of motion of a rigid expenditure as

$$g_t - g = \rho_g \left(g_{t-1} - g\right) + \phi_{g,y}\tilde{y}_{t-1} + \phi_{g,b}\left(\frac{b_{t-1}}{y_{t-1}} - \frac{b}{y}\right) + \exp\left(\sigma_{g,t}\right)\varepsilon_{g,t}, \quad \varepsilon_{g,t} \sim \mathcal{N}(0,1) \quad (2.6)$$

where g is the mean public expenditure as a share of output, $\tilde{y}_{t-1}$ is lagged detrended log output, and b_t is public debt. If replacing $\tilde{y}_{t-1}$ with GDP growth, the output parameter is denoted as $\tilde{\phi}_{g,y}$. This specification captures the following characteristics of fiscal behavior: the expected public expenditure based on the past value of expenditure, on the business cycle, and on the public debt, yet taking into account possible deviations due to new legislations and other unexpected fiscal actions.

Fernández-Villaverde et al (2015) focuses on the time-varying volatility of fiscal policy innovation, measured by $\exp(\sigma_{g,t})$. Due to their research questions, such studies tend to focus on the error term instead of the coefficient (and rightfully so). Yet it will be useful to start paying attention to the persistent/rigid part denoted by ρ_g, which measures how much of the past value determines today's public expenditure. While ENIGH is a pooled cross-section dataset, it is possible to convert it into time series disaggregated by public expenditure items and household types (e.g., high, low incomes). The values used in each year—17 years in total—can be an average of household-level observations (one potential problem is the two-year gap between the data). The random-sampling nature of the survey ensures the comparability and consistency of data across years.

Focusing on pension and wage, I have used Mexico's quarterly aggregate data (real terms) in 1998-2019 to estimate the rigidity parameter. Similar to Fernández-Villaverde et al (2015), Christiano-Fitzgerald (CF) filter detrends the output. Besides, real GDP growth is used as an alternative variable (the parameter in this case is $\tilde{\phi}_{g,y}$). Tables 2.21 and 2.22 report the estimation of pension rigidity in the inter-temporal sense; the main parameter of interest is ρ_g. There are three types of estimation: AR(1) for pension data, OLS for Equation (2.6), and Bayesian for Equation (2.6).[39] The Fernández-Villaverde et al (2015) paper employs a Bayesian approach to estimate fiscal rules, using U.S. aggregate, quarterly data (1970Q1 to 2014Q2), and reports the posterior median for the government spending parameter as 0.99.

For pension, Column 1 of Table 2.21 shows that Mexico's rigidity parameter

[39]The estimations that follow Equation (2.6) do not include the term $\exp(\sigma_{g,t})$

Table 2.21: Parameters of Inter-Temporal Pension Rigidity

Estimation	(1) AR(1)	(2) OLS1	(3) OLS2	(4) Bayesian
ρ_g	0.9996	0.7864	0.8228	0.7871
	[0.9818, 1.0173]	[0.6545, 0.9182]	[0.6914, 0.9541]	[0.7862, 0.7882]
$\phi_{g,y}$		-0.0086		-0.0107
		[-0.0195, 0.0024]		[-0.0133 -0.0081]
$\tilde{\phi}_{g,y}$			-0.0001	
			[-0.0003, 0.00007]	
$\phi_{g,b}$		0.0003	0.00006	-0.0005
		[-0.0025, 0.0030]	[-0.0027, 0.0028]	[-0.0023, 0.0010]

Note: Results in Columns (2)-(4) use a variant of Equation (2.6), $g_t - g = \rho_g (g_{t-1} - g) + \phi_{g,y}\tilde{y}_{t-1} + \phi_{g,b}\left(\frac{b_{t-1}}{y_{t-1}} - \frac{b}{y}\right) + \varepsilon_{g,t}$. Sample period: 1998Q1-2019Q4. 95% confidence interval are reported in brackets. "OLS1" refers to using detrended GDP variable (through CF filter); "OLS2" uses real GDP growth. Following Fernández-Villaverde et al (2015), the Bayesian estimation here uses flat priors & Markov Chain Monte Carlo to sample from the posterior. The results for Bayesian are posterior medians. OLS and Bayesian both contain a trend component.

is over 0.99 from AR(1). For OLS estimation, there are two different specifications: detrended output using the CF filter, and real GDP growth. ρ_g is 0.7864 in the first specification, and is 0.8228 in the second specification. The result of the Bayesian approach is nearly identical to the first OLS estimation. In summary, the inter-temporal rigidity of pension expenditure is around 0.8, as illustrated by Column 2, with an upward limit of 0.99. In comparison, Table 2.22 shows that public wage bill has a much higher degree of rigidity. This is consistent with the results in Table 2.4 that when faced with need for fiscal adjustment due to debt distress, pension is much more responsive to sovereign debt spread than public wage spending.

Table 2.22: Parameters of Inter-Temporal Public Wage Rigidity

	(1)	(2)	(3)	(4)
Estimation	AR(1)	OLS1	OLS2	Bayesian
ρ_g	0.9801	0.9291	0.9295	0.9183
	[0.9498, 1.010]	[0.8527, 1.0055]	[0.8555, 1.0034]	[0.8414, 0.9978]
$\phi_{g,y}$		0.0036		0.0022
		[-0.0594, 0.0666]		[-0.0677 -0.0596]
$\tilde{\phi}_{g,y}$			0.0001	
			[-0.0008, 0.0011]	
$\phi_{g,b}$		-0.0021	-0.0028	-0.0021
		[-0.0207, 0.0163]	[-0.0205, 0.0150]	[-0.0227, 0.0145]

Note: Results in Columns (2)-(4) use a variant of Equation (2.6), $g_t - g = \rho_g (g_{t-1} - g) + \phi_{g,y}\tilde{y}_{t-1} + \phi_{g,b}\left(\frac{b_{t-1}}{y_{t-1}} - \frac{b}{y}\right) + \varepsilon_{g,t}$. Sample period: 1993Q1-2019Q4. 95% confidence interval are reported in brackets. "OLS1" refers to using detrended GDP variable (through CF filter); "OLS2" uses real GDP growth. Following Fernández-Villaverde et al (2015), the Bayesian estimation here uses flat priors & Markov Chain Monte Carlo to sample from the posterior. The results for Bayesian are posterior medians. OLS and Bayesian both contain a trend component.

2.6 Conclusion

In this chapter, I examine how sovereign debt default risks transmit into household consumption behavior, and the role played by fiscal transfer, using data from the National Survey of Household Income and Expenditure (ENIGH) of Mexico. This chapter establishes a novel empirical link between default risks and household consumption. More specifically, when the government faces financial pressures and higher debt servicing costs, it adjusts expenditures and revenues to ensure debt sustainability. I show that expenditure types such as pension payments are reduced in response to rising default risks, while other items such as public wage bill are more rigid. This consequently generates consumption loss of households who rely on government transfers like pension, and this effect is particularly pronounced for discretionary spending. Finally, properly measuring public expenditure rigidity contributes to the understanding of this link, for which I conduct estimates that illustrate feasible measurement approaches. For future research, results in this chapter provide the empirical basis for constructing more realistic structural sovereign default models that consider fiscal rigidity and spillovers into household behavior.

2.7 Appendix

Table 2.23: First Stage OLS Regression with Lagged Sovereign Risk (Aggregate, Real, Per Capita)

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
3-month spread, lagged (log)	-0.105***	-0.173***	-0.097***	-0.228	-0.049	-0.455**	0.020	-0.021	0.047*	-0.193***
	(0.028)	(0.036)	(0.020)	(0.279)	(0.051)	(0.218)	(0.074)	(0.044)	(0.028)	(0.041)
trend	0.002***	0.018***	0.003***	0.025***	0.011***	-0.010*	0.007***	0.019***	0.005***	-0.005***
	(0.001)	(0.001)	(0.000)	(0.007)	(0.001)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	88	107	107	106	107	107	107	107	107	107
R-squared	0.394	0.927	0.675	0.293	0.673	0.044	0.209	0.875	0.484	0.233
F test:	27.69	662.6	107.9	21.39	106.8	2.372	13.74	362.4	48.69	15.84

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
EMBI, lagged (log)	-0.077**	-0.203***	-0.059***	-0.156	-0.029	-0.449*	0.141*	-0.003	0.065**	-0.222***
	(0.035)	(0.042)	(0.022)	(0.337)	(0.062)	(0.255)	(0.083)	(0.051)	(0.031)	(0.047)
trend	0.003***	0.019***	0.005***	0.032***	0.013***	-0.010*	0.010***	0.019***	0.005***	-0.004***
	(0.001)	(0.001)	(0.000)	(0.006)	(0.001)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	83	99	99	98	99	99	99	99	99	99
R-squared	0.327	0.923	0.723	0.325	0.678	0.042	0.318	0.866	0.465	0.209
F test:	19.45	576.6	125.2	22.89	101	2.121	22.35	310.1	41.79	12.71

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Spread (in percentage) is the difference between Mexico 3-month and U.S. 3-month yields. All dependent variables are seasonally adjusted, and are in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, FRED, JPMorgan EMBI

Table 2.24: First Stage OLS Regression with Log Diff (Aggregate, Real, Per Capita)

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
3-month spread(log-dif)	-0.020	-0.051*	-0.059	0.065	0.031	0.167	-0.148	0.020	-0.072	0.101
	(0.116)	(0.029)	(0.040)	(0.798)	(0.082)	(0.428)	(0.175)	(0.062)	(0.059)	(0.095)
Observations	87	107	107	105	107	107	107	107	107	107
R-squared	0.000	0.029	0.020	0.000	0.001	0.001	0.007	0.001	0.014	0.011
F test:	0.0282	3.147	2.153	0.00670	0.144	0.152	0.721	0.106	1.476	1.149

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
EMBI(log-dif)	0.030	-0.081***	-0.025	-0.859	0.108	0.724*	-0.261	0.076	0.010	0.218**
	(0.090)	(0.027)	(0.037)	(0.814)	(0.082)	(0.385)	(0.161)	(0.059)	(0.050)	(0.091)
Observations	81	98	98	96	98	98	98	98	98	98
R-squared	0.001	0.084	0.005	0.012	0.018	0.036	0.027	0.017	0.000	0.056
F test:	0.111	8.757	0.457	1.114	1.725	3.539	2.616	1.671	0.0416	5.677

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Spread (in percentage) is the difference between Mexico 3-month and U.S. 3-month yields. All dependent variables are seasonally adjusted, and are in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, FRED, JPMorgan EMBI

Table 2.25: First Stage OLS Regression with CF Filter (Aggregate, Real, Per Capita)

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
3-month spread(CF filter)	0.196	-0.086	0.036	0.162	0.015	0.015	-0.228	-0.037	-0.308	-0.048
	(0.121)	(0.113)	(0.161)	(0.177)	(0.110)	(0.133)	(0.138)	(0.115)	(0.263)	(0.174)
Observations	19	29	23	32	22	34	31	28	23	28
R-squared	0.133	0.021	0.002	0.027	0.001	0.000	0.086	0.004	0.062	0.003
F test:	2.610	0.584	0.0510	0.838	0.0187	0.0123	2.720	0.104	1.378	0.0764

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Fed transfer	(2) Pension	(3) Education	(4) Wage	(5) Health	(6) Energy	(7) Transport	(8) Welfare	(9) Defense	(10) Agro
EMBI(CF filter)	-0.328	-0.571**	-0.013	0.229	-0.282	0.106	-0.247	0.117	-0.095	-0.018
	(0.277)	(0.256)	(0.279)	(0.274)	(0.182)	(0.369)	(0.288)	(0.191)	(0.351)	(0.285)
Observations	17	17	24	23	22	25	25	26	24	25
R-squared	0.086	0.249	0.000	0.032	0.107	0.004	0.031	0.015	0.003	0.000
F test:	1.405	4.984	0.00207	0.699	2.395	0.0822	0.732	0.376	0.0737	0.00392

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Spread (in percentage) is the difference between Mexico 3-month and U.S. 3-month yields. All dependent variables are seasonally adjusted, and are in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, FRED, JPMorgan EMBI

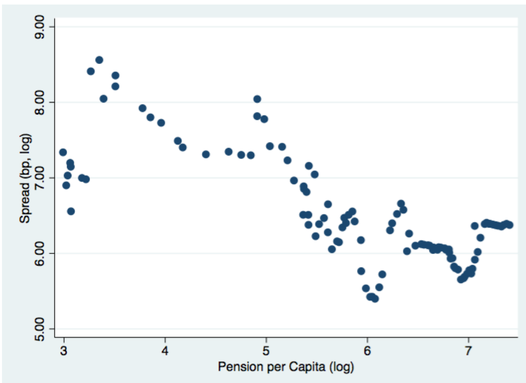
Table 2.26: Pension Expenditure Rigidity at State Level

VARIABLES	(1) Pension (per HH, log)	(2) Pension (per HH, log)	(3) Pension (per HH, log)	(4) Δ Pension	(5) Δ Pension	(6) Δ Pension
State GDP growth	-0.00251	-0.00204	-0.00184	-0.00159	-0.00168	-0.00169
	(0.00609)	(0.00611)	(0.00614)	(0.00850)	(0.00852)	(0.00854)
State elderly population (log)	1.112**					
	(0.453)					
State population (log)		0.975**				
		(0.481)				
State age index			-0.186			
			(0.477)			
Δ Elderly population				1.174		
				(1.164)		
Δ Population					-0.444	-0.405
					(1.101)	(1.183)
Δ Age index						0.00242
						(0.0266)
Constant	-5.088	-6.310	-5.331	-3.530***	-3.308***	-3.316***
	(4.984)	(6.642)	(7.106)	(0.244)	(0.180)	(0.203)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	352	352	352	352	352	352
R-squared	0.730	0.729	0.729	0.863	0.863	0.863

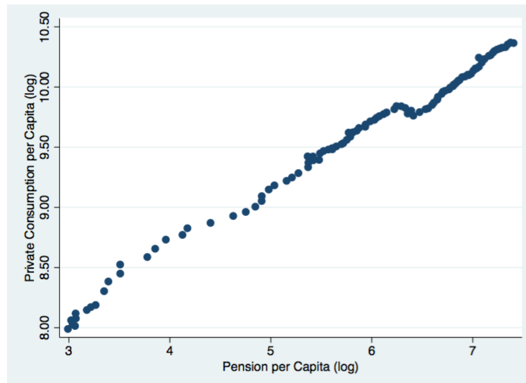
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables are in real terms and at state level. Sample period: 1998-2018.
All Δ variables are first differenced level variables
Pension data: unweighted averages at a household level by state.
Age index is defined as the ratio of older adults (60 and over) for every hundred children and youth (0 to 14 years of age). Elderly population is defined as anyone older than 60 years old.
Only the variable of age index exhibits a minor upward trend
Sources: Mexico's National Institute of Statistics and Geography

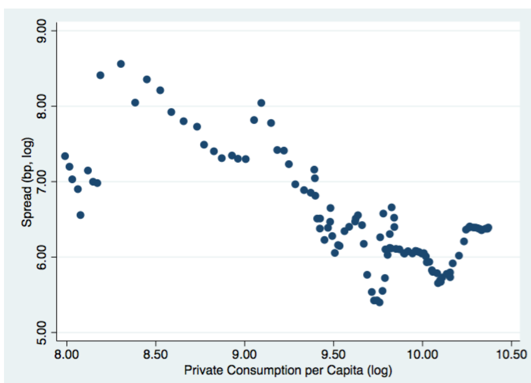
Figure 2.6: Default Risk, Pension, and Consumption of Mexico (Per Capita, 1993-2019, Quarterly)



(a) Sovereign Debt Spread and Pension Expenditure



(b) Household Consumption and Pension Expenditure



(c) Sovereign Debt Spread and Household Consumption

Source: OECD, FRED, and Mexico's Ministry of Finance and Public Credit

Table 2.27: First Stage OLS Regression with Lag Spread and First Differencing (Aggregate, Real, Per Capita)

VARIABLES	(1) Δ Pension (log)	(2) Δ Pension (log)	(3) Δ Pension (log)	(4) Δ Pension (log)
Δ Spread (lag)	-0.0582**	-0.0376	-0.0382	-0.0677**
	(0.0230)	(0.0250)	(0.0248)	(0.0274)
realGDPgrowth		0.00843*	0.00874**	0.00512
		(0.00433)	(0.00429)	(0.00514)
Δ Labor force (log)			1.114*	
			(0.669)	
Δ Pension revenue (log)				-0.0377
				(0.143)
Constant	0.0201***	0.0154***	0.0151***	0.0190***
	(0.00512)	(0.00561)	(0.00556)	(0.00603)
Observations	106	106	106	99
R-squared	0.058	0.092	0.116	0.116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Spread (in basis points) is the difference between Mexico 3-month and U.S. 3-month yields. Pension, revenue, and labor force participate rate are seasonally adjusted. All in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, OECD, FRED, ILO, National Institute of Statistics and Geography

Table 2.28: Aggregate Data—Second Stage OLS Regression (Real, Per Capita)

VARIABLES	(1) Δ Consumption	(2) Δ Consumption	(3) Δ Consumption	(4) Δ Consumption
Δ pension	-0.00743	-0.0342	0.0180	-0.0343
	(0.0549)	(0.0351)	(0.0396)	(0.0353)
realGDPgrowth		0.0104***	0.00843***	0.0105***
		(0.000838)	(0.000910)	(0.00123)
Δ earning			-0.0483	
			(0.248)	
Δ saving				-0.0327
				(0.350)
Constant	-0.000227	-0.0138	0.00283	-0.0139
	(0.0157)	(0.0101)	(0.0116)	(0.0101)
Observations	107	107	99	107
R-squared	0.000	0.597	0.488	0.597

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Predicted pension refers to the observations generated from the predicted values using the spread coefficient -0.0450 from Stage 1. Pension and savings are seasonally adjusted. All in real, per capita terms.
Sources: Mexico's Ministry of Finance and Public Credit, OECD, FRED, ILO, National Institute of Statistics and Geography

Table 2.29: State-Level Second-Stage Fixed Effect Regression—With Sovereign Default Shock (Total Consumption)

VARIABLES	(1) Δ Consumption	(2) Δ Consumption	(3) Δ Consumption	(4) Δ Consumption	(5) Δ Consumption
Δ Pension (predicted)	-3.669***	-4.187***	-2.439***	-3.464***	-3.071***
	(0.657)	(0.875)	(0.618)	(0.675)	(0.573)
Δ Other Income (log-diff)		0.0359			
		(0.0328)			
reform	0.257**	-0.00427	-0.693***	0.279**	0.212*
	(0.107)	(0.260)	(0.160)	(0.113)	(0.110)
Δ Wage (log-diff)			0.534***		
			(0.0647)		
Δ Wealth (log-diff)				0.0823***	
				(0.0162)	
Δ Work Hours (log-diff)					0.144***
					(0.0246)
Constant	-1.280***	-1.369***	-0.309	-1.243***	-1.060***
	(0.300)	(0.323)	(0.304)	(0.314)	(0.266)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	447	447	447	447	447
R-squared	0.600	0.602	0.700	0.628	0.671
Number of state	32	32	32	32	32

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

Table 2.30: State-Level Second-Stage Fixed Effect Regression—With Sovereign Default Shock (Food Consumption)

VARIABLES	(1) Δ Food Consump.	(2) Δ Food Consump.	(3) Δ Food Consump.	(4) Δ Food Consump.	(5) Δ Food Consump.
Δ Pension (predicted)	-2.093***	-1.044	-1.399***	-1.997***	-2.045***
	(0.558)	(0.773)	(0.510)	(0.554)	(0.541)
Δ Other Income (log-diff)		-0.0726*			
		(0.0413)			
reform	7.216***	7.745***	6.670***	7.226***	7.212***
	(0.108)	(0.320)	(0.158)	(0.107)	(0.106)
	(0.0849)	(0.138)	(0.105)	(0.0832)	(0.0846)
Δ Wage (log-diff)			0.308***		
			(0.0754)		
Δ Wealth (log-diff)				0.0383***	
				(0.0128)	
Δ Work Hours (log-diff)					0.0122
					(0.0473)
Constant	-4.010***	-3.830***	-3.458***	-3.993***	-3.993***
	(0.275)	(0.305)	(0.271)	(0.272)	(0.266)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	443	443	443	443	443
R-squared	0.970	0.970	0.971	0.970	0.970
Number of state	32	32	32	32	32

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

Table 2.31: State-Level Second-Stage Fixed Effect Regression—With Sovereign Default Shock (Discretionary Consumption)

VARIABLES	(1) Δ Nonfood Consum.	(2) Δ Nonfood Consum.	(3) Δ Nonfood Consum.	(4) Δ Nonfood Consum.	(5) Δ Nonfood Consum.
Δ Pension (predicted)	-1.527**	-3.090***	-1.023	-1.417*	-1.010
	(0.683)	(1.073)	(0.733)	(0.709)	(0.730)
Δ Other Income (log-diff)		0.108**			
		(0.0495)			
reform	-6.967***	-7.755***	-7.363***	-6.955***	-7.003***
	(0.145)	(0.397)	(0.236)	(0.146)	(0.155)
Δ Wage (log-diff)			0.224**		
			(0.105)		
Δ Wealth (log-diff)				0.0440**	
				(0.0194)	
Δ Work Hours (log-diff)					0.131**
					(0.0516)
Constant	2.755***	2.486***	3.156***	2.775***	2.941***
	(0.330)	(0.393)	(0.389)	(0.343)	(0.353)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	443	443	443	443	443
R-squared	0.965	0.966	0.966	0.965	0.967
Number of state	32	32	32	32	32

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

Table 2.32: State-Level Baseline Fixed Effect Regression (First Differenced)—No Sovereign Default Shock (Total Consumption)

VARIABLES	(1) Δ Consumption	(2) Δ Consumption	(3) Δ Consumption	(4) Δ Consumption	(5) Δ Consumption
Δ Pension (first diff)	0.210***	0.625***	0.145***	0.199***	0.181***
	(0.0316)	(0.0390)	(0.0243)	(0.0298)	(0.0246)
Δ Other Income (log-diff)		0.519***			
		(0.0408)			
reform	0.952***	-1.495***	-0.0699	0.932***	0.821***
	(0.163)	(0.203)	(0.194)	(0.152)	(0.134)
Δ Wage (log-diff)			0.442***		
			(0.0645)		
Δ Wealth (log-diff)				0.0711***	
				(0.0181)	
Δ Work Hours (log-diff)					0.126***
					(0.0219)
Constant	-0.104	1.051***	0.392***	-0.126	-0.0829
	(0.0801)	(0.101)	(0.0989)	(0.0747)	(0.0657)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	447	447	447	447	447
R-squared	0.665	0.818	0.727	0.686	0.718
Number of state	32	32	32	32	32

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

Note: unweighted averages at a household level by state.
Sources: ENEGI and other data from Mexico's National Institute of Statistics and Geography

Table 2.33: State-Level Baseline Fixed Effect Regression (First Differenced)—No Sovereign Default Shock (Food Consumption)

VARIABLES	(1) Δ Food Consump.	(2) Δ Food Consump.	(3) Δ Food Consump.	(4) Δ Food Consump.	(5) Δ Food Consump.
Δ Pension (first diff)	0.103***	0.105	0.0631***	0.0978***	0.102***
	(0.0252)	(0.100)	(0.0195)	(0.0247)	(0.0242)
Δ Other Income (log-diff)		0.00236			
		(0.114)			
reform	7.509***	7.498***	6.881***	7.500***	7.506***
	(0.165)	(0.514)	(0.195)	(0.161)	(0.160)
Δ Wage (log-diff)			0.273***		
			(0.0778)		
Δ Wealth (log-diff)				0.0333**	
				(0.0126)	
Δ Work Hours (log-diff)					0.00346
					(0.0469)
Constant	-3.294***	-3.289***	-2.989***	-3.304***	-3.294***
	(0.0801)	(0.238)	(0.0986)	(0.0748)	(0.0783)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	443	443	443	443	443
R-squared	0.971	0.971	0.971	0.971	0.971
Number of state	32	32	32	32	32

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

Note: unweighted averages at a household level by state.
Sources: Mexico's National Institute of Statistics and Geography

Table 2.34: State-Level Baseline Fixed Effect Regression (First Differenced)—No Sovereign Default Shock (Discretionary Consumption)

VARIABLES	(1) Δ Nonfood Consum.	(2) Δ Nonfood Consum.	(3) Δ Nonfood Consum.	(4) Δ Nonfood Consum.	(5) Δ Nonfood Consum.
Δ Pension (first diff)	0.104***	0.518***	0.0798***	0.0984***	0.0776***
	(0.0249)	(0.114)	(0.0254)	(0.0254)	(0.0240)
Δ Other Income (log-diff)		0.516***			
		(0.128)			
reform	-6.575***	-9.001***	-6.961***	-6.586***	-6.694***
	(0.152)	(0.534)	(0.250)	(0.155)	(0.158)
Δ Wage (log-diff)			0.168		
			(0.106)		
Δ Wealth (log-diff)				0.0380*	
				(0.0210)	
Δ Work Hours (log-diff)					0.123**
					(0.0517)
Constant	3.198***	4.343***	3.386***	3.186***	3.215***
	(0.0750)	(0.256)	(0.131)	(0.0751)	(0.0761)
Fixed Effects	State & Year	State & Year	State & Year	State & Year	State & Year
Observations	443	443	443	443	443
R-squared	0.966	0.971	0.966	0.966	0.967
Number of state	32	32	32	32	32

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

Note: unweighted averages at a household level by state.
Sources: Mexico's National Institute of Statistics and Geography

Chapter 3

Climate Risks and Sovereign Default: Scenario Analysis of Fiscal Conditions

3.1 Introduction

Climate change is a pressing environmental and economic challenge, and it poses increasing physical and financial risks.[1] Its acceleration has materialized as increasing frequencies of natural disasters globally, which often result in damages to properties, people, and the broader economy.[2] Seminal studies such as Nordhaus (1992), Nordhaus (2017), Burke *et al.* (2015), Burke *et al.* (2018) have documented how physical risks of climate change negatively affect economic output.[3] These challenges call for efforts in adaptation as well as in mitigation. For governments worldwide, there

[1] For example, see a 2015 speech by Mark Carney, then Governor of the Bank of England

[2] For an illustration of increasing frequencies of climate disasters, see Figure 3.3 in the Appendix

[3] Reisinger *et al.* (2020) define *physical risks* as those resulting from "climate change impacts and climate-related hazards"

is immense need for climate financing and consequently potentially high fiscal costs. To limit the temperature increase to 1.5°C, the Intergovernmental Panel on Climate Change (IPCC (2022)) estimates that the global financing need for the energy sector is \$2.3 trillion per year between now and 2052. On climate adaptation, developing countries' financing needs will likely be \$310-555 billion per year by 2050 (UNEP (2021)). It is not only developing countries that may be facing financing shortfalls.

In the United States, the federal government forecasts that due to climate change, the federal revenue loss could be up to 1.9% of GDP in 2100.[4] On the expenditure side, the federal government could face additional expenditure of up to \$128 billion annually. Besides physical risks, transition risks of climate change are another cause of concern for public finance. Reisinger *et al.* (2020) with IPCC define *transition risks*[5] as any non-physical risks associated with the economy shifting to being less-carbon intensive. In other words, transition risks are the potential downsides of structural adjustments in the economy in mitigating and adapting to climate change.[6] These transition risks put upward pressure on sovereign debt borrowing, as the climate-related spending rises and the tax base weakens.[7]

[4]See United States Office of Management and Budget (2021), "Federal Budget Exposure to Climate Risk". The result of federal revenue loss uses a 10 percent impact on U.S. GDP, which represents the 95th percentile of estimated economic damages under the NGFS 'Current Policy' scenario.

[5]Such risks could arise in a *disorderly transition* (disruptive, unanticipated, sudden, and/or late policy actions) in which fuel security is disrupted, energy markets become volatile, and assets become stranded (e.g., loss of value)

[6]FSB (2020). IEA (2021); definition of "disorderly transition" from NGFS (2020). See this link for definition of "stranded assets." In essence, transition risks are part of the uncertainty posed by climate change. As described by Goolgasian & Delongchamp (2020), the specific drivers of transition risks include: 1) Shift from fossil fuels to renewable energy; 2) Change in asset valuation, access to finance, and profitability in sectors that rely on fossil fuels; 3) Regulations that curb carbon emission; 4) Change in social norms and consumption behavior; 5) Labor market changes due to climate migration; 6) Technological innovations.

[7]Lorans & Moussavi (2019)

With such financing gaps, governments are more likely to rely on debt for these climate efforts, yet there are limited understandings of how climate change affects sovereign default risks, particularly in relation to fiscal policy and fiscal conditions. This chapter helps answer this question by employing a qualitative sovereign default model, combined with empirical analysis, taking into account fiscal conditions. More specifically, fiscal conditions refer to any factors that can modulate the conduct of fiscal policy, and include two broad categories: fiscal rule and fiscal rigidity. Fiscal rule (*how* to adjust) generally entails placing numerical constraints on budget and debt. On the other hand, fiscal rigidity measures *whether* a government can adjust its expenditure or revenue. Put another way, when a government has high degree of fiscal rigidity, there is "little room to maneuver": the government has limited inability to adjust tax or spending in the short term.

There are few studies on fiscal rigidity in general or in the context of climate change risks. Herrera & Olaberria (2020) is one such study that exploits cross-sectional variations to show that on average 70% of government spending in Latin American and Caribbean is rigid (meaning a significantly high portion of the spending cannot be adjusted in the short term). In Chapter 2, taking an approaching focusing on inter-temporal variations, I show that in Mexico as much as 82% of the expenditure is difficult to adjust. Understandings of the fiscal conditions, especially fiscal rigidity, matter for the analysis of climate risks, as they illustrate the potential paths to adjustment and transition to a low-carbon economy. My chapter makes contributions by providing empirical analysis of how both physical and transition risks affect sovereign default.

More importantly, the results illustrate the ways fiscal conditions matter in how climate risks affect sovereign default, which have important policy implications for structural reforms.

The organization of the chapter is the followings: Section 3.2 summarizes existing literature and highlights my contributions. Section 3.3 discusses the main datasets used to measure climate vulnerability and physical hazards, in addition to fiscal conditions. In Section 3.4, I take panel logistic regression as the estimation method, and discuss the empirical strategy to estimate the role of fiscal conditions and the impact of transition risks. In Section 3.5 I build a two-period model to illustrate that high fiscal rigidity makes the government more financially constrained, therefore even more susceptible to default due to climate change. Section 3.6 concludes.

3.2 Related Studies

While the explicit focus on climate change is relatively new, existing studies have examined how natural disasters affect fiscal costs and debt level. Koetsier (2017) find that sovereign debt level increases in response to natural disasters. Other studies such as Deryugina (2017) and Noy & Nualsri (2011) both find that public spending increases following natural disasters. Focusing on default probability, Klomp (2017) employs a logit model in which the dependent variable is the incident of default,[8] and find that disasters such as storms and earthquakes raise default probability by 3%.

[8] According to this measure, a country is in default if 1) debt arrears are over 5% of total debt; 2) debt relief; 3) support from the IMF; 4) being classified as default by Standard & Poor's.

There is also emerging empirical evidence that climate change has significant impact on sovereign debt, and in most cases it raises default risks. While not equivalent to default probabilities, government credit ratings by agencies such as Standard & Poor's (S&P) provide insights into financial market's perception of risks. Following the S&P methodology, Klusak *et al.* (2021) conduct simulations and show that increased temperature volatility could lead to sovereign credit rating downgrades. In particular, under the "business as usual" scenario, many economies would experience credit rating cuts, with downgrade of 2.48 notches on average by the year 2100[9].

Other studies use historical observations to examine the link between climate change and sovereign default. Cevik & Jalles (2020b) use a panel dataset of 98 economies for 1995-2017, and specifically focus on the measurements of climate vulnerability and resilience. They find that country's climate vulnerability increases its sovereign spread, while climate resilience reduces it. Kling *et al.* (2018) also find that climate vulnerability increases cost of sovereign debt borrowing. Similarly, Beirne *et al.* (2020) find that climate vulnerability has a bigger effect than climate resilience on sovereign risks. In some cases, climate-related disasters can also trigger events of sovereign default. Asonuma *et al.* (2018) find that Grenada's debt restructuring in 2004-06 was triggered by Hurricane Ivan (causing damage worth 200 percent of GDP) in September 2004. Grenada started missing debt payments in October 2004, then was downgraded to "selective default." The ensuing debt restructuring resulted in net present value (NPV) haircut of 38.4 percent.

[9] The rating is on a 20-notch scale

Much attention on the climate change impact is on the physical damage, and the projections often are in a long-term horizon (e.g., a hundred years from now). Yet in the intermediate term, climate change may pose non-physical risks that have important ramifications for the financial market. In fact, firms and the financial sector are not oblivious to such risks[10]. Bolstad *et al.* (2019) employ textual analysis of public companies' annual 10k filings with the U.S. Securities and Exchange Commission (SEC)[11], and show that on average in each company's filing, there are more mentions of climate transitions risks than physical risks. At the same time, researchers in academia and financial markets have started to notice the importance of measuring transition risks for firms' stock returns.[12] Engle *et al.* (2020), Meinerding *et al.* (2020), and Sautner *et al.* (2021) use textual analysis of news and corporate earnings calls to measure climate transition risks. In particular, Sautner *et al.* (2021) do find that investors demand compensation *ex ante* for stocks more exposed to climate risks, though the movement of risk premium over time is not monotonic.[13]

[10]For example, see Krueger *et al.* (2020) for survey of institutional investors' perceptions of climate regulatory risks

[11]While the 10k form is mandatory, companies voluntarily disclose their perceptions of climate risks. The companies here are in the Russell 3000 Index

[12]Giese *et al.* (2021) focus on specific sectors' carbon emission as a measurement of transition risk, while Bolton & Kacperczyk (2021) use firm-level data in 77 countries. Despite the focus on carbon emission, the two studies seem to have arrived at contradictory results: Bolton & Kacperczyk (2021) find that higher-emission companies observe higher stock returns, as investors demand a "carbon premium." This contrast suggests the challenge of properly measuring transition risks. Additionally, such measures may suffer from selection bias, as carbon emission disclosure tends to be voluntary, at least in the United States

[13]Nevertheless, such narrative-based measures are not free from sample selection bias, as they are dependent on information that is publicly disclosed. More importantly, the measures from all these papers (all focusing on equity markets), regardless of focus on carbon or not, only capture firm-level or sector-level climate risks and can only partially explain sovereign climate risks. Peszko *et al.* (2020) is the only study I am aware of that has touched on the measurement of transitions risks for countries. However, their methodology focuses on fossil fuel revenue (e.g., oil exporting countries) and has limited external validity. Moreover, their measurement is only for year 2019

On the theory and structural modeling side, Mallucci (2020) and Phan & Schwartzman (2021) represent a nascent set of literature that examines the nexus between climate change and sovereign default though numerical methods. However, their papers mainly focus on physical hazard (e.g., hurricane and cyclones), and do not account for fiscal policy. Additionally, my chapter is related to two other strands of literature: 1) rare disaster risks; 2) climate change risks, especially the transition risks due to policy uncertainty. Rare disaster literature such as Barro (2006), Rebelo *et al.* (2018), and Gourio (2012) are informative in explaining the impact of extreme disaster events on asset pricing. But these studies do not directly address the risks of climate change, especially transition risks.[14] In the second type of studies, papers such as Barnett *et al.* (2020), Fried *et al.* (2021), Karydas & Xepapadeas (2019), Barnett (2019), Carattini *et al.* (2021), and Bretschger & Soretz (2018) quantify the transition risks of climate policy uncertainty, in relation to a wide range of issues including assess pricing, carbon taxation, and macroprudential policies,[15] but not sovereign debt default.[16]

[14]The main limitations of the rare disaster studies include: 1) Climate change risks have different probability distributions compared with rare disasters; 2) the framework of rare disaster cannot capture the transition risks posed by climate mitigation strategies, such as carbon taxation and technology innovation; 3) Investors could "price in" the risks of climate change, for example, based on firms' and countries' carbon emissions. Painter (2020) shows that investors are already pricing in climate risks in municipal bonds. Ilhan *et al.* (2020) show that investors in the option market price in climate policy uncertainty.

[15]Other relevant studies include Battiston *et al.* (2019) and Battiston & Monasterolo (2020)

[16]In particular, by modeling stochastic jump of oil input in aggregate production, Barnett (2019) shows that the transition risks of climate policy can lead to accelerated extraction of oil, leading to downward pressure on oil prices and valuation of oil firms. Similarly, Bretschger & Soretz (2018) measure policy risk in the form of carbon tax that follows a Poisson process, so that the model captures unexpected changes of taxation due to political and/or environmental reasons. The mechanism of climate policy in Karydas & Xepapadeas (2019) also follows a Poisson process. In comparison, the paper by Fried *et al.* (2021) models the policy risk as the probability of introducing a permanent, one-time carbon tax policy—thus the economy transitions between pre- and post-tax steady states. The mechanism of transition risk in my model is similar to Barnett (2019) and Bretschger & Soretz (2018) in that there is time-varying stochastic volatility of policy risk, as opposed to the one-time, permanent change as in Fried *et al.* (2021).

While a relatively new field, an increasing number of studies examine the link between climate change and sovereign debt default. But the main gap in the literature is that a government's ability to conduct fiscal adjustment is not properly accounted for. Moreover, another point requiring more attention is that physical and transition risks are not clearly differentiated or measured.[17] My chapter makes two main contributions to the literature. First, the empirical estimation of my chapter makes contributions by measuring the *vulnerability* to physical and transition risks of climate change separately. The analysis reveals such vulnerability, especially the aspects unrelated to physical hazards, increase sovereign default probabilities. My second contribution is the incorporation of fiscal rigidity into a qualitative sovereign default model, and the analysis shows how governments with unfavorable fiscal conditions can experience even higher default risks due to climate change.

3.3 Data

The main types of datasets used are climate vulnerability, climate disasters, sovereign default incidents, and macroeconomic control variables. All the data are historical observations, thus cannot directly measure the risks of climate change, which are forward-looking metrics. However, the data and empirical analysis do capture the *vulnerability* to climate risks. The dataset of the Notre Dame Global Adaptation Ini-

[17] The only exception is an empirical paper by Beirne *et al.* (2020), who do try to account for transition risk using carbon emission standards. But the transition risk measure is used more for a robustness test, and its importance is clearly understated in this paper. Specifically, this measure is based on the gap between carbon emission trend and target by 2050. For physical risks, their measure is based on sea-level exposure, agriculture's sensitivity to climate, and deaths due to climate extremes

tiative (ND-GAIN) measures a country's climate vulnerability[18] based on the exposure, sensitivity, and adaptive capacity of 6 areas: infrastructure, habitat, health, water, food, and ecosystem.[19] The vulnerability measure is a composite index based on 36 indicators including engagement in international environmental conventions, projected change of crop yields, water withdrawal rate, access to sanitation, biome distribution, and dependency on imported energy.[20] The measurement is constructed by scoring each indicator's distance to an ideal state for each country. The database is annual, covering years 1995–2018 for 184 countries.

The "climate vulnerability" variable in ND-GAIN in effect measures both a country's physical and transition susceptibility to climate change risks. In this dataset, the exposure component mainly measures the physical risks[21] from climate change, adaptive capacity component mainly measures the transition risks,[22] and the sensitivity component can measure both. Even with such classifications, however, it is not straightforward to delineate physical versus transition risks. Moreover, it is likely that physical risks and transition risks interact: for example, a snow storm may damage power grids, a physical risk, but may also reduce the affected area's electricity access and capacity in the longer term, a transition risk.

Thus it is necessary to properly measure non-physical climate vulnerability by decomposing the ND-GAIN data. There are two ways to achieve it: 1) Isolate

[18] Chen *et al.* (2015)

[19] GDP per capita and the *impact* of climate-related disasters are excluded from the index

[20] see Table 1 of Chen *et al.* (2015) for a complete list of indicators

[21] In the dataset, such indicators include flood hazard, precipitation, and population living under sea level

[22] In the dataset, such indicators include hydropower capacity, agricultural technology, environmental conventions, and health infrastructure

non-physical risks from overall climate risks, by using the residuals from regression of ND-GAIN and disasters; 2) Construct a new dataset similar to ND-GAIN but focus on transition risks only.[23] It is important to minimize the endogeneity bias of the climate measures by ensuring they are orthogonal to macroeconomic conditions. I use the variable "vulnerability, adjusted for GDP" from ND-GAIN, which is constructed from the combined residual (effect plus error term) from a regression of the original vulnerability variable against GDP per capita.[24] Therefore, the climate vulnerability measure I use from ND-GAIN is decoupled from each country's GDP per capita (this also implicitly detrends the variable).

To measure physical hazards, I use the Emergency Events Database (EM-DAT)[25] housed at the Centre for Research on the Epidemiology of Disasters (CRED), University of Louvain. It provides data of disaster events worldwide from 1900 and present. There are three types of variables in EM-DAT[26]: 1) Count of events by disaster subgroups: geophysical, meteorological, hydrological, climatological, and biological; 2) Count of events by disaster type: e.g., earthquake and drought; 3) Number of deaths, number of people affected, and economic losses. The EM-DAT dataset is monthly, but is aggregated to yearly frequency to match ND-GAIN.

While ND-GAIN is one of the most comprehensive measures of climate risks, it

[23] I plan to use select data series of ND-GAIN to construct such a measure

[24] This description is based on my own replication of the "vulnerability, adjusted for GDP" variable. The documentation from ND-GAIN is relatively vague: "There is a correlation between ND-GAIN scores and GDP per capita. To account for this, we introduce the 'GDP adjusted ND-GAIN score'. This score is defined as the distance of a country's measured ND-GAIN score and its expected value based on the regression of ND-GAIN and GDP." See the ND-GAIN website.

[25] This dataset is also used by the IMF to measure physical risks. See `https://climatedata.imf.org/pages/fi-indicators`

[26] `https://public.emdat.be/about`

may still suffer from endogeneity bias. Thus it is useful to include alternative measures that are commonly used in climate science. In this chapter, as robustness checks, I use temperature change data and the Palmer Drought Severity Index (PDSI).[27] The mean change of global surface temperature is from the National Aeronautics and Space Administration's Goddard Institute for Space Studies (NASA-GISS).[28] PDSI is based on precipitation and temperature data to measure relative dryness, thus one key effect of climate change. The original PDSI is monthly, gridded data of weather stations around the world (organized by geographic coordinates). In order to ensure they conform to the format of my estimation, I convert the gridded data to country-level by matching coordinates and taking the mean of all observations in each country.

To measure sovereign default, I use the BoC–BoE Sovereign Default Database by Beers *et al.* (2020). Covering 147 countries for years 1960 to 2019, the database records the events and amount of sovereign default organized by types of creditors. "Default" is defined as any material losses that investors experience due to the followings: 1) Nonpayment of debt service; 2) Maturity extension or interest rate reduction based on sovereign-creditors agreement; 3) Debt buyback or exchange at discount; 4) Currency redenomination from foreign to local currencies; 5) Sovereign debt swapped into equity; 6) Retrospective taxation on debt payments; 7) Converting central bank notes at discount.

The BoC-BoE dataset broadly identifies the creditor and currency types: i) Private creditors, including foreign currency bank loans ii) Official creditors: Interna-

[27]It seems not many economics papers, with the exception of Hong *et al.* (2019), have used PDSI data
[28]The data are downloaded through FAOSTAT Temperature Change

tional Monetary Fund (IMF), International Bank for Reconstruction and Development (IBRD), International Development Association (IDA), Paris Club, and China; iii) foreign currency bonds; iv) local currency debt.

The macroeconomic control variables come from the IMF World Economic Outlook, the Chicago Board Options Exchange's CBOE Volatility Index (VIX) are from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis, and the real effective exchange rate data[29] are from Bruegel.

3.3.1 Summary Statistics

Table 3.1 summarizes the key moments of the main variables: 1) Climate vulnerability from ND-GAIN—the higher the number, the greater the vulnerability; 2) Count of climate-related disasters from EM-DAT; 3) Incident of sovereign default on total debt from the BoC-BoE database; 4) Drought severity from PDSI—the lower the number, the relatively drier a country is; 5) Temperature anomaly (in celsius) with respect to the baseline years 1951–1980.

Since this is a panel data, the between-group and within-group moments are also reported. For the *within* measures, since they are calculated as the deviation from a country's mean, the minimum values of variables such as climate disasters and total sovereign default are negative.

There are three notable findings from the summary statistics: 1) Climate vulnerability exhibits relatively higher variability than other climate variables (especially

[29]The paper uses a narrow index of 67 trading partners

temperature anomaly), and the variability is driven by between-group variation; 2) The ranges of climate disasters are large for the overall, between, and within measures, despite relatively low standard deviations—suggesting that there are observations with very extreme values; 3) The unconditional probability of default in this sample is 3% (0.73 over years 1995-2018).

Table 3.1: Summary of Key Variables

Variable		**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
Climate vulnerability	*overall*	0.46	6.48	-12.75	21.13	N = 3240
	between		6.40	-10.85	18.90	n = 135
	within		1.13	-6.40	12.68	T = 24
Climate disasters	*overall*	1.51	2.44	0.00	30.00	N = 3408
	between		2.03	0.00	14.54	n = 142
	within		1.38	-7.37	18.63	T = 24
Total sovereign default	*overall*	0.73	0.44	0.00	1.00	N = 3408
	between		0.34	0.00	1.00	n = 142
	within		0.29	-0.23	1.69	T = 24
Palmer drought index	*overall*	-0.66	1.74	-6.69	5.89	N = 2080
	between		1.04	-4.22	1.86	n = 104
	within		1.39	-6.27	4.40	T = 20
Temperature anomaly	*overall*	0.89	0.50	-0.78	2.77	N = 2778
	between		0.28	0.17	1.48	n = 120
	within		0.42	-1.09	2.65	T-bar = 23.15

3.4 Empirical Estimation

In order to examine how climate risks affect sovereign default probability, I use a panel logit econometric specification shown in Equation 3.1.

$$\mathbf{Pr}\left[\,default_{\;it} = 1\right] = \gamma climate_{it} + \beta_k \mathbf{x}_{it} + u_i + \eta_t + e_{it} \tag{3.1}$$

where $default$ is a binary variable of whether country i has defaulted in year t (=1 if default). This variable is based on the BoC-BoE dataset, and can be examined in terms of default on total sovereign debt, debt to private creditor, local currency debt, debt to Paris Club, and debt to other official creditors.[30]

climate is a measure of vulnerability to climate change risks for each country in each year. At the baseline, I use the variable of ND-GAIN climate vulnerability, adjusted for GDP per capita. In other words, this baseline variable measures vulnerability to both the physical and transition risks of climate change.

Further, $\mathbf{x}_{it}$ refers to a vector of control variables: real GDP growth, fiscal balance (share of GDP), inflation rate, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and Chicago Board Options Exchange's CBOE Volatility Index (VIX). Most of these control variables are standard in the sovereign default literature, and VIX is included to control for correlates of the global financial cycle. u_i and η_t are year and country fixed effects, and e_{it} is the error term.

In addition, in order to disentangle transition risks from physical risks, I use the variable of climate-related natural disasters from EM-DAT. First, I add the EM-DAT climate disasters and their interaction terms with ND-GAIN climate vulnerability to Equation 3.1, in order to flesh out whether the impact of climate vulnerability depends on the frequency of climate-related natural disasters (in other words, whether physical hazards dominate the effect of the overall climate risks).

[30] My analysis is limited to these types of default, though the BoC-BoE dataset covers more types of creditors

Following Equation 3.2, I then create a new measure of vulnerability to transition risks by conducting a linear fixed effect regression:

$$climate_{it} = \xi disaster_{i,t-1} + u_i + \eta_t + transition_{it} \tag{3.2}$$

where climate vulnerability is the dependent variable and climate disasters (lagged by one period[31]) are the independent variable. The residuals $transition_{it}$ from the regression thus measure the components of climate risks that are not explained by physical hazards—thus vulnerability to transition risks.

3.4.1 Baseline Results

Table 3.2 shows the baseline regression following Equation 3.1, where the explanatory variable is the ND-GAIN climate vulnerability measure.[32] The original coefficients from the logit regression are in log-odds, thus difficult to interpret. In order to facilitate interpretation, the average marginal effects of climate vulnerability are reported. Column 1 of the table shows that higher climate vulnerability increases the default probability on total sovereign debt. In terms of magnitude, a percentage increase in climate vulnerability increases the default probability by 5.6 percentage points. The impact of climate vulnerability on defaulting on the private creditors is significant around the 89% level, and the magnitude of 7% is slightly bigger than that for total debt. Column 4 shows that the impact is significant for defaulting on Paris Club cred-

[31]This choice accounts for the possibility that the relationship between climate disasters and climate vulnerability are not contemporaneous

[32]The baseline regression is similar to that in Cevik & Jalles (2020a). My empirical analysis improves upon what is done in that paper as I decompose the climate vulnerability into physical and transition components. Moreover, the purpose of the empirical analysis here is to motivate the structural model in my chapter, whereas Cevik & Jalles (2020a) is a purely empirical paper

Table 3.2: Climate Vulnerability and Default Probability (Marginal Effects)

VARIABLES	(1) total	(2) private creditor	(3) local currency	(4) Paris Club	(5) Other official creditor
Climate vulnerability	0.056**	0.071	0.003	0.043***	0.036
	(0.027)	(0.043)	(0.040)	(0.017)	(0.023)
Observations	876	850	224	414	975
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows Equation (3.1), $\mathbf{Pr}\left[\, default_{\ it} = 1\right] = \gamma climate_{it} + \beta_k \mathbf{x}_{it} + u_i + \eta_t + e_{it}$. Average marginal effects are reported (instead of log-odds) to facilitate interpretation.
Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX.
"Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 5 is due to countries being dropped for lacking within-group variations

itors as well. The coefficients are also economically significant. Sovereign default are relatively rare events: the unconditional probability of sovereign default for a country is generally between 2.2% and 2.9% (in other words, at most once every 33 years).[33]

3.4.2 Extension: Transition Risks

In order to better measure physical and non-physical risks, I extend the baseline regression of Equation 3.1 to control for climate-related natural disasters and their interaction with climate vulnerability. To measure disasters, I use two variables from the EM-DAT dataset: meteorological and climatological disasters. Climatological disasters include examples such as drought, wildfire, and glacial lake outburst. Meteorological disasters include tropical storms, rain, tornado, and winter storm. In this chapter, "cli-

[33] See Reinhart *et al.* (2003) and Borensztein & Panizza (2009). By calculating the "liquidity premium" of bonds issued post-default, Sturzenegger & Zettelmeyer (2008) estimate the default probability to be 2.7%.

mate disasters" encompass meteorological, climatological, and hydrological disasters.[34]

Table 3.3 shows the results and reports the original coefficients of the logit regression. The purpose here is not necessarily to interpret individual coefficients, but to check whether the interaction of climate vulnerability and natural disasters are significant. As the table shows, for total debt and Paris Club debt, the majority of the interaction terms are not statistically significant. However, for debt owed to the private sector, the effect of climatological disasters on default probability is significant, and the interaction term between climate vulnerability and climatological disasters is positive and significant. This means that for a country that experiences more frequent climatological disasters, their climate vulnerability also has a bigger impact on the probability of defaulting on debt to the private sector. Nevertheless, the results for total debt and Paris Club echo that in Bolton & Kacperczyk (2021) where they find the effect of carbon emission does not depend on countries' physical risks. This suggests that the impact of climate vulnerability on default probability may have a weak association with the frequency of physical climate disasters.

The estimations so far, however, have yet to directly decompose climate vulnerability into the physical hazard and transition risks dimensions. To do so, I estimate Equation 3.2 using three types of specifications: 1) Climate disasters as a whole; 2) A combination of types of climate disasters; 3) Disasters lagged by one period. The results presented in Table 3.4 are interesting: overall, higher frequency of climate disasters decrease climate vulnerability, and the magnitudes of effect are bigger when the disasters

[34] hydrological disasters are not included in the regression here because they are significantly correlated with climate vulnerability, thus may lead to multicollinearity

Table 3.3: Climate Vulnerability, Disasters, and Default Probability (Log-Odds)

VARIABLES	(1) total	(2) private creditor	(3) Paris Club	(4) Other official creditor
Climate vulnerability	0.661**	0.372	1.666**	0.345
	(0.315)	(0.333)	(0.732)	(0.262)
Meteorological disasters	0.092	-0.015	0.281	0.080
	(0.116)	(0.144)	(0.542)	(0.180)
Climatological disasters	0.491	0.919*	-0.532	0.002
	(0.337)	(0.534)	(1.507)	(0.289)
Vulnerability *interact* Meteorological	-0.031	-0.006	0.323*	-0.026
	(0.030)	(0.034)	(0.188)	(0.032)
Vulnerability *interact* Climatological	0.056	0.155**	-0.251	-0.020
	(0.053)	(0.071)	(0.280)	(0.041)
Observations	566	623	257	652
Country FE	Yes	Yes	Yes	Yes
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 follows a variant of Equation (3.1) considering climate disasters and interactions between climate vulnerability and disasters, $\mathbf{Pr}\,[\,default_{\;it} = 1] = \gamma climate_{it} + \delta disasters_{it} + \xi(climate_{it} \times disasters_{it}) + \beta_k \mathbf{x}_{it} + u_i + \eta_t + e_{it}$. Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX.
Local currency default not reported here as the regression failed to converge.
"Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 4 is due to countries being dropped for lacking within-group variations

are lagged by 1 year. While seemingly counter-intuitive, this direction of effect makes sense: climate disasters induce more actions in mitigation and adaptation, thus reducing the overall vulnerability. Additionally, the effect is mainly driven by hydrological disasters (e.g., flood).

Most importantly, Table 3.4 suggests estimation that neglects transition risks (or only focus on natural disasters), thus not considering mitigation and adaption, may be misrepresenting the true direction of impact from climate change on sovereign default.

The estimation of residuals $transition_{it}$ from Equation 3.2 thus provides a possible solution. The original ND-GAIN variable measures the vulnerability to both physical and transition risks. Assuming climate disasters are good measurements of physical hazards, Equation 3.2 essentially means that the variable *disaster* explains well the physical risks. Thus controlling for country and year fixed effects, the residuals $transition_{it}$ measure the "vulnerability to transition risks." Table 3.8 in Appendix provides summary statistics of this variable by region.

Then I extend the baseline logit regression by using this newly constructed variable, which now appears on the right hand side as $climate_{it}$ in Equation 3.1. In other words, instead of the overall climate vulnerability, the estimation now specifically focuses on the vulnerability to transition risks, as the variable is decoupled from (uncorrelated with) climate-related physical hazards.

Table 3.5 shows the results, which demonstrate that vulnerability to transition risks are significant for default probability. The magnitudes of the effects are in fact on par or slightly bigger than those in the baseline shown in Table 3.2. In particular, for

Table 3.4: Regressions of Climate Vulnerability and Climate Disasters

VARIABLES	(1) climate vulnerability	(2) climate vulnerability	(3) climate vulnerability	(4) climate vulnerability	(5) climate vulnerability
Total climate	-0.037*				
	(0.020)				
Total climate (t-1)		-0.041**			
		(0.019)			
Climatological			-0.007	-0.016	
			(0.070)	(0.067)	
Meteorological			-0.021	-0.015	
			(0.048)	(0.045)	
Hydrological				-0.046**	
				(0.019)	
Climatological (t-1)					-0.041
					(0.064)
meteorological (t-1)					-0.018
					(0.041)
Hydrological (t-1)					-0.050***
					(0.019)
Observations	3,240	3,105	2,131	2,131	2,042
R-squared	0.023	0.024	0.017	0.019	0.022
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster	Cluster

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

Note: Regression specification follows Equation (3.2), $climate_{it} = \xi disaster_{i,t-1} + u_i + \eta_t + transition_{it}$. The residuals $transition_{it}$ from the regression thus measure the components of climate risks that are not explained by physical hazards—thus vulnerability to transition risks. "total climate" is a sum of climatological, meteorological, and hydrological disasters. According to EM-DAT, the definitions of these disasters are 1) Meteorological: "A hazard caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from minutes to days"; 2) Hydrological: "A hazard caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater"; 3) Climatological: "A hazard caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability" .

Table 3.5: Transition Risks Vulnerability and Default Probability (Marginal Effects)

VARIABLES	(1) total	(2) private creditor	(3) local currency	(4) Paris Club	(5) Other official creditor
Vulnerability to transition risks	0.054*	0.074*	-0.002	0.043***	0.034
	(0.028)	(0.043)	(0.043)	(0.016)	(0.023)
Observations	876	850	224	414	975
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows Equation (3.1), but using the transition risk vulnerability measure, $\mathbf{Pr}\left[\, default\ _{it} = 1\right] = \gamma climate_{it} + \beta_k \mathbf{x}_{it} + u_i + \eta_t + e_{it}$. Average marginal effects are reported (instead of log-odds) to facilitate interpretation.
Control variables: climate disasters, real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX.
"Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 5 is due to countries being dropped for lacking within-group variations

default on the private creditor, the coefficient is now 7.3% and significant. The result suggests that while existing studies tend to focus on physical risks such as hurricanes, transition risks may have already played an important role in sovereign default decisions.

Moreover, as Burke *et al.* (2015) suggest, climate change may have heterogeneous impact on the output and default risks for different regions. Therefore, it is important to conduct the estimation by different groups. Table 3.6 shows the how transition risks vulnerability affects the total default probability by geographic regions. Such effect is highly significant for Europe, Middle East, and South Asia. For Latin America, the coefficient is significant at the 78% confidence level. It is also striking that compared with Europe and Latin America, the differential impact for Southeast Asia and South Asia can be as big as 27.1 percentage points. Tables 3.10 and 3.11 in the Appendix provide additional estimations by region and by income group.

Table 3.6: Total Default Probability by Region (Marginal Effects)

TOTAL DEFAULT BY REGION	(1) Europe	(2) Latin America & Caribbean	(3) Middle East/North Africa	(4) Southeast Asia	(5) South Asia
Vulnerability to transition risks	0.056***	0.058	0.097***	0.165	0.327**
	(0.010)	(0.051)	(0.035)	(0.303)	(0.146)
Observations	222	237	136	72	74
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression specification follows Equation (3.1) using transition risk vulnerability. separately estimated for each region, $\mathbf{Pr}\,[\,default_{\ it} = 1] = \gamma climate_{it} + \beta_k \mathbf{x}_{it} + u_i + \eta_t + e_{it}$. Average marginal effects are reported (instead of log-odds) to facilitate interpretation.
Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX.

3.4.3 Extension: Fiscal Conditions

To show how fiscal conditions play a role in sovereign default probability, I extend the baseline estimation by considering such factors. The model in section (3.5) discusses in detail how fiscal rigidity, as a form of fiscal condition, may interact with climate risks in affecting default probability. There are limited cross-country data specifically measuring fiscal rigidity, and the Fiscal Rules dataset of IMF provides the best proxy for fiscal conditions. In this dataset, the key variables are categorical variables. I specifically use the variable called the budget balance rule (BBR); this rule places a constraint on the fiscal deficit and subsequently the debt ratio. In any particular year, if a government adopts or maintains a budget rule, the BBR variable is coded as 1; otherwise it is 0.

When adopting or maintaining a budget balance rule, a government exhibits fiscal efforts. Such efforts are the inverse of fiscal rigidity (Equation (3.10) in Section (3.5) illustrates this). In short, when a government has a budget balance rule, it can help reduce the fiscal rigidity. More specifically, the specification now includes the balance rule variable $rule_{it}$ and its interaction with the climate vulnerability variable.

$$\mathbf{Pr}\,[\, default_{\,it} = 1] = \eta(climate_{it} \times rule_{it}) + \gamma climate_{it} + \xi rule_{it} + \beta_k \mathbf{x}_{it} + u_i + \eta_t + e_{it} \tag{3.3}$$

Table (3.7) presents the results of the estimation. The direction of effect for the climate vulnerability variable is consistent with the baseline: higher vulnerability leads to higher default probability. The interaction term of vulnerability and budget rule can be interpreted the following way: having a fiscal rule in place, how default probability responds to climate vulnerability. With the exception of Paris Club debt, given a fiscal rule, increasing climate vulnerability continues to raise default probability. The overall effect of climate vulnerability and the budget rule is the sum of the main and interaction effects. Given a unit increase in vulnerability, the overall effects on debt owed to all investors, private creditors, and other official creditors are in fact negative. While the estimates are fiscal rule are relatively imprecise, the results suggest that reducing fiscal rigidity (having fiscal rule in place) could potentially alleviate the impact of climate risks on default probability.

3.4.4 Robustness Check

To check the robustness of Tables 3.2, 3.5, and 3.6, the control variables are lagged by one period. The results are reported in Tables 3.12, 3.13, and 3.14 in Appendix: in most cases, there are no major differences in the magnitudes nor significance. However, in Table 3.13 (the lagged version of Table 3.5), the coefficient for private cred-

Table 3.7: Climate Vulnerability with Fiscal Rule

VARIABLES	(1) total	(2) private creditor	(3) Paris Club	(4) Other official creditor
Vulnerability × Fiscal rule	0.031	0.174	-0.185	0.026
	(0.103)	(0.161)	(0.198)	(0.062)
Climate vulnerability	0.283	0.463*	0.332	0.229
	(0.191)	(0.252)	(0.484)	(0.196)
Fiscal rule	-0.804	-0.812	0.473	-0.940
	(0.809)	(0.938)	(1.299)	(0.750)
Observations	570	459	139	523
Country FE	Yes	Yes	Yes	Yes
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 follows Equation (3.3), $\mathbf{Pr}\,[\,default_{\,it} = 1] = \eta(climate_{it} \times rule_{it}) + \gamma climate_{it} + \xi rule_{it} + \beta_k \mathbf{x}_{it} + u_i + \eta_t + e_{it}$. Control variables: real GDP growth, inflation, unemployment rate. "Other official creditors" exclude the IMF and the World Bank.

itor is now significant at 87% percent. The coefficient for South Asia lost significance and magnitude. Nevertheless, the main results from the original estimation hold.

Further, I use alternative measures of vulnerability to climate risks—PDSI[35] and temperature anomaly. Estimations results are shown in Tables 3.15 and 3.16 in Appendix. The results are partly consistent with Table 3.2: using PDSI, climate change has a significant impact on the total default probability, and the coefficient is 3.3%. When using the measure of temperature anomaly, the significance only holds for the default probability on Paris Club debt. At minimum, Tables 3.15 and 3.16 confirm that by using PDSI and temperature anomaly, two measures commonly used by climate scientists, we still observe a significant relationship between climate change and sovereign

[35]The process of converting PDSI from gridded data to country data is not yet complete; there are some missing observations

default.

3.5 Model

In this section, I build a qualitative model of fiscal rigidity based on Faria *et al.* (2021), but incorporate climate risks and consider the interactions between such risks and fiscal conditions.

3.5.1 Environment

In this 2-period economy, there is a representative government and lender. The government issues debt to finance consumption. In this environment, I assume that climate risks, especially physical risks, affect productivity of the economy. There is emerging evidence that climate change, especially extreme heat, can create productivity loss, especially in labor and agriculture as shown in studies such as Zhao *et al.* (2021) and Ortiz-Bobea *et al.* (2021). To make the model tractable, the probability of being in the high-productivity state (or boom state) in period 2 is represented by p_s. The *higher* climate risks are, the *lower* p_s is.

The government's primary surplus is characterized by the difference between tax revenue and and expenditure, namely $E = T - G$.

In period 1, the debt issued is

$$\varphi = -E_0/q = -E_0(1+r) \tag{3.4}$$

where E_0 is the government's initial primary balance, q is the price of debt, and r is the interest rate.

In period 2, the government decides whether and how much to pay debt of its debt. The decision is based on the state of the economy s,

$$D_s = E_s^+ \tag{3.5}$$

where $0 \leq D_s \leq \varphi$ and is the amount of debt repayment.

In states $s \in \Gamma$, there are three broad cases of default:

1) Complete default. That is, $D_s = 0, \forall s \in \Gamma'$

2) Partial default if $\exists s \in \Gamma : 0 < D_s = E_s < \varphi$

3) No default if $0 < D_s = E_s = \varphi, \forall s \in \Gamma$. In this chapter, I focus on the cases of partial default.

Definition 1 (**2nd Period Primary Surplus**). *In the 2nd period, given the uncertainty of climate risk, the government's primary surplus is*

$$E_s = E_0 + \bar{A} \times \mathcal{I}_s \tag{3.6}$$

where $\bar{A} > 0$, *and with* $\mathcal{I}_s = \left(\frac{2(s-1)}{S-1} - 1\right) \in [-1, 1]$

(a) $\bar{A}$ *is amplitude of the income stream.* $\mathcal{I}_s$ *measures the degree to which the economy is in a good or bad state*

(b) The probability of a particular climate state $P = (p_s : s = 1, \ldots, S) > 0$*. That is,* $p_s > 0, \forall s = 1, \ldots, S$*. The higher* s *is, the better the state.*

The primary surplus of the government also faces fiscal disturbance that modulates the income stream $\bar{A}$. Fiscal disturbance is introduced as it helps with the forthcoming discussion of fiscal rigidity.

Definition 2 (**Fiscal disturbance**)**.**

$$\alpha = -\frac{\bar{A}}{E_0} \tag{3.7}$$

Here α captures the size of financing needs in relation to the 2nd period fiscal innovation.

3.5.2 Baseline Results

Having introduced some key definitions, in this section I derive expected repayment rate for this economy:

Proposition 1 (Default Rate)**.** *The repayment rate in state s is*

$$1 - \pi_s = \frac{E_0 + \bar{A}\mathcal{I}_s}{-(1+r)E_0},\ s \in \Gamma \tag{3.8}$$

The expected repayment rate is

$$1 - \tilde{\pi} = \frac{\sum_{s \in \Gamma} p_s \left(\alpha \mathcal{I}_s - 1\right)}{1+r} \tag{3.9}$$

Proof. The repayment rate is the calculated based on the 2nd period primary surplus (as in Equation 3.6), divided by the amount the debt issued in the 1st period (as in Equation 3.4). In other words, the government's cash available in the 2nd period is the amount available for debt repayment.

To derive the expected payment rate, first define $1 - \tilde{\pi} = \Sigma_{s \in \Gamma} p_s (1 - \pi_s)$. This means the expected payment rate is a weighted average of repayment rates across states. Using equation of fiscal disturbance Equation 3.7, substitute $\bar{A} = -\alpha E_0$ into Equation 1, we obtain $1 - \pi_s = \frac{\alpha I_s - 1}{1+r}$. Sum this over all possible states, and we obtain the expected repayment rate. $\square$

Equation 3.9 can be interpreted in the following ways: when the probability of being in a good climate state p_s increases, the expected default rate $\tilde{\pi}$ decreases. In other words, the expected repayment rate increases when climate risks decrease.

3.5.3 Results with Fiscal Rigidity

Now we introduce fiscal rigidity into the analysis. Recall in the empirical section that fiscal rigidity is an inter-temporal concept: it describes that the the current fiscal behavior (e.g., spending) is proportion to the future fiscal behavior. In the context of the model:

Definition 3 (**Fiscal Rigidity**).

$$\begin{aligned} &\eta_1 = \rho\eta_0 + (1-\rho)\bar{A} \\ &\Leftrightarrow \eta_1 = \rho\left(\eta_0 - \bar{A}\right) + \bar{A} \end{aligned} \tag{3.10}$$

where ρ is fiscal rigidity, and fiscal efforts in periods 1 and 2 are η_0 and η_1 respectively. Fiscal policy follows 'bad habit' if

$$\eta_1 \leq \eta_0 \Leftrightarrow \bar{A} \leq \eta_0$$

The 'bad habit' means that the fiscal effort in the second period is affected by that in the first period, and by the fiscal rigidity term ρ due to $\bar{A} \leq \eta_0$.

Since Equation (3.10) defines the relation between ρ and $\bar{A}$, we can endogenize fiscal disturbance as the following

$$\alpha(\rho) = -\frac{\bar{A}(\rho)}{E_0} \equiv \frac{\eta_1 - \rho\eta_0}{1-\rho}\frac{1}{-E_0}$$

The aforementioned results allow for the result of how climate change affects default probability, and the role of fiscal rigidity.

Proposition 2 (Climate Risk & Default)**.** *Climate risks, by making boom probability p_s less likely, increase default probability*

$$\frac{\partial\tilde{\pi}}{\partial p_s} = -\frac{\alpha\mathcal{I}_s - 1}{1+r} < 0 \tag{3.11}$$

where in partial default states, $\alpha\mathcal{I}_s - 1 > 0$.

This follows by taking partial derivative of Equation (3.9)

Proposition 3 (Rigidity & Default)**.** *Fiscal rigidity increases default probability*

$$\frac{\partial\tilde{\pi}}{\partial\rho} = \underbrace{\frac{\partial\tilde{\pi}}{\partial\alpha(\rho)}}_{<0} \quad \underbrace{\frac{\partial\bar{A}(\rho)}{\partial\rho}}_{\frac{\eta_1-\eta_0}{(1-\rho)^2}<0} > 0 \tag{3.12}$$

Proof. $\tilde{\pi} = 1 - \frac{\sum_{s\in\Gamma} p_s(\alpha(\rho)\mathcal{I}_s - 1)}{1+r} \Rightarrow \frac{\partial\tilde{\pi}}{\partial\alpha(\rho)} = -\frac{\sum_{s\in\Gamma} p_s\mathcal{I}_s}{1+r} < 0.$

Given $\alpha(\rho) = -\frac{\bar{A}(\rho)}{E_0} \equiv \frac{\eta_1-\rho\eta_0}{1-\rho}\frac{1}{-E_0}$, $\bar{A}(\rho) = \frac{\eta_1-\rho\eta_0}{1-\rho} \Rightarrow \frac{\partial\bar{A}(\rho)}{\partial\rho} = \frac{\eta_0(1-\rho)+(\eta_1-\rho\eta_0)}{(1-\rho)^2} = \frac{(\eta_1-\eta_0)}{(1-\rho)^2}$

Note we assume there is fiscal rigidity, or fiscal policy follows 'bad habit', thus $\eta_1 < \eta_0$, thus $\frac{\partial\bar{A}(\rho)}{\partial\rho} < 0$. Therefore $\frac{\partial\tilde{\pi}}{\partial\rho} > 0$. $\square$

Corollary 1 (Rigidity & Risk Premium)**.** *The sovereign default premium can be ex-*

pressed as

$$\begin{aligned} r^{pr} &= (1+r) - (1+i) \\ &= \left(\frac{\sum_{s\in\Gamma} p_s\left(\alpha(\rho)\mathcal{I}_s - 1\right)}{1-\widetilde{\pi}}\right) - \left(\frac{\sum_{s\in\Gamma} p_s\left(\alpha(\rho)\mathcal{I}_s - 1\right)}{\sum_{s\in\Gamma} p_s}\right) \end{aligned} \tag{3.13}$$

Thus can show that risk premium increases with fiscal rigidity

$$\left(r^{pr}\right)'(\rho) = \underbrace{\left(r^{pr}\right)'(\alpha)}_{<0}\underbrace{\alpha'(\rho)}_{<0} > 0 \tag{3.14}$$

Proof. $1+r = \left(\frac{\sum_{s\in\Gamma} p_s(\alpha(\rho)\mathcal{I}_s - 1)}{1-\widetilde{\pi}}\right)$ follows from Equation (3.9)

To derive he interest for the risk-free asset, note that the expected repayment rate is the weighted sum of actual repayment rate across state, or $1-\tilde{\pi} = \Sigma_{s\in\Gamma} p_s(1-\pi_s)$. When there is no default, $\pi_s = 0$, and then $\tilde{\pi} = 1 - \Sigma_{s\in\Gamma} p_s$. Thus $1+r = \left(\frac{\sum_{s\in\Gamma} p_s(\alpha(\rho)\mathcal{I}_s - 1)}{\sum_{s\in\Gamma} p_s}\right)$.

$\alpha'(\rho) = \frac{(\eta_1-\eta_0)}{(1-\rho)^2}\left(\frac{1}{-E_0}\right) < 0, where - E_0 > 0.$

Also $\left(r^{pr}\right)'(\alpha) = \frac{\partial r^{pr}}{\partial\alpha} + \frac{\partial r^{pr}}{\partial\tilde{\pi}} \cdot \frac{\partial\tilde{\pi}}{\partial\alpha} = \left(\frac{\sum_{s\in\Gamma} p_s\mathcal{I}_s}{1-\widetilde{\pi}}\right) - \left(\frac{\sum_{s\in\Gamma} p_s\mathcal{I}_s}{\sum_{s\in\Gamma} p_s}\right) + \frac{\sum_{s\in\Gamma} p_s(\alpha\mathcal{I}_s - 1)}{(1-\tilde{\pi})^2} \cdot \frac{\partial\tilde{\pi}}{\partial\alpha}$,

and now substitute with $\frac{\partial\tilde{\pi}}{\partial\alpha} = -\frac{\sum_{s\in\Gamma} p_s\mathcal{I}_s}{1+r}$ and $(1-\tilde{\pi})(1+r) = \sum_{s\in\Gamma} p_s(\alpha\mathcal{I}_s - 1)$,

$\left(r^{pr}\right)'(\alpha) = \frac{\sum_{s\in\Gamma} p_s\mathcal{I}_s(1-\tilde{\pi})(1+r)}{(1-\widetilde{\pi})^2(1+r)} - \left(\frac{\sum_{s\in\Gamma} p_s\mathcal{I}_s}{\sum_{s\in\Gamma} p_s}\right) - \frac{\sum_{s\in\Gamma} p_s(\alpha\mathcal{I}_s - 1)\sum_{s\in\Gamma} p_s\mathcal{I}_s}{(1-\widetilde{\pi})^2(1+r)}$

$= -\left(\frac{\sum_{s\in\Gamma} p_s\mathcal{I}_s}{\sum_{s\in\Gamma} p_s}\right) < 0.$

Thus $\left(r^{pr}\right)'(\rho) > 0$ follows from $\left(r^{pr}\right)'(\alpha) < 0$ and $\alpha'(\rho) < 0$. □

3.5.4 Scenario Analysis

In the results so far, I have shown that climate change risks and fiscal rigidity both affect sovereign default probability. More specifically, as climate risks increase, the probability of a being in a boom state p_s becomes less likely. This generally leads lower primary surplus in the 2nd period E_s, resulting in default probability $\tilde{\pi}$ to increase.

At the same time, if the government has high fiscal rigidity ρ, the fiscal innovation (disturbance) α decreases. This also leads to lower E_s, resulting in higher $\tilde{\pi}$. In both cases, as $\tilde{\pi}$ increase, the risk premium r^{pr} also increases.

Based on such baseline results, I further analyze the implications of the model given different scenarios of climate risks and fiscal conditions. In a simple 2-state case: high climate risk versus low climate risk, and the probability of low climate risk is fixed as p. In this 2-state case, and when there is no default, or $\tilde{\pi} = 0$, Equation (3.9) is simplified to

$$1 + r = p(\alpha - 1)$$

When endogenizing α, we now have

$$m(\boldsymbol{\rho}) = \alpha(\boldsymbol{\rho}) - 1 = -\frac{1}{E_0}\frac{\eta_1 - \boldsymbol{\rho}\eta_0}{1 - \boldsymbol{\rho}} - 1 \tag{3.15}$$

Definition 4. *Define*

$$L_\rho : 1 + r = m(\boldsymbol{\rho})p \tag{3.16}$$

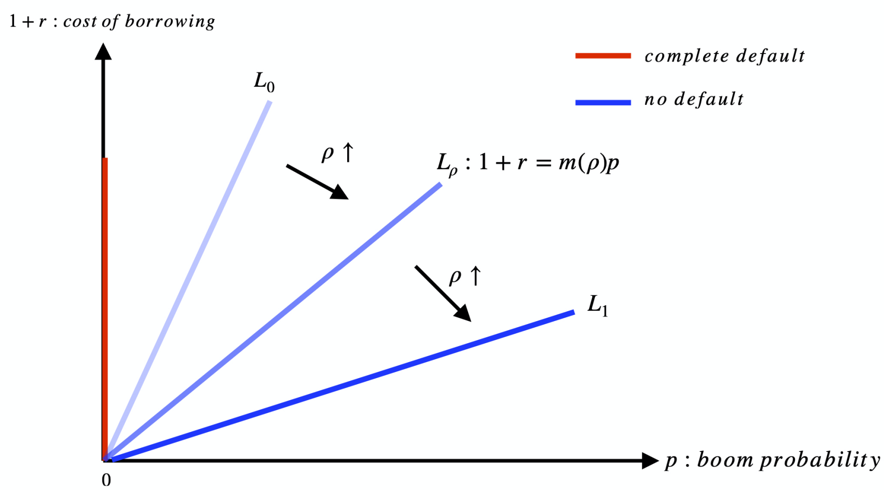
as the no default line, where $m(\boldsymbol{\rho}) = \alpha(\boldsymbol{\rho}) - 1 = -\frac{1}{E_0}\frac{\eta_1 - \boldsymbol{\rho}\eta_0}{1-\boldsymbol{\rho}} - 1$*, and* $m'(\boldsymbol{\rho}) < 0$

In other words, $m(\boldsymbol{\rho})$ is the slope of the line representing the relationship between between climate risks and cost of borrowing, and Figure (3.1) is a visual illustration of this. Since $m'(\boldsymbol{\rho}) < 0$, as ρ increases, $m(\boldsymbol{\rho}) < 0$ decreases. As shown in the figure, going from L_0 to L_1, the no-default line becomes flatter.

The region between the complete default line and the no default line is simply the partial-default region: when in this region, the government will default on part of its debt. When the no-default line becomes flatter, it also means that the partial-default region becomes wider. The fiscal rigidity parameter ρ governs the shift of the no-default line.

The implications of being in a wider default region is worth noting. Given the same cost of borrowing $1 + r$ (when fitting a horizontal line), when ρ is high, it requires much higher boom probability p for the government to not default. Given the same boom probability p (when fitting a vertical line), it is much more likely for a government with higher ρ to not be on the no-default line: for example, a small increase in $1 + r$ could induce the government to default.

Figure 3.1: Default Region by Fiscal Rigidity



To further analyze the interactions of fiscal rigidity and risk premium, first rewrite Equation (3.9) when in a world with no default (risk-free rate) as

$$R = \sum_{s \in \Gamma} p_s(\alpha I_s - 1) \tag{3.17}$$

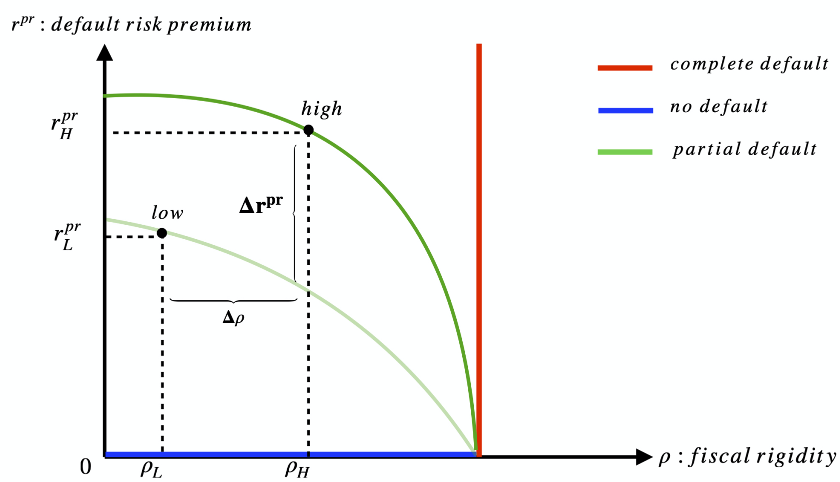
Substitute Equation (3.17) into Equation (3.9), and subtract both sizes by R, we obtain the following

$$r^{pr} = \frac{\tilde{\pi}}{1-\tilde{\pi}} R \tag{3.18}$$

In a 2-state world and with α endogenized, Equation (3.18) can be re-written as

$$r^{pr} = p\frac{\tilde{\pi}}{1-\tilde{\pi}}\left(\alpha(\boldsymbol{\rho}) - 1\right) = p\frac{\tilde{\pi}}{1-\tilde{\pi}} m(\boldsymbol{\rho}) \tag{3.19}$$

Figure 3.2: Risk Premium by Fiscal Rigidity



Using Equation (3.19), Figure (3.2) shows how default risk premium responds to fiscal rigidity. With ρ being a variable, and due to the functional form of $m(\boldsymbol{\rho})$, the relationship is a curve and non-decreasing in ρ. In this case, when ρ changes, so does $\tilde{\pi}$. Therefore, when ρ increases, the critical value of risk premium of the *partial default* line decreases due to both ρ and $\tilde{\pi}$.

The area between the curves and the horizontal axis is the no-default region. Here we can examine two scenarios: p is low versus high. The low p case is represented by the light green curve, while the high p case by the dark green curve. When the climate risks are low, or with high p, the no default region is larger.

In the low p scenario, when fiscal rigidity is high, or $\rho = \rho_H$, it is much easier for the government is reach the partial default line. In other words, when fiscal rigidity is high, the risk premium r^{pr} cannot increase as much before the government has to default, compared to when $\rho = \rho_L$. The same goes for the high p scenario. In other words, given the same climate scenario, investors are more willing to accept the risk premium when the fiscal rigidity is low.

At the same time, given the same fiscal rigidity, the lower the climate risks are (high p), the higher risk premium r^{pr} investors are willing to accept before a government has to default. The difference of the acceptable risk premium is illustrated as Δr^{pr} in the figure. Taken together, the results show that when climate risks are high, there is not much room to maneuver for a government with high fiscal rigidity. But a high degree of fiscal rigidity is acceptable if the exposure to climate risks can be reduced.

3.6 Conclusion

In this chapter, I investigate how climate change risks affect sovereign default probability, taking into account the role of fiscal rigidity. Improving upon existing literature that focus on physical risks, I also consider the transitions risks of climate change. First I use panel logistic regressions to show that vulnerability to transition risks has significant impact on sovereign default probability. In most cases, higher vulnerability implies higher default risk. Then the qualitative model in the chapter formalizes that fiscal rigidity reduces government's primary surplus, therefore increasing the default probability and cost of borrowing. When faced with climate risks, a government with high fiscal rigidity is much more financially constrained and less likely to convince lenders to continue financing, even if paying higher risk premium. The results suggest the importance of structural reform and improving efficiency in aspects of government financing. This can help reduce fiscal rigidity, which would then expand the financial options a government has, and contribute to a smoother path of green transition.

3.7 Appendix

Additional Figure

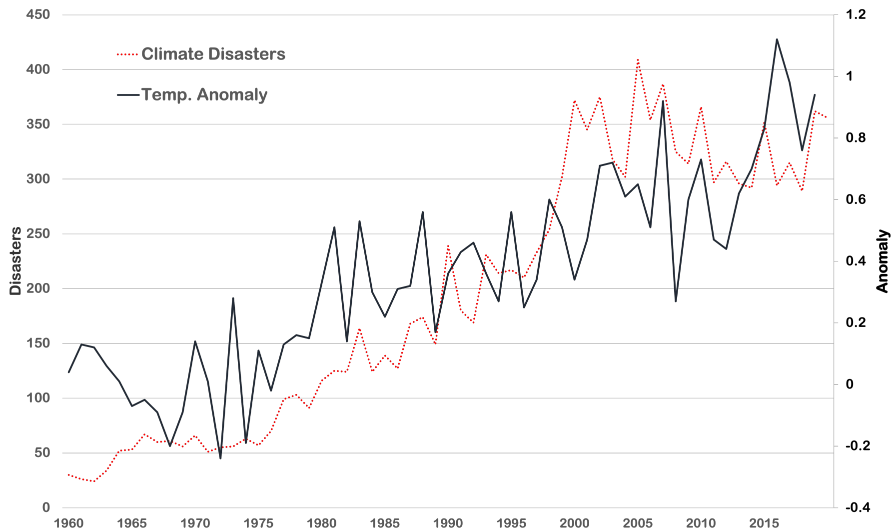


Figure 3.3: Global Climate Disasters and Temperature Anomaly

Sources: NOAA and Emergency Events Database (EM-DAT)

Table 3.8: Summary of Vulnerability to Transition Risks by Region

Region		Mean	Std. Dev.	Min	Max	Obs
World	*overall*	-3.34E-10	1.093	-6.498	11.544	N = 3105
	between		4.70E-09	-1.49E-08	2.25E-08	n = 135
	within		1.093	-6.498	11.544	T = 23
Central and East Asia	*overall*	-6.48E-10	1.441	-3.034	4.861	N = 138
	between		4.78E-09	-7.77E-09	5.18E-09	n = 6
	within		1.441	-3.034	4.861	T = 23
Europe	*overall*	-1.65E-09	1.591	-6.498	11.544	N = 391
	between		5.30E-09	-1.49E-08	7.77E-09	n = 17
	within		1.591	-6.498	11.544	T = 23
Latin America & Caribbean	*overall*	-7.28E-10	0.835	-3.065	2.872	N = 690
	between		4.10E-09	-8.10E-09	1.62E-08	n = 30
	within		0.835	-3.065	2.872	T = 23
Middle East/North Africa	*overall*	-1.09E-09	0.764	-2.251	2.363	N = 345
	between		2.76E-09	-6.80E-09	2.67E-09	n = 15
	within		0.764	-2.251	2.363	T = 23

Table 3.9: Summary of Vulnerability to Transition Risks by Region

Region		Mean	Std. Dev.	Min	Max	Obs
Oceania	*overall*	-1.47E-09	1.033	-2.608	4.096	N = 138
	between		1.95E-09	-4.54E-09	6.07E-10	n = 6
	within		1.033	-2.608	4.096	T = 23
South Asia	*overall*	-2.13E-09	1.247	-3.551	3.435	N = 207
	between		4.53E-09	-1.20E-08	1.66E-09	n = 9
	within		1.247	-3.551	3.435	T = 23
Southeast Asia	*overall*	5.58E-10	1.031	-3.086	3.254	N = 161
	between		4.61E-09	-5.18E-09	9.07E-09	n = 7
	within		1.031	-3.086	3.254	T = 23
Sub-Saharan Africa	*overall*	1.09E-09	1.040	-6.112	3.886	N = 1035
	between		5.47E-09	-7.77E-09	2.25E-08	n = 45
	within		1.040	-6.112	3.886	T = 23

Appendix: Additional Regressions by Region and Country Groups

Table 3.10: Default Probability on Private Creditor Debt by Region (Marginal Effects)

DEFAULT ON PRIVATE BY REGION	(1) Europe	(2) Latin America & Caribbean	(3) Southeast Asia	(4) South Asia
vulnerability to transition risks	-0.134***	0.125*	0.000	0.397
	(0.044)	(0.073)	(0.000)	(0.000)
Observations	171	271	48	54
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Average marginal effects are reported (instead of log-odds) to facilitate interpretation.
Control variables: real GDP growth, fiscal balance, inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX. Though not reported in a table, for Latin American & Caribbean, the effect of transition risks on the default probability on Paris Club debt is 0.173, and is significant at 99% level.

Table 3.11: Climate Vulnerability and Default Probability by Income Groups (Marginal Effects)

VARIABLES	(1) EM-total	(2) EM-private	(3) EM-Paris	(4) EM-other official	(5) Developing-total	(6) Developing-private	(7) Developing-other official
vulnerability to transition risks	0.038	0.055	0.020	0.002	0.165**	0.111	0.126
	(0.044)	(0.049)	(0.039)	(0.040)	(0.082)	(0.083)	(0.078)
Observations	515	542	176	553	250	253	292
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Average marginal effects are reported (instead of log-odds) to facilitate interpretation. Estimation includes the interaction effects of PDSI and meteorological disasters and climatological disasters; the interaction effects are not significant. Control variables: real GDP growth, fiscal balance, inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX. "Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 4 is due to countries being dropped for lacking within-group variations. "EM" stands for emerging market. "Developing" country group here excludes heavily indebted poor countries (HIPC).

Appendix: Robustness Test

Table 3.12: Climate Vulnerability and Default Probability, Control Vars$_{t-1}$ (Marginal Effects)

	(1)	(2)	(3)	(4)
VARIABLES	total	private creditor	Paris Club	Other official creditor
climate vulnerability	0.065**	0.067	0.038**	0.037
	(0.032)	(0.045)	(0.017)	(0.024)
Observations	814	793	395	930
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Average marginal effects are reported (instead of log-odds) to facilitate interpretation. Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX. "Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 4 is due to countries being dropped for lacking within-group variations

Table 3.13: Transition Risks Vulnerability and Default Probability, Control Vars$_{t-1}$ (Marginal Effects)

	(1)	(2)	(3)	(4)
VARIABLES	total	private creditor	Paris Club	Other official creditor
vulnerability to transition risks	0.064*	0.069	0.037**	0.036
	(0.033)	(0.045)	(0.016)	(0.024)
Observations	814	793	395	930
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Average marginal effects are reported (instead of log-odds) to facilitate interpretation. Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX. "Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 4 is due to countries being dropped for lacking within-group variations

Table 3.14: Total Default Probability by Region, Control Vars$_{t-1}$ (Marginal Effects)

TOTAL DEFAULT BY REGION	(1) Europe	(2) Latin America & Caribbean	(3) Middle East/North Africa	(4) Southeast Asia	(5) South Asia
vulnerability to transition risks	0.064**	0.082	0.094***	0.093	0.000
	(0.026)	(0.064)	(0.036)	(0.346)	(0.000)
Observations	190	226	129	68	71
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Average marginal effects are reported (instead of log-odds) to facilitate interpretation. Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX.

Table 3.15: PDSI and Default Probability (Marginal Effects)

VARIABLES	(1) total	(2) private creditor	(3) Paris Club	(4) Other official creditor
PDSI	0.033**	-0.002	-0.020	0.007
	(0.015)	(0.020)	(0.015)	(0.018)
Observations	438	454	265	461
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Average marginal effects are reported (instead of log-odds) to facilitate interpretation. Estimation includes the interaction effects of PDSI and meteorological disasters and climatological disasters; the interaction effects are not significant. Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX. "Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 4 is due to countries being dropped for lacking within-group variations

Table 3.16: Temperature Anomaly and Default Probability (Marginal Effects)

VARIABLES	(1) total	(2) private creditor	(3) local currency	(4) Paris Club	(5) Other official creditor
Temperature Anomaly	-0.036	-0.055	0.061	0.108*	-0.032
	(0.037)	(0.042)	(0.142)	(0.058)	(0.034)
Observations	774	688	177	281	850
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Robust SE	Cluster	Cluster	Cluster	Cluster	Cluster

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Average marginal effects are reported (instead of log-odds) to facilitate interpretation. Control variables: real GDP growth, fiscal balance (share of GDP), inflation, unemployment rate, debt to GDP ratio, change of real effective exchange rate, change of current account, change of GDP per capita, and VIX. "Other official creditors" exclude the IMF and the World Bank. The discrepancy of observation numbers between columns 1 and 5 is due to countries being dropped for lacking within-group variations

Bibliography

Acevedo, Sebastian. 2016 (Oct.). *Gone with the Wind; Estimating Hurricane and Climate Change Costs in the Caribbean.* IMF Working Papers 2016/199. International Monetary Fund.

Ackerman, Frank, Stanton, Elizabeth A., & Bueno, Ramón. 2013. Epstein–Zin Utility in DICE: Is Risk Aversion Irrelevant to Climate Policy? *Environmental and Resource Economics*, **56**(1), 73–84.

Aguilar, Jonathan, Gramig, Greta G., Hendrickson, John R., Archer, David W., Forcella, Frank, & Liebig, Mark A. 2015. Crop Species Diversity Changes in the United States: 1978–2012. *PLOS ONE*, **10**(8), 1–14.

Alonso, Javier, Hoyo, Carmen, & Tuesta, David. 2015. A model for the pension system in Mexico: diagnosis and recommendations. *Journal of Pension Economics and Finance*, **14**(1), 76–112.

Anzoategui, Diego. 2022. Sovereign spreads and the effects of fiscal austerity. *Journal of International Economics*, **139**, 103658.

Arellano, Cristina. 2008. Default Risk and Income Fluctuations in Emerging Economies. *American Economic Review*, **98**(3), 690–712.

Arellano, Cristina, & Bai, Yan. 2017. Fiscal austerity during debt crises. *Economic Theory*, **64**(4), 657–673.

Arteta, Carlos, & Hale, Galina. 2008. Sovereign debt crises and credit to the private sector. *Journal of International Economics*, **74**(1), 53–69.

Asonuma, Tamon, Chamon, Marcos, & Sasahara, Akira. 2016 (Nov.). *Trade Costs of Sovereign Debt Restructurings: Does a Market-Friendly Approach Improve the Outcome?* IMF Working Papers 2016/222. International Monetary Fund.

Asonuma, Tamon, Li, Xin, Papaioannou, Michael, & Thomas, Saji. 2018. Sovereign Debt Restructurings in Grenada: Causes, Processes, Outcomes and Lessons Learned. *Journal of Banking and Financial Economics*, **2**, 67–105.

Balke, Neele. 2023. *The Employment Cost of Sovereign Default.* Tech. rept.

Banks, James, Crawford, Rowena, Crossley, Thomas F., & Emmerson, Carl. 2013. Financial Crisis Wealth Losses and Responses among Older Households in England. *Fiscal Studies*, **34**(2), 231–254.

Barnett, Michael. 2019. A Run on Oil: Climate Policy, Stranded Assets, and Asset Prices.

Barnett, Michael, Brock, William, & Hansen, Lars Peter. 2020. Pricing Uncertainty Induced by Climate Change. *The Review of Financial Studies*, **33**(3), 1024–1066.

Barrell, Ray, Davis, E. Philip, & Pomerantz, Olga. 2006. Costs of financial instability, household-sector balance sheets and consumption. *Journal of Financial Stability*, **2**(2), 194–216.

Barro, Robert J. 2006. Rare Disasters and Asset Markets in the Twentieth Century*. *The Quarterly Journal of Economics*, **121**(3), 823–866.

Barro, Robert J., & Jin, Tao. 2011. On the Size Distribution of Macroeconomic Disasters. *Econometrica*, **79**(5), 1567–1589.

Battiston, Stefano, & Monasterolo, Irene. 2020. The Climate Spread of Corporate and Sovereign Bonds.

Battiston, Stefano, Jakubik, Petr, Monasterolo, Irene, Riahi, Keywan, & van Ruijven, Bas. 2019. Climate Risk Assessment of the Sovereign Bond Portfolio of European Insurers. Dec.

Bauer, Michael D., & Rudebusch, Glenn D. 2020. The Rising Cost of Climate Change: Evidence from the Bond Market.

Beers, David, Jones, Elliot, & Walsh, John. 2020. BoC–BoE Sovereign Default Database: Methodology, Assumptions and Sources. *Bank of Canada Technical Report*, **117**.

Beirne, John, Renzhi, Nuobu, & Volz, Ulrich. 2020. Feeling the Heat: Climate Risks and the Cost of Sovereign Borrowing. *ADBI Working Paper*, **1160**.

Blanchard, Olivier, & Perotti, Roberto. 2002. An Empirical Characterization of the

Dynamic Effects of Changes in Government Spending and Taxes on Output. *The Quarterly Journal of Economics*, **117**(4), 1329–1368.

Blickle, Kristian S., Hamerling, Sarah Ngo, & Morgan, Donald P. 2021 (Nov.). *How Bad Are Weather Disasters for Banks?* Staff Reports 990. Federal Reserve Bank of New York.

Blundell, Richard, Pistaferri, Luigi, & Preston, Ian. 2008. Consumption Inequality and Partial Insurance. *American Economic Review*, **98**(5), 1887–1921.

Bolstad, Parker, Frank, Sadie, Gesick, Eric, & Victor, David G. 2019. Flying blind: What do investors really know about climate change risks in the U.S. equity and municipal debt markets? *The Hutchins Center Working Papers.*

Bolton, Patrick, & Kacperczyk, Marcin. 2021. Global Pricing of Carbon-Transition Risk. Feb.

Bord, Vitaly M., Ivashina, Victoria, & Taliaferro, Ryan D. 2021. Large banks and small firm lending. *Journal of Financial Intermediation*, **48**, 100924.

Borensztein, Eduardo, & Panizza, Ugo. 2009. The Costs of Sovereign Default. *IMF Staff Papers*, **56**(4), 683–741.

Boz, Emine. 2011. Sovereign default, private sector creditors, and the IFIs. *Journal of International Economics*, **83**(1), 70–82.

Brei, Michael, Mohan, Preeya, & Strobl, Eric. 2019. The impact of natural disasters on the banking sector: Evidence from hurricane strikes in the Caribbean. *The Quarterly Review of Economics and Finance*, **72**, 232–239.

Bretschger, Lucas, & Soretz, Susanne. 2018. *Stranded Assets: How Policy Uncertainty affects Capital, Growth, and the Environment.* CER-ETH Economics working paper series 18/288.

Bunn, Philip, Le Roux, Jeanne, Reinold, Kate, & Surico, Paolo. 2018. The consumption response to positive and negative income shocks. *Journal of Monetary Economics*, **96**, 1–15.

Burke, Marshall, & Emerick, Kyle. 2016. Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy*, **8**(3), 106–40.

Burke, Marshall, Hsiang, Solomon M., & Miguel, Edward. 2015. Global non-linear effect of temperature on economic production. *Nature*, **527**(7577), 235–239.

Burke, Marshall, Davis, W. Matthew, & Diffenbaugh, Noah S. 2018. Large potential reduction in economic damages under UN mitigation targets. *Nature*, **557**(7706), 549–553.

Caldara, Dario, Fernández-Villaverde, Jesús, Rubio-Ramírez, Juan F., & Yao, Wen. 2012. Computing DSGE models with recursive preferences and stochastic volatility. *Review of Economic Dynamics*, **15**(2), 188–206.

Carattini, Stefano, Heutel, Garth, & Melkadze, Givi. 2021. Climate Policy, Financial Frictions, and Transition Risk. March.

Catalano, Michele, Forni, Lorenzo, & Pezzolla, Emilia. 2020a. Climate-change adaptation: The role of fiscal policy. *Resource and Energy Economics*, **59**, 101111.

Catalano, Michele, Forni, Lorenzo, & Pezzolla, Emilia. 2020b (Nov.). *Fiscal tools to reduce transition costs of climate change mitigation.* Working Papers 0265. Dipartimento di Scienze Economiche.

Cevik, Serhan, & Jalles, Joao. 2020a. An Apocalypse Foretold: Climate Shocks and Sovereign Defaults. *IMF Working Papers*, **20**(11).

Cevik, Serhan, & Jalles, João Tovar. 2020b. This Changes Everything: Climate Shocks and Sovereign Bonds.

Chen, C., Noble, I., Hellmann, J., Coffee, J., Murillo, M., & Chawla, N. 2015. University of Notre Dame Global Adaptation Index: Country Index Technical Report.

Chodorow-Reich, Gabriel, Darmouni, Olivier, Luck, Stephan, & Plosser, Matthew. 2021. Bank liquidity provision across the firm size distribution. *Journal of Financial Economics.*

Cortés, Kristle Romero, & Strahan, Philip E. 2017. Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, **125**(1), 182–199.

Cuadra, Gabriel, Sanchez, Juan M., & Sapriza, Horacio. 2010. Fiscal policy and default risk in emerging markets. *Review of Economic Dynamics*, **13**(2), 452–469.

Dai, Aiguo, & et al. 2019. *The Climate Data Guide: Palmer Drought Severity Index (PDSI).* https://climatedataguide.ucar.edu/climate-data/palmer-drought-severity-index-pdsi.

Daniel, Kent D, Litterman, Robert B, & Wagner, Gernot. 2016. Applying Asset Pricing Theory to Calibrate the Price of Climate Risk. November.

Deryugina, Tatyana. 2017. The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance. *American Economic Journal: Economic Policy*, **9**(3), 168–98.

Diffenbaugh, Noah S, Davenport, Frances V, & Burke, Marshall. 2021. Historical warming has increased U.S. crop insurance losses. *Environmental Research Letters*, **16**(8), 084025.

DiSalvo, Jim. 2021. Banking Trends: Is Small-Business Lending Local? *Federal Reserve Bank of Philadelphia*.

Dovis, Alessandro, Golosov, Mikhail, & Shourideh, Ali. 2016. *Political Economy of Sovereign Debt: A Theory of Cycles of Populism and Austerity.* NBER Working Papers 21948. National Bureau of Economic Research, Inc.

Eaton, Jonathan, & Gersovitz, Mark. 1981. Debt with Potential Repudiation: Theoretical and Empirical Analysis. *The Review of Economic Studies*, **48**(2), 289–309.

Engle, Robert F, Giglio, Stefano, Kelly, Bryan, Lee, Heebum, & Stroebel, Johannes. 2020. Hedging Climate Change News. *The Review of Financial Studies*, **33**(3), 1184–1216.

Etwire, Prince Maxwell, Koomson, Isaac, & Martey, Edward. 2022. Impact of climate change adaptation on farm productivity and household welfare. *Climatic Change*, **170**(1), 11.

Faria, J. R., McAdam, P., & Orrillo, J. 2021 (Dec.). *Serial sovereign default: the role of shocks and fiscal habits*. Working Paper Series 2629. European Central Bank.

FEMA. 2021. A Guide to the Disaster Declaration Process and Federal Disaster Assistance. *Federal Emergency Management Agency*. `https://www.fema.gov/pdf/rrr/dec_proc.pdf`.

Fernández-Villaverde, Jesús, Guerrón-Quintana, Pablo, Kuester, Keith, & Rubio-Ramírez, Juan. 2015. Fiscal Volatility Shocks and Economic Activity. *American Economic Review*, **105**(11), 3352–84.

Ferriere, Axelle. 2015. *Sovereign Default, Inequality, and Progressive Taxation*. Tech. rept.

FFIEC. 2015. A Guide to CRA Data Collection and Reporting. *Federal Financial Institutions Examination Council*. `https://www.ffiec.gov/cra/pdf/2015_CRA_Guide.pdf`.

FFIEC. 2021. *National Aggregates, 1996-2019*. `https://www.ffiec.gov/cra`.

Fink, Fabian, & Scholl, Almuth. 2016. A quantitative model of sovereign debt, bailouts and conditionality. *Journal of International Economics*, **98**, 176–190.

Fried, Stephie, Novan, Kevin, & Peterman, William. 2021. The Macro Effects of Climate Policy Uncertainty.

FSB. 2020. The Implications of Climate Change for Financial Stability.

GAO. 2019. Agricultural Lending: Information on Credit and Outreach to Socially Disadvantaged Farmers and Ranchers Is Limited. *United States Government Accountability Office: Report to Congressional Committees.*

Garbarino, Nicola, & Guin, Benjamin. 2021. High Water, No Marks? Biased Lending After Extreme Weather. *Journal of Financial Stability.*

Garbinti, Bertrand, Lamarche, Pierre, Lecanu, Charlélie, & Savignac, Frédérique. 2020. *Wealth effect on consumption during the sovereign debt crisis: Households heterogeneity in the Euro area.* Tech. rept.

Giese, Guido, Nagy, Zoltán, & Rauis, Bruno. 2021. Foundations of Climate Investing: How Equity Markets Have Priced Climate Transition Risks.

Goolgasian, Chris, & Delongchamp, Julie. 2020. *Climate 101: What Are Transition Risks?* `https://www.hartfordfunds.com/market-perspectives/climate-101-what-are-the-transition-risks.html`.

Gourio, François. 2012. Disaster Risk and Business Cycles. *American Economic Review*, **102**(6), 2734–66.

Gu, Grace Weishi. 2021. Sovereign Default, Trade, and Terms of Trade. *Macroeconomic Dynamics*, **25**(6), 1346–1380.

Hansen, James, Sato, Makiko, & Ruedy, Reto. 2012. Perception of climate change. *Proceedings of the National Academy of Sciences*, **109**(37), E2415–E2423.

Hatchondo, Juan Carlos, Martinez, Leonardo, & Roch, Francisco. 2022. Fiscal Rules and the Sovereign Default Premium. *American Economic Journal: Macroeconomics*, **14**(4), 244–73.

Herrera, Santiago, & Olaberria, Eduardo. 2020. *Budget Rigidity in Latin America and the Caribbean : Causes, Consequences, and Policy Implications*. International Development in Focus. World Bank.

Holland, Greg, & Bruyère, Cindy L. 2014. Recent intense hurricane response to global climate change. *Climate Dynamics*, **42**(3), 617–627.

Holmstrom, Bengt, & Tirole, Jean. 1998. Private and Public Supply of Liquidity. *Journal of Political Economy*, **106**(1), 1–40.

Hong, Harrison, Li, Frank Weikai, & Xu, Jiangmin. 2019. Climate risks and market efficiency. *Journal of Econometrics*, **208**(1), 265–281. Special Issue on Financial Engineering and Risk Management.

Hsiang, Solomon. 2016. Climate Econometrics. *Annual Review of Resource Economics*, **8**(1), 43–75.

ICC. 2012. *2012 International Energy Conservation Code*.

IEA. 2021. Net Zero by 2050: A Roadmap for the Global Energy Sector. `https://www.iea.org/reports/net-zero-by-2050`.

Ilhan, Emirhan, Sautner, Zacharias, & Vilkov, Grigory. 2020. Carbon Tail Risk. *The Review of Financial Studies*, **34**(3), 1540–1571.

IPCC. 2022. *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, UK and New York, NY, USA: Cambridge University Press.

Ivanov, Ivan, Macchiavelli, Marco, & Santos, João A. C. 2020. Bank Lending Networks and the Propagation of Natural Disasters. *Working Paper.*

Jappelli, Tullio, & Pistaferri, Luigi. 2014. Fiscal Policy and MPC Heterogeneity. *American Economic Journal: Macroeconomics*, **6**(4), 107–36.

Jeon, Kiyoung, & Kabukcuoglu, Zeynep. 2018. Income inequality and sovereign default. *Journal of Economic Dynamics and Control*, **95**, 211–232.

Jiang, Yong, Zhou, Zhongbao, & Liu, Cenjie. 2019. Does economic policy uncertainty matter for carbon emission? Evidence from US sector level data. *Environmental Science and Pollution Research*, **26**(24), 24380–24394.

Kahn, Matthew E, Mohaddes, Kamiar, Ng, Ryan N.C., Pesaran, M. Hashem, Raissi, Mehdi, & Yang, Jui-Chung. 2019 (August). *Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis.* Working Paper 26167. National Bureau of Economic Research.

Karantounias, Anastasios G. 2018. Optimal Fiscal Policy with Recursive Preferences. *The Review of Economic Studies*, **85**(4), 2283–2317.

Karydas, Christos, & Xepapadeas, Anastasios. 2019. Pricing climate change risks: CAPM with rare disasters and stochastic probabilities. Jan.

Keenan, Jesse M., & Mattiuzzi, Elizabeth. 2019. Climate Adaptation Investment and the Community Reinvestment Act. *Federal Reserve Bank of San Francisco: Community Development Research Brief*, **5**.

Kirsch, Florian, & Rühmkorf, Ronald. 2017. Sovereign borrowing, financial assistance, and debt repudiation. *Economic Theory*, **64**(4), 777–804.

Kling, Gerhard, Lo, Yuen C, Murinde, Victor, & Volz, Ulrich. 2018. Climate Vulnerability and the Cost of Debt.

Kling, Gerhard, Volz, Ulrich, Murinde, Victor, & Ayas, Sibel. 2021. The impact of climate vulnerability on firms' cost of capital and access to finance. *World Development*, **137**, 105131.

Klomp, Jeroen. 2017. Flooded with debt. *Journal of International Money and Finance*, **73**, 93–103.

Klusak, P., Agarwala, M., Burke, M., Kraemer, M., & Mohaddes, K. 2021. Rising Temperatures, Falling Ratings: The Effect of Climate Change on Sovereign Creditworthiness. Mar.

Koetsier, Ian. 2017. The fiscal impact of natural disasters. *Utrecht School of Economics Working Papers*.

Koetter, Michael, Noth, Felix, & Rehbein, Oliver. 2020. Borrowers under water! Rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation*, **43**, 100811.

Kotlikoff, Laurence, Kubler, Felix, Polbin, Andrey, Sachs, Jeffrey, & Scheidegger, Simon. 2021. MAKING CARBON TAXATION A GENERATIONAL WIN WIN. *International Economic Review*, **62**(1), 3–46.

Kreitman, Ty, & Cowley, Cortney. 2020. *Ag Banks Trim Farm Lending*. `https://www.kansascityfed.org/agriculture/agfinance-updates/ag-banks-trim-farm-lending/`.

Krueger, Philipp, Sautner, Zacharias, & Starks, Laura T. 2020. The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies*, **33**(3), 1067–1111.

Lizarazo, Sandra Valentina. 2013. Default risk and risk averse international investors. *Journal of International Economics*, **89**(2), 317–330.

Lorans, Thomas, & Moussavi, Julien. 2019. *How could climate change impact sovereign risk?* `https://www.ftserussell.com/research/how-could-climate-change-impact-sovereign-risk`.

MacDonald, Jim. 2021. *Small Farms, Big Differences*. https://www.usda.gov/media/blog/2010/05/18/small-farms-big-differences.

Mallucci, Enrico. 2020 (Dec.). *Natural Disasters, Climate Change, and Sovereign Risk*. FEDS Notes 2020-12-18-1. Board of Governors of the Federal Reserve System (U.S.).

McKenzie, David J. 2003. How do Households Cope with Aggregate Shocks? Evidence from the Mexican Peso Crisis. *World Development*, **31**(7), 1179–1199. Economic Crises, Natural Disasters, and Poverty.

McKenzie, David J. 2006. The Consumer Response to the Mexican Peso Crisis. *Economic Development and Cultural Change*, **55**(1), 139–172.

Meinerding, Christoph, Schüler, Yves Stephan, & Zhang, Philipp. 2020. Shocks to Transition Risk.

Michaud, Amanda, & Rothert, Jacek. 2018. Redistributive fiscal policies and business cycles in emerging economies. *Journal of International Economics*, **112**, 123–133.

Mkhaiber, Achraf, & Werner, Richard A. 2021. The relationship between bank size and the propensity to lend to small firms: New empirical evidence from a large sample. *Journal of International Money and Finance*, **110**, 102281.

Moore, Frances C., Obradovich, Nick, Lehner, Flavio, & Baylis, Patrick. 2019. Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. *Proceedings of the National Academy of Sciences*, **116**(11), 4905–4910.

Munoz, Ercio, & Olaberria, Eduardo. 2019 (Aug.). *Are Budget Rigidities a Source of Fiscal Distress and a Constraint for Fiscal Consolidation ?* Policy Research Working Paper Series 8957. The World Bank.

Nakamura, Emi, & Steinsson, Jón. 2018. Identification in Macroeconomics. *Journal of Economic Perspectives*, **32**(3), 59–86.

Neumann, James E., Willwerth, Jacqueline, Martinich, Jeremy, McFarland, James, Sarofim, Marcus C., & Yohe, Gary. 2020. Climate Damage Functions for Estimating the Economic Impacts of Climate Change in the United States. *Review of Environmental Economics and Policy*, **14**(1), 25–43.

NGFS. 2020. Guide to climate scenario analysis for central banks and supervisors. `https://www.ngfs.net/sites/default/files/medias/documents/ngfs_guide_scenario_analysis_final.pdf`.

NOAA. 2021. *Maximum Temperature.* `https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00005`.

Nordhaus, William D. 1992. An Optimal Transition Path for Controlling Greenhouse Gases. *Science*, **258**(5086), 1315–1319.

Nordhaus, William D. 2017. Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences*, **114**(7), 1518–1523.

Noy, Ilan, & Nualsri, Aekkanush. 2011. Fiscal Storms: Public Spending and Revenues in the Aftermath of Natural Disasters. *Environment and Development Economics*, **16**(Dec.), 113–128.

OECD. 2016. *OECD Reviews of Pension Systems: Mexico.*

Ortiz-Bobea, Ariel, Ault, Toby R., Carrillo, Carlos M., Chambers, Robert G., & Lobell, David B. 2021. Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, **11**(4), 306–312.

Painter, Marcus. 2020. An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, **135**(2), 468–482.

Peszko, Grzegorz, van der Mensbrugghe, Dominique, Golub, Alexander, Ward, John, Zenghelis, Dimitri, Marijs, Cor, Schopp, Anne, Rogers, John A., & Midgley, Amelia. 2020. *Diversification and Cooperation in a Decarbonizing World.* World Bank Publications, no. 34011. The World Bank.

Petkov, Ivan. 2019. The Economic Impact of Hurricanes in the US: Does Local Finance Matter? *Working Paper.*

Phan, Toan, & Schwartzman, Felipe. 2021. Climate Defaults and Financial Adaptation.

Pouzo, Demian, & Presno, Ignacio. 2016. Sovereign Default Risk and Uncertainty Premia. *American Economic Journal: Macroeconomics*, **8**(3), 230–66.

Rebelo, Sergio, Wang, Neng, & Yang, Jinqiang. 2018 (Sept.). *Rare Disasters, Financial Development, and Sovereign Debt.* NBER Working Papers 25031. National Bureau of Economic Research, Inc.

Reinhart, Carmen M, Rogoff, Kenneth S, & Savastano, Miguel A. 2003. Debt Intolerance. August.

Reisinger, Andy, Howden, Mark, Vera, Carolina, & et al. 2020. The Concept of Risk in the IPCC Sixth Assessment Report: A Summary of Cross-Working Group Discussions. *Intergovernmental Panel on Climate Change, Geneva.*

Sales-Sarrapy, Carlos, Solis-Soberon, Fernando, & Villagomez-Amezcua, Alejandro. 1998. Pension System Reform: The Mexican Case. *Pages 135–175 of: Privatizing Social Security*. NBER Chapters. National Bureau of Economic Research, Inc.

Sautner, Zacharias, van Lent, Laurence, Vilkov, Grigory, & Zhang, Ruishen. 2021. Pricing Climate Change Exposure.

Schlenker, Wolfram, & Roberts, Michael J. 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, **106**(37), 15594–15598.

Schüwer, Ulrich, Lambert, Claudia, & Noth, Felix. 2018. How do banks react to catastrophic events? evidence from Hurricane Katrina. *Review of Finance*, **23**(1), 75–116.

Sommer, Judith E., & Hines, Fred K. 1991 (July). *Diversity in U.S. Agriculture: A New Delineation by Farming Characteristics*. Agricultural Economic Reports 308152. United States Department of Agriculture, Economic Research Service.

Soto, Mauricio, & Karpowicz, Ms. Izabela. 2018 (Oct.). *Rightsizing Brazil's Public-Sector Wage Bill*. IMF Working Papers 2018/225. International Monetary Fund.

Sturzenegger, Federico, & Zettelmeyer, Jeromin. 2008. Haircuts: Estimating investor losses in sovereign debt restructurings, 1998–2005. *Journal of International Money and Finance*, **27**(5), 780–805.

Sufi, Amir. 2007. Bank Lines of Credit in Corporate Finance: An Empirical Analysis. *The Review of Financial Studies*, **22**(3), 1057–1088.

Thompson, Wyatt, Gerlt, Scott, Campbell, J. Elliott, Kueppers, Lara M., Lu, Yaqiong, & Snyder, Mark A. 2017. A cost of tractability? Estimating climate change impacts using a single crop market understates impacts on market conditions and variability. *Applied Economic Perspectives and Policy*, **39**(2), 346–362.

UNEP. 2021. *The Gathering Storm: Adapting to Climate Change in a Post-pandemic World - Adaptation Gap Report 2021*. Tech. rept.

USDA. 2000. Farm Resource Regions. *Agricultural Information Bullentin Number 760*. `https://www.ers.usda.gov/publications/pub-details/?pubid=42299`.

USDA. 2021. *Farm Structure: Classifying Diverse Farms*. `https://www.ers.usda.gov/topics/farm-economy/farm-structure-and-organization/farm-structure/`.

Vasilev, Aleksandar. 2018. Optimal fiscal policy with Epstein-Zin preferences and utility-enhancing government services: lessons from Bulgaria (1999-2016).

Vose, R.S., Easterling, D.R., Kunkel, K.E., LeGrande, A.N., & Wehner, M.F. 2017. Temperature changes in the United States. *Chap. 6 of:* Wuebbles, D.J., Fahey, D.W., Hibbard, K.A., Dokken, D.J., Stewart, B.C., & Maycock, T.K. (eds), *Climate Science Special Report: Fourth National Climate Assessment*, vol. I.

Walthall, C.L., Hatfield, J., & Backlund., P. 2012. Climate Change and Agriculture in the United States: Effects and Adaptation. *USDA Technical Bulletin*, **1935**.

Yamano, Norihiko, & Guilhoto, Joaquim. 2020 (Nov.). *CO2 emissions embodied in international trade and domestic final demand: Methodology and results using the OECD Inter-Country Input-Output Database.* OECD Science, Technology and Industry Working Papers 2020/11. OECD Publishing.

Zhao, Mengzhen, Lee, Jason Kai Wei, Kjellstrom, Tord, & Cai, Wenjia. 2021. Assessment of the economic impact of heat-related labor productivity loss: a systematic review. *Climatic Change*, **167**(1), 22.

Zymek, Robert. 2012. Sovereign Default, International Lending, and Trade. *IMF Economic Review*, **60**(3), 365–394.